ML4AI: What Next?

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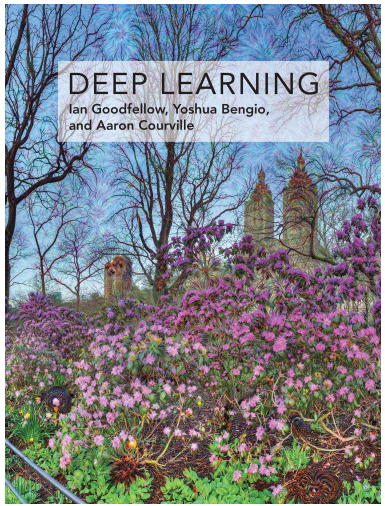

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ICRA INSTITUT CANADIEN DE RECHERCHES AVANCÉES

Current AI is far from Human-Level AI

- Sample complexity is too high for supervised learning, even more for RL
  - Real-world actions can be lethal, experience is limited & costly
  - We don’t have a good simulator of the real world (esp.w/ humans)
- High-level concepts typically need to be provided by human designers or labelers
- Errors made by trained systems reveal that their ‘understanding’ is very shallow and superficial
- The dream of deep learning discovering and disentangling high-level explanatory variables is far from achieved

What I don't believe works towards human-level AI

- NLP based purely on text
- Generative models purely on sensory data (generating images is cute, though)
- Relying on very strong prior knowledge (e.g. the graphics engine for vision)
- Working on algorithms with no chance to scale to brain-size (e.g., tabular distributions, non-distributed or non-learned representations
- Theories not compatible with the situation of animal/human agents, e.g., iid assumption
- Agents with a perfect simulator of the environment
- Planning in pixel space every 100ms

What Next?
Grounded Language Understanding

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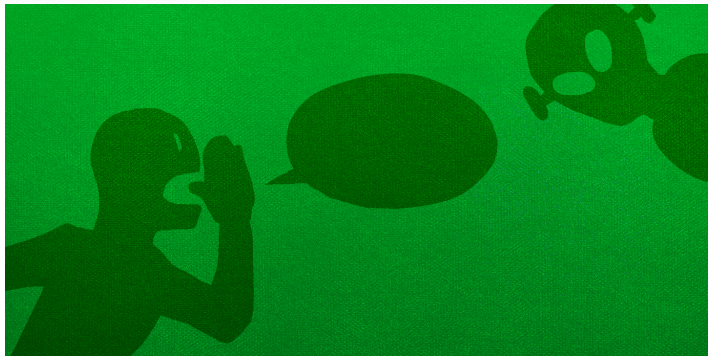
Alien Language Understanding: a Thought Experiment

- Imagine yourself approaching another planet and observing the bits of information exchanged by aliens communicating with each other

- Unlike on Earth, their communication channel is noisy, but like on Earth, bandwidth is expensive → the best way to communicate is to maximally compress the messages, which leads to sequences of random bits being actually exchanged.

- If we only observe the compressed messages, there is no way we can ever understand the alien language



Alien Language Understanding: a Thought Experiment

- How can we learn to understand the alien language?
- We need to do grounde language learning: we need to observe what the aliens are doing jointly with their messages, to try to decipher their intentions, context, etc.
- For this we need to build an 'Alien World Model' which captures the causal structure of their behaviors and resulting changes in their environment.

Jointly Learning Natural Language and a World Model

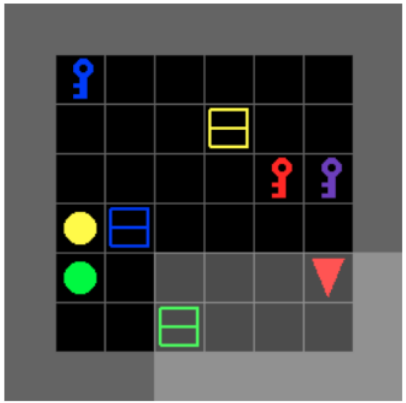
- Should we first learn a world model and then a natural language description of it?
- Or should agents jointly learn about language and about the world?
- I lean towards the latter.
- Consider top-level representations from supervised ImageNet classifiers. They tend to be much better and easier to learn than those learned by unsupervised learning. Why?
- Because language (here object categories) provides to the learner clues about relevant semantic high-level factors from which it is easier to generalize.
- See my earlier paper on cultural evolution, which posits that culture can help a learner escape from poor optimization, guide (through curricula) the learner to better explanations about the world.

BabyAI Platform *Chevalier-Boisvert et al & Bengio ICLR 2019*

Purpose: simulate language learning from a human and study data efficiency

Comprises:

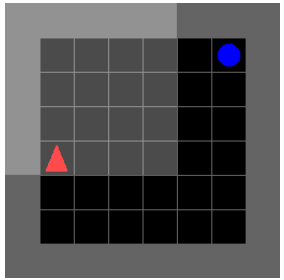
- a gridworld with partial observability (Minigrid)
- a compositional natural-looking Baby language with over 10^19 instructions
- 19 levels of increasing difficulty
- a heuristic stack-based expert that can solve all levels



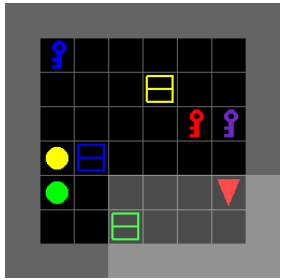
(b) PutNextLocal: "put the blue key next to the green ball"

github.com/mila-udem/babyai

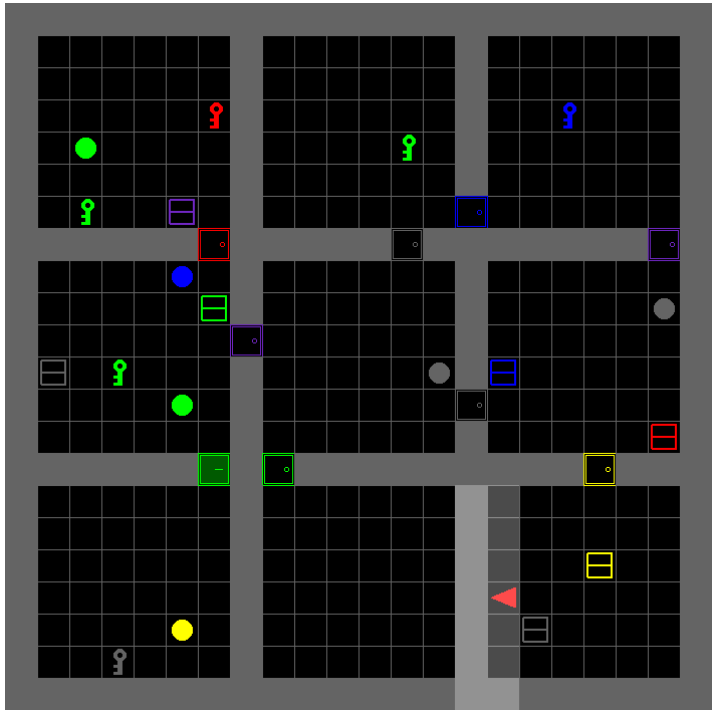
Early Steps in Baby AI Project



(a) GoToObj: "go to the blue ball"



(b) PutNextLocal: "put the blue key next to the green ball"



(c) BossLevel: "pick up the grey box behind you, then go to the grey key and open a door". Note that the green door near the bottom left needs to be unlocked with a green key, but this is not explicitly stated in the instruction.

- Designing and training experts for each level, which can serve as teachers and evaluators for the Baby AI learners
- Partially observable, 2-D grid, instructions about objects, locations, actions

go to the red ball

open the door on your left

put a ball next to the blue door

open the yellow door and go to the key behind you

put a ball next to a purple door after you put a blue box next to a grey box and pick up the purple box

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Integrating System 1 and System 2

- System 2 model is very coarse and imperfect
- System 2 abstract concepts need to be grounded via system 1
- System 2 thinking allows counterfactual reasoning, i.e., imagining scenarios which did not and will not happen, as an exercise (e.g. for credit assignment, if I had done that…), allows generalization far from the training data, imagine dangerous scenarios without having to take the actual risks
- System 2 is too slow and inefficient, compile to system 1 into habits and intuitive behavior

What Next? Generative Models in Latent Space

The Need for Unsupervised Learning

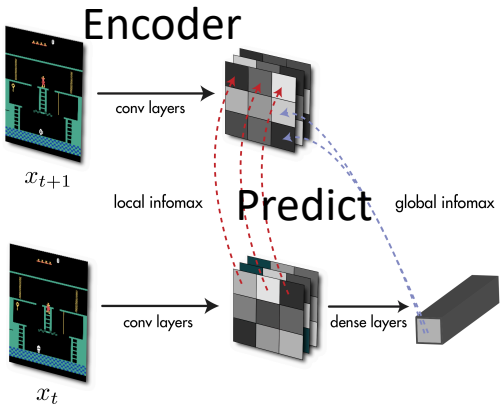
- **"The brain has about 10^14 synapses and we only live for about 10^9 seconds. So we have a lot more parameters than data. This motivates the idea that we must do a lot of unsupervised learning since the perceptual input (including proprioception) is the only place we can get 10^5 dimensions of constraint per second."**
  - Geoffrey Hinton
- Plus, unlabeled or un-rewarded data is much cheaper to obtain

Self-Supervised Learning

- Predict parts (or functions) of the data from other parts
  - E.g. denoising auto-encoders (some inputs are masked)
- SOTA in NLP is using self-supervised learning
  - Word2Vec, BERT, XLNet

Generative Models in Latent Space

- For human-like brains, generative models are useful for planning (**model-based RL**), imagination, counterfactuals, inference over causes and explanations, high-level credit assignment
  - NONE OF THIS REQUIRES WORKING IN PIXEL SPACE
- Current generative models are trained wrt pixel-space objectives, how to train purely in the space of abstract representations? We want the encoder mapping pixel space to abstract space to be trained wrt the high-level goals too.
- There is an issue of possible collapse of representations if we maximize predictability (e.g. max likelihood) in latent space

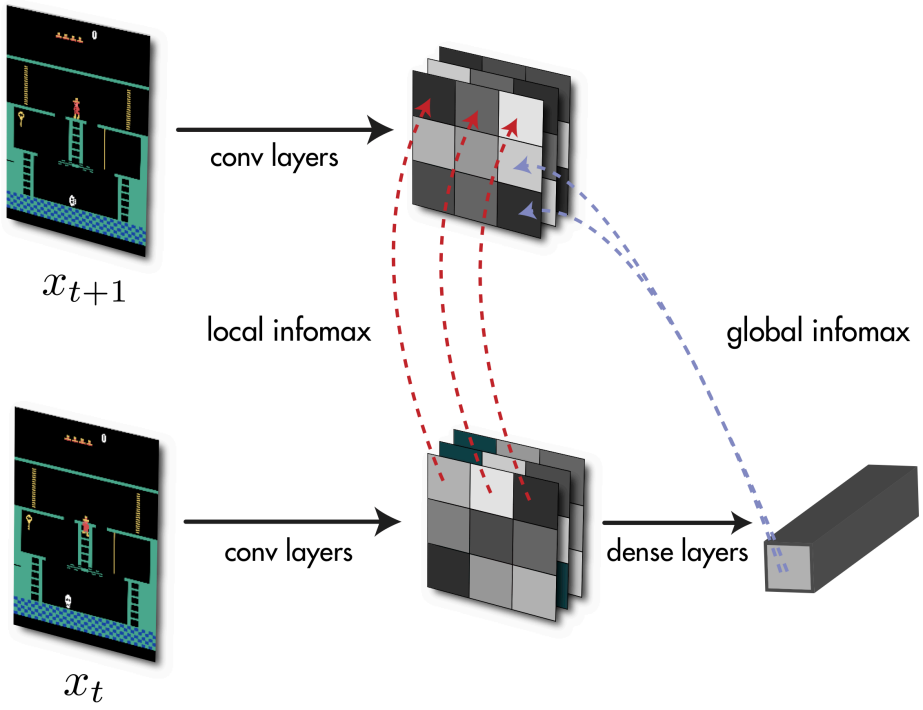


Spatio-Temporal Deep InfoMax (STDIM)

Self-supervised learning in latent space rather than data space

We can avoid the collapse by using entropy maximizagion or maximizing mutual information involving the encoder output

Deep InfoMax or DIM
(Hjelm et al & Bengio ICLR 2019)



Learning « How the world ticks »

- So long as our machine learning models « cheat » by relying only on superficial statistical regularities, they remain vulnerable to out-of-distribution examples

- Humans generalize better than other animals thanks to a more accurate internal model of the **underlying causal relationships**

- To predict future situations (e.g., the effect of planned actions) far from anything seen before while involving known concepts, an essential component of reasoning, intelligence and science

Generating Just Selected Dimensions: the Consciousness Prior

- Human planning, counterfactuals, reasoning, etc. does not take place over the full state-space (even at the abstract level)

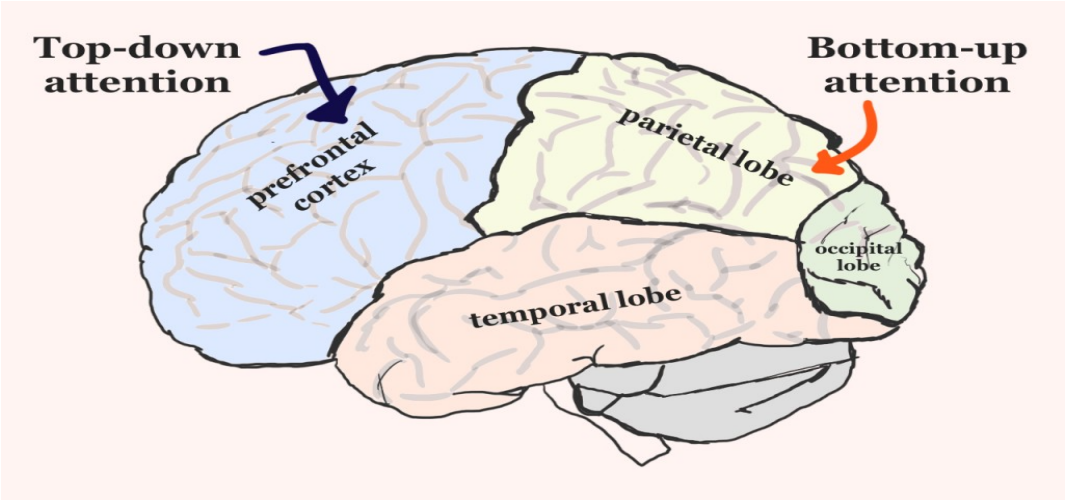
- If we don't predict and sample all high-level variables, what kind of training objective to use? again, not maximum likelihood even in latent space, because that would maximize P(full next state | full previous state)

- Again, information-theoretical objectives may come to the rescue, along with attention mechanisms to select what to predict about the future, what to pay attention to during learning

On the Relation between Abstraction, Thought and Attention

- **A thought is a low-dimensional object**, few aspects of the state
- Attention allows us to focus on a few elements out of a large set
- Soft-attention allows this process to be trainable with gradient-based optimization and backprop

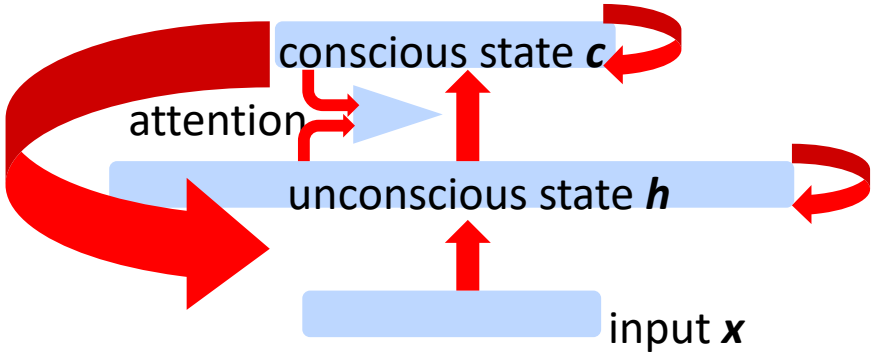
Attention focuses on a few appropriate abstract or concrete elements of mental representation



The Consciousness Prior

Bengio 2017, arXiv:1709.08568

- 2 levels of representation:
  - High-dimensional abstract representation space (all known concepts and factors) ***h***
  - Low-dimensional conscious thought ***c***, extracted from ***h***



- ***c*** includes names (keys) and values of factors

Why do I call it a Prior?

- There is something very special about the kind of high-level variables which we manipulate with language:
  - we can predict some given very few others
    - E.g. "if I drop the ball, it will fall on the ground"
  - corresponds to a sparse **factor graph**

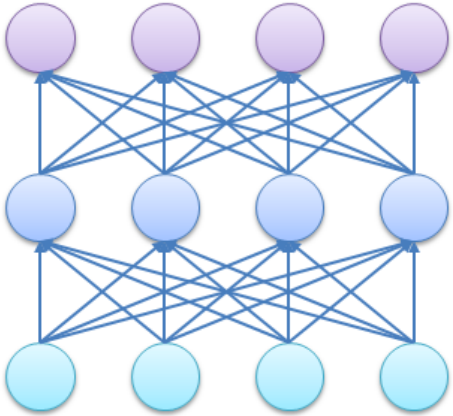
$$P(V) \propto \prod_k \phi(V_{s_k})$$

where V_{s_k} is the subset of V with indices s_k

What Next?
Linking Agency and Representation

How to Discover Good Disentangled Representations

- How to discover abstractions?
- What is a good representation? ***(Bengio et al 2013)***
- Need clues (= priors) to help **disentangle** the underlying factors (**not necessarily statistically independent**), such as
  - Spatial & temporal scales
  - Approximate marginal independence
  - Simple dependencies between factors
    - *Consciousness prior*
  - Causal / mechanism independence
    - *Controllable factors*



Acting to Guide Representation Learning & Disentangling

(E. Bengio et al, 2017; V. Thomas et al, 2017)

- **Some factors (e.g. objects) correspond to 'independently controllable' aspects of the world**
  - Corresponds to maximizing mutual information between intentions (goal-conditioned policies) and changes in the state (trajectories), conditioned on the current state.
- *Can only be discovered by acting in the world*
  - *Control linked to notion of objects & agents*
  - *Causal but agent-specific & subjective: affordances*

Unsupervised Agents & Intrinsic Rewards

- Curiosity, novelty, knowledge seeking
  - need to estimate model uncertainty, information gain
  - should be novel in the abstract space, not just pixel space
  - need to avoid the trap of inherently unpredictable (white noise TV)
  - must be not just novel but not easily explainable with current abstract model, requires learning (seek situations where you learn)
  - exploratory policy maximizes that while at the same time we train a model to explain away observations, i.e., minimize future surprises (adversarial setting)
  - when exploring, need to take safety into account (less so when you are young!)
- Controllability, empowerment
  - babies clearly learn to control their environment and their body
  - related to notion of freedom, maximizing entropy of set of future trajectories

What Next?
Transfer Learning and Meta-Learning

Meta-Learning / Learning to Learn

- Generalize the idea of hyper-parameter optimization
  - Inner loop optimization (normal training), a fn of meta-params

$$\theta_t(\omega) = \text{approxmin}_\theta C(\theta, \omega, \mathcal{D}^t_{train})$$

  - Outer loop optimization (meta-training), optimize meta-params

$$\omega = \text{approxmin}_\omega \sum_t L(\theta_t(\omega), \omega, \mathcal{D}^t_{test})$$

- Meta-parameters can be the learning rule itself (Bengio & Bengio 1991; Schmidhuber 1992), learn to optimize
- Meta-learn an objective or reward function, or a shared encoder
- Meta-learning can be used to learn to generalize or transfer
- Can backprop through θ_t , use RL, evolution, or other tricks

Missing from Current ML: Understanding & Generalization Beyond the Training Distribution

- Learning theory only deals with generalization within the same distribution
- Models learn but do not generalize well (or have high sample complexity when adapting) to modified distributions, non-stationarities, etc.
- Poor reuse, poor modularization of knowledge
- Meta-learning is an end-to-end learning approach to improving transfer learning and fast adaptation to changes in distribution

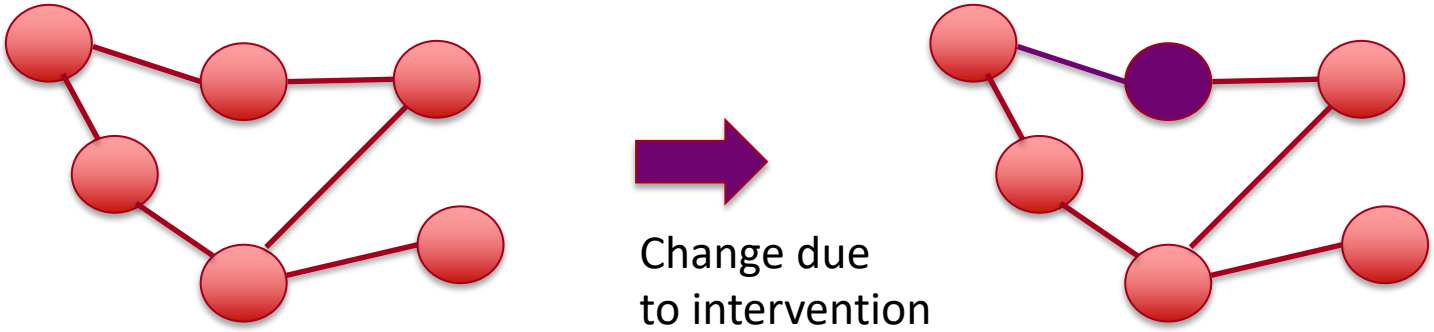
Beyond iid: Hypotheses about how the environment changes
Independent Mechanisms and the Small Change Hypothesis

- Independent mechanisms:
  - changing one mechanism does not change the others *(Peters, Janzig & Scholkopf 2017)*
- Small change:
  - Non-stationarities, changes in distribution, involve few mechanisms at a time (e.g. the result of a single-variable intervention)
- How can we discover these independent mechanisms, i.e., factor knowledge?

What Next?
Breaking Knowledge into Re-Composable Pieces

Separating Knowledge in Small Re-Usable Pieces

- Pieces which can be re-used combinatorially
- Pieces which are stable vs nonstationary, subject to interventions



Wrong Knowledge Factorization Leads to Poor Transfer

- With the wrong factorization P(B) P(A|B), a change in ground truth P(A) influences both modules, all the parameters
  - poor transfer: all the parameters must be adapted
- This is the normal situation with standard neural nets: every parameter participates to every relationship between all the variables
  - this causes ***catastrophic forgetting, poor transfer, difficulties with continual learning or domain adaptation, etc***

What Next?
Discovering Causal Variables and Causal Structure

Causality not Captured by Joint Distribution

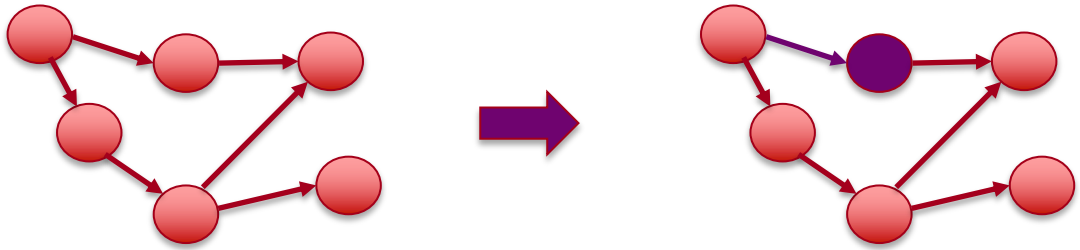
- Knowing the full joint distribution generally does not tell us which variable is a cause, which is an effect, and in general the question of causality may be meaningless in the wrong space
- Agents need to know about causal structure in order to properly infer how the joint distribution would change under interventions (theirs or of other agents)
- Understanding causal structure allows counterfactual reasoning and making sense of changes in distribution due to agents

Deep Learning Objective: discover high-level representation capturing cause and effect variables

- What are the right representations?
  - Causal variables explaining the data
- How to discover them? (learn the mythical encoder)
- How to discover their causal relationship, the causal graph?

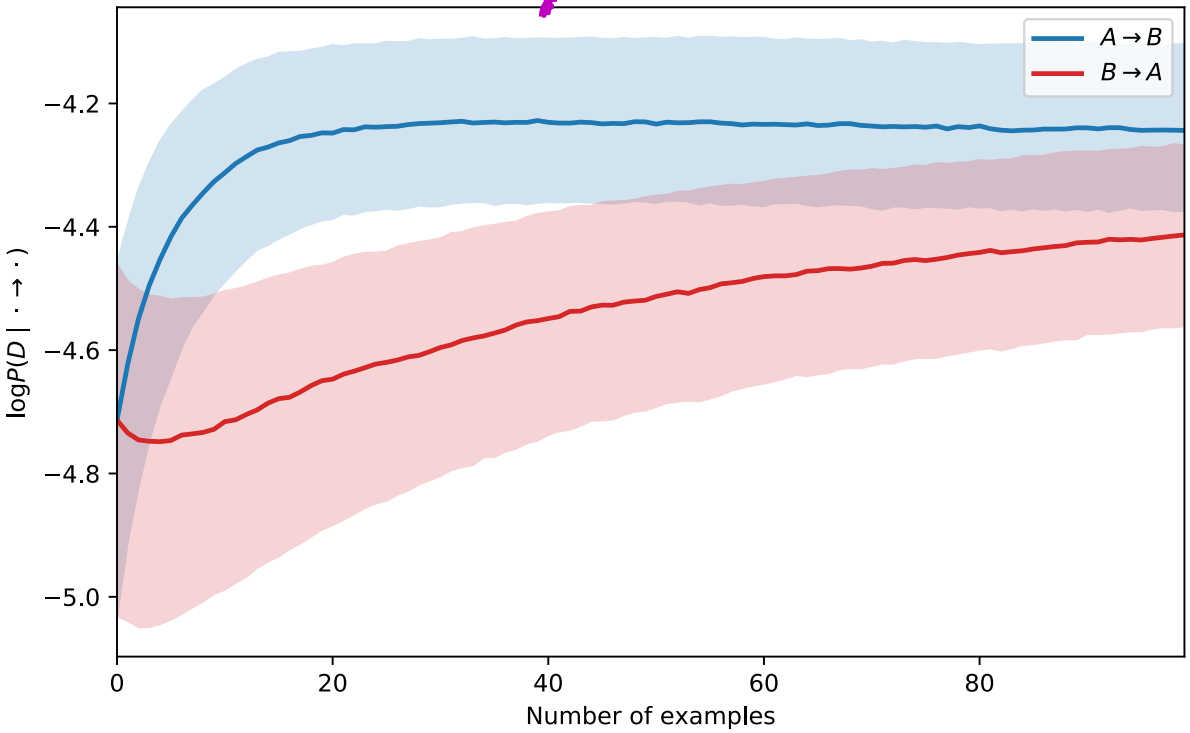
Small Change ➔ Small Sample Complexity

Few parameters need to change ➔ small L2 change ➔ few examples needed to recover from the change



Under the right parametrization ➔ fast adaptation to interventions

Empirical Confirmation: Correct Causal Structure Leads to Faster Adaptation



A→B is the correct causal structure: faster online adaptation to modified distribution = lower NLL regret

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Turning a Hindrance into a Useful Signal

ArXiv paper, Bengio et al 2019: *A Meta-Transfer Objective for Learning to Disentangle Causal Mechanisms*

- Changes in distribution (nonstationarities in agent learning, transfer scenarios, etc) are seen as a bug in ML, a challenge
- Turn them into a feature, an asset, to help discover causal structure, or more generally to help **factorize knowledge:**
- **Tune knowledge factorization (e.g. causal structure) to maximize fast transfer**
- *”Nature does not shuffle environments, we shouldn’t”*

L. Bottou

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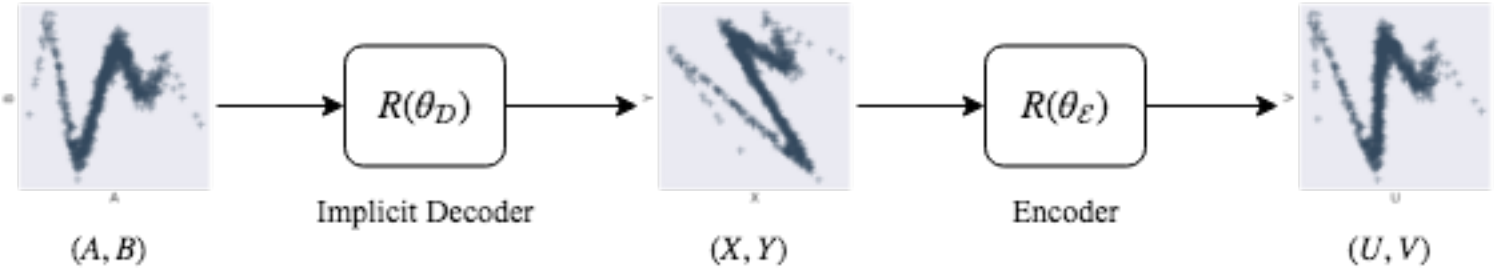
Disentangling the Causes

- Realistic settings: causal variables are not directly observed
- Need to learn an encoder which maps raw data to causal space
- Consider both the encoder parameters and the causal graph structural parameters as meta-parameters trained together wrt proposed meta-transfer objective



Experiments successful in 2-D with simple linear mappings, Bengio et al 2019.

Observing Other Agents

- Can infants figure out causal structure in spite of being almost passive observers?
- Yes, if they exploit and infer the interventions made by other agents
- Our approach does not require the learner to know what the action/intervention was (but it could do inference over interventions)
- But more efficient learning if you can experiment and thus test hypotheses about cause & effect

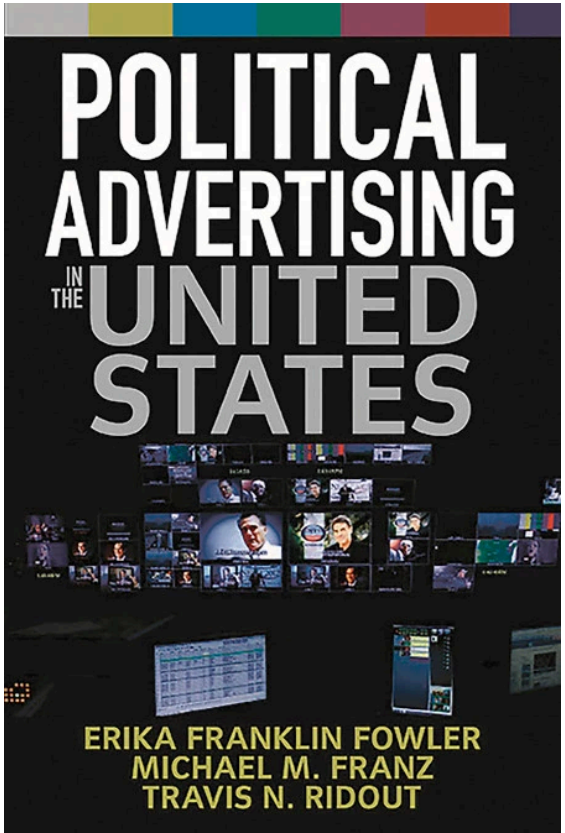
What about AI and Society?

Dangers and Concerns with AI

- Big Brother and killer robots
- Misery for jobless people, at least in transition
- Manipulation from advertising and social media
- Reinforcement of social biases and discrimination
- Increased inequality and power concentration in few companies

Advertising is Psychological Manipulation & Hurts Innovation

- **Moral hazard:**
  - Psychological manipulation: for who's benefit? The advertiser.
  - Targeting children forbidden in Canada because they are vulnerable
  - Political advertising
  - Need to draw a red line
- **Economic drag:**
  - favours large incumbants and thus slows innovation
- **Bad Nash equilibrium**



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Killer Robots: Moral & Security Threat

- 62% worldwide in favour of a ban to limit LAWS
- UN Secretary General: ’’The prospect of machines with the discretion and power to take human lives is morally repugnant… could trigger new arms races”
- 28 states calling for an international ban
- Leading AI scientists signed letters to governments
- 4000 Google employees named “Arms Control Person of the Year”
- Companies, countries, civil society must rise
- Example of landmines

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Applications I don't want to work on

- How does it fit with my values? Ask
  - How is this technology going to be used?
  - Who will benefit or suffer from it?
  - How much and what impact?
- I do not wish to work on
  - military applications, especially lethal autonomous weapons
  - ML to beat the stock market
  - increasing the efficiency of advertising
  - increasing the efficiency of oil & gas industry, meat industry…

The Wisdom Race

- Collective and individual wisdom has increased, e.g., the decrease in crimes, wars and extreme poverty
- But not fast enough to catch up with the rise in power of the tools we are building, which enable power concentration and can be dangerous
- This gives those with influence, in particular AI researchers, a responsibility

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Montreal Declaration: Ten Principles

Well-being

Respect for autonomy

Protection of privacy

Solidarity

Democratic participation

Equity

Diversity

Prudence

Responsibility

Sustainable development