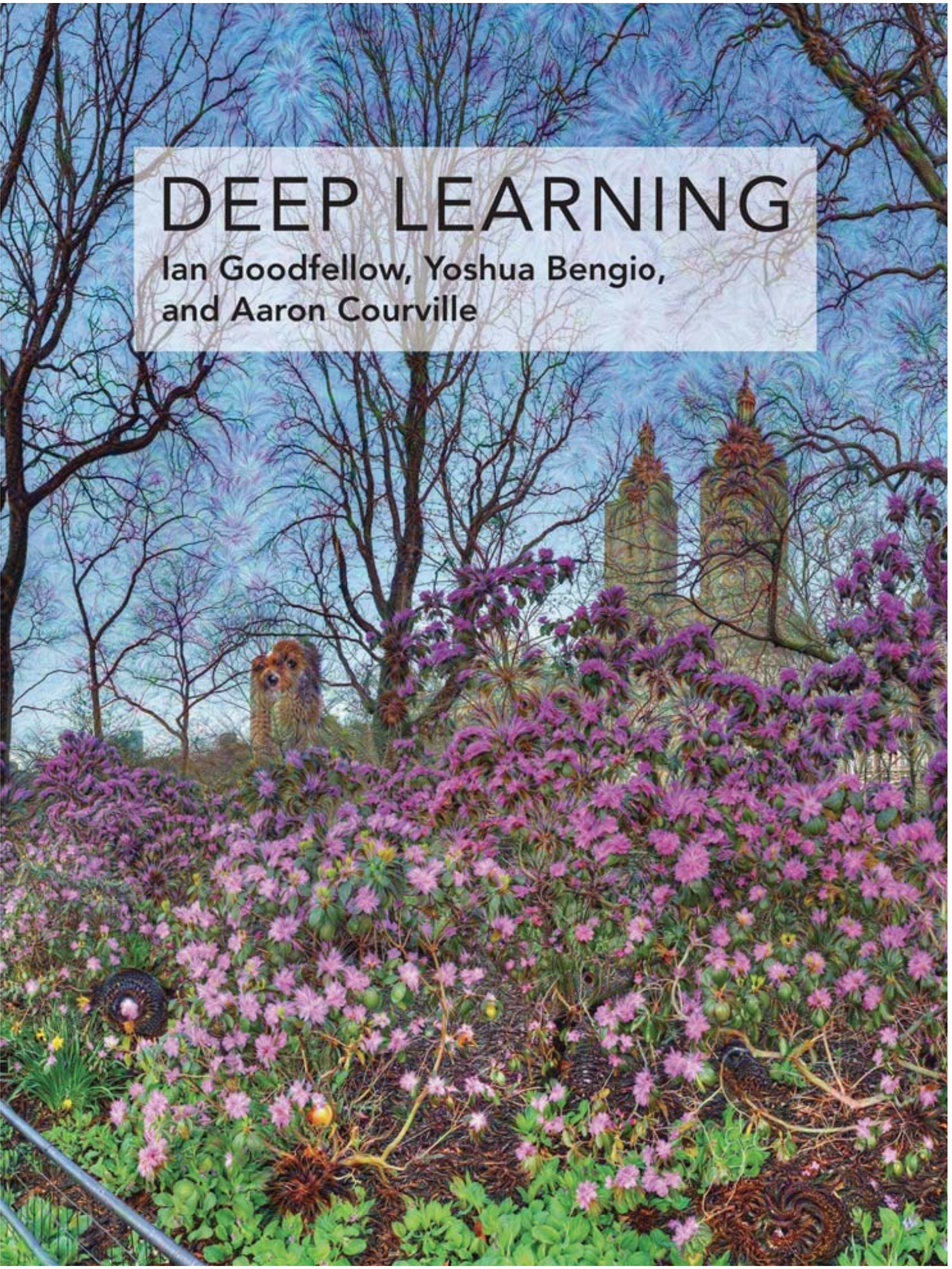

FROM SYSTEM 1 DEEP LEARNING TO SYSTEM 2 DEEP LEARNING

YOSHUA BENGIO

NeurIPS'2019 Keynote
December 11th, 2019, Vancouver BC

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Université de Montréal

CIFAR | ICRA
CANADIAN INSTITUTE FOR ADVANCED RESEARCH | INSTITUT CANADIEN DE RECHERCHES AVANCÉES

THE STATE OF **DEEP LEARNING**

Just get a bigger brain?

Amazing progress in this century

- Is it enough to just grow datasets, model sizes, computer speed?

Still far from human-level AI!

- Sample efficiency
- Human-provided labels
- Stupid errors
- Next step completely different from deep learning?

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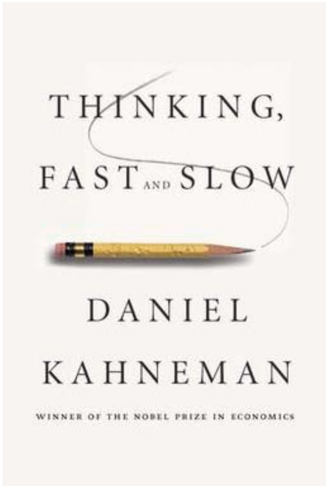
SYSTEM 1 VS. SYSTEM 2 COGNITION

2 systems (and categories of cognitive tasks):

Manipulates high-level / semantic concepts, which can be recombined combinatorially

System 1

- Intuitive, fast, **UNCONSCIOUS**, non-linguistic, habitual
- Current DL



System 2

- Slow, logical, sequential, **CONSCIOUS**, linguistic, algorithmic, planning, reasoning
- Future DL

MISSING TO EXTEND DEEP LEARNING TO REACH **HUMAN-LEVEL AI**

- **Out-of-distribution generalization & transfer**
- **Higher-level cognition: system 1 → system 2**
  - *High-level semantic representations*
  - *Compositionality*
  - *Causality*
- **Agent perspective:**
  - *Better world models*
  - *Knowledge-seeking*
- **Connections between all 3 above!**

CONSCIOUSNESS FUNCTIONALITIES: **ROADMAP FOR PRIORS EMPOWERING SYSTEM 2**

- ML Goals: handle changes in distribution, necessary for agents
- System 2 basics: attention & consciousness
- Consciousness prior: sparse factor graph
- Theoretical framework: meta-Learning, localized change hypothesis, causal discovery
- Structured architecture: operating on sets of pointable objects with dynamically recombined modules

DEALING WITH CHANGES IN DISTRIBUTION

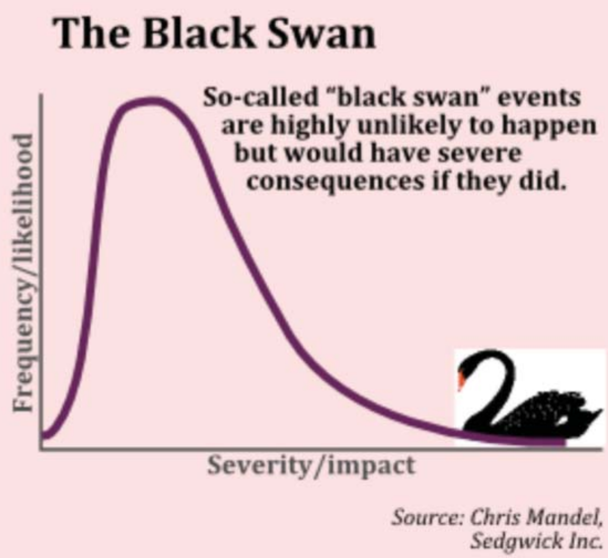
FROM **IID TO OOD**

Classical ML theory for iid data

Artificially shuffle the data to achieve that?

Out-of-distribution generalization

No free lunch: need new assumptions to replace iid assumption, for ood generalization



AGENT LEARNING NEEDS **OOD GENERALIZATION**

Agents face non-stationarities

Changes in distribution due to

- their actions
- actions of other agents
- different places, times, sensors, actuators, goals, policies, etc.

Multi-agent systems: many changes in distribution
Ood generalization needed for continual learning

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COMPOSITIONALITY HELPS IID AND OOD GENERALIZATION

Different forms of compositionality

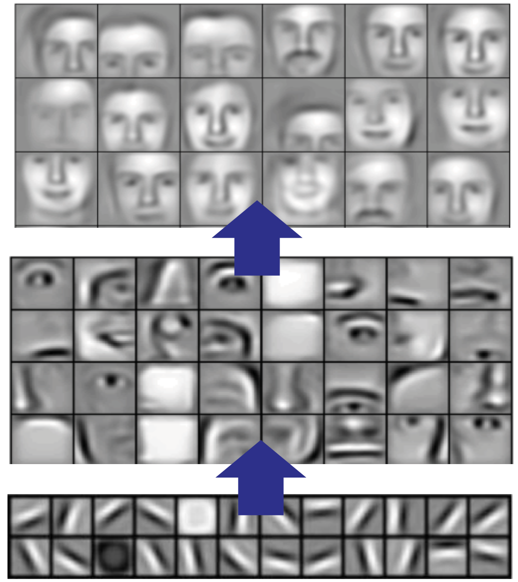
- Distributed representations

  (Pascanu et al ICLR 2014)

- Composition of layers in deep nets

  (Montufar et al NeurIPS 2014)

- **Systematic generalization in language, analogies, abstract reasoning? TBD**



(Lee, Grosse, Ranganath & Ng, ICML 2009)

SYSTEMATIC GENERALIZATION

- Studied in linguistics
- **Dynamically recombine existing concepts**
- Even when new combinations have 0 probability under training distribution
  - E.g. Science fiction scenarios
  - E.g. Escaping a car by hitting the glass window with a headrest
- Not very successful with current DL

(Bahdanau et al & Courville ICLR 2019)
(Lake & Baroni 2017)

(Lake et al 2015)

CONTRAST WITH **THE SYMBOLIC AI PROGRAM**

Avoid pitfalls of classical AI rule-based symbol-manipulation

- Need efficient large-scale learning
- Need semantic grounding in system 1
- Need distributed representations for generalization
- Need efficient = trained search (also system 1)
- Need uncertainty handling

But want

- Systematic generalization
- Factorizing knowledge in small exchangeable pieces
- Manipulating variables, instances, references & indirection

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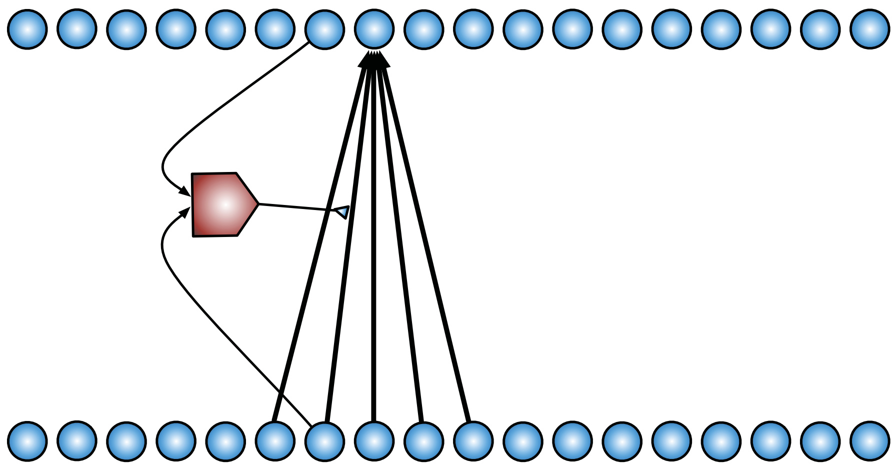
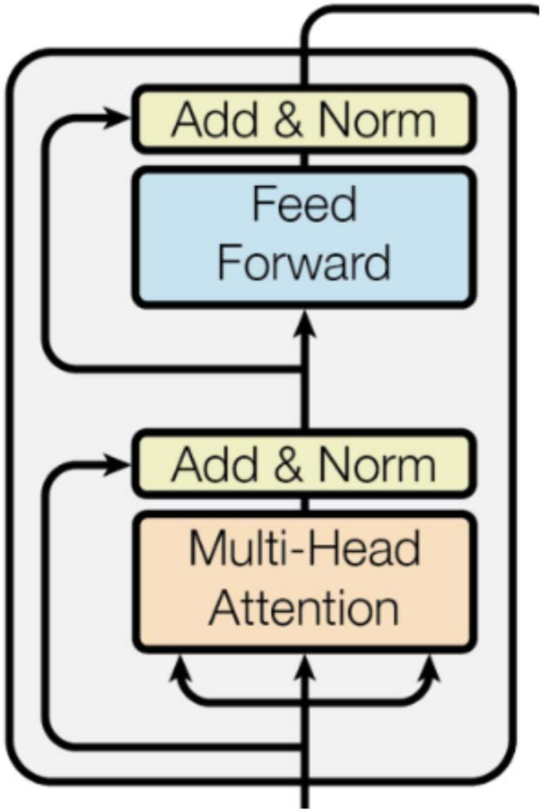
SYSTEM 2 BASICS: ATTENTION AND CONSCIOUSNESS

CORE INGREDIENT FOR CONSCIOUSNESS: **ATTENTION**

- **Focus** on a one or a few elements at a time
- **Soft attention** is convenient, can backprop to learn where to attend
- Attention is an internal action, needs a **learned attention policy** *(Egger et al 2019)*

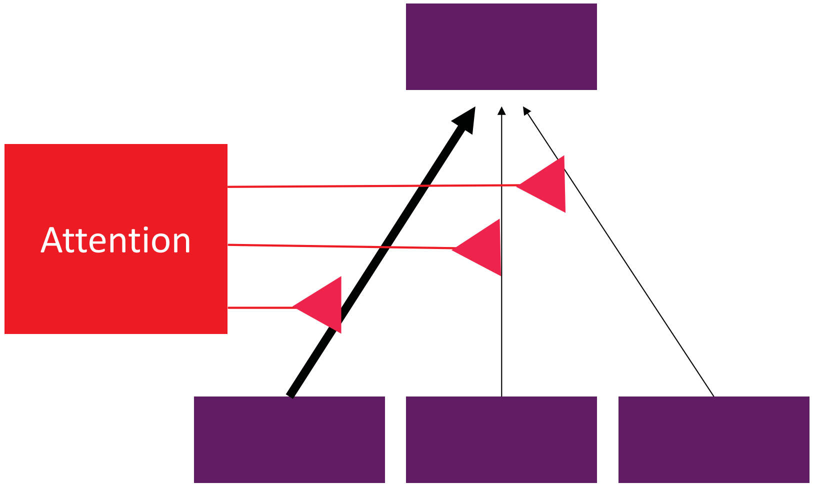


ATTENTION BENEFITS



- Neural Machine Translation revolution
  (Bahdanau et al ICLR 2015)
- Memory-extended neural nets
- Address vanishing gradients *(Ke & al NeurIPS 2018)*
- SOTA in NLP (self-attention, transformers)
- Operating on unordered SETS of (key, value) pairs

FROM ATTENTION TO **INDIRECTION**



- Attention = dynamic connection
- Receiver gets the selected value
- Value of what? From where?

  → Also send 'name' (or key) of sender
- Keep track of 'named' objects: indirection
- Manipulate sets of objects (transformers)

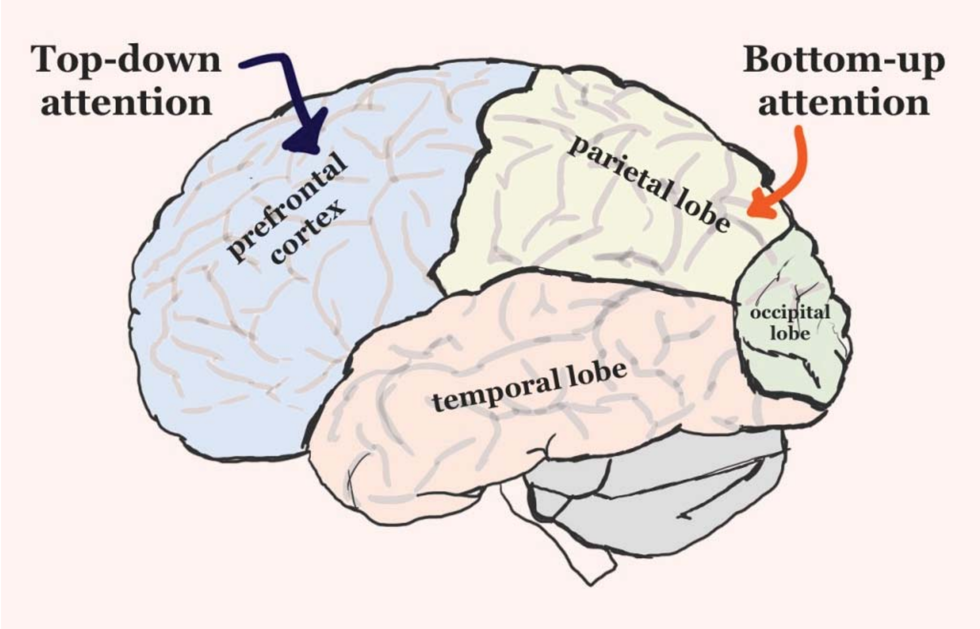
FROM ATTENTION TO **CONSCIOUSNESS**

C-word not taboo anymore in cognitive neuroscience

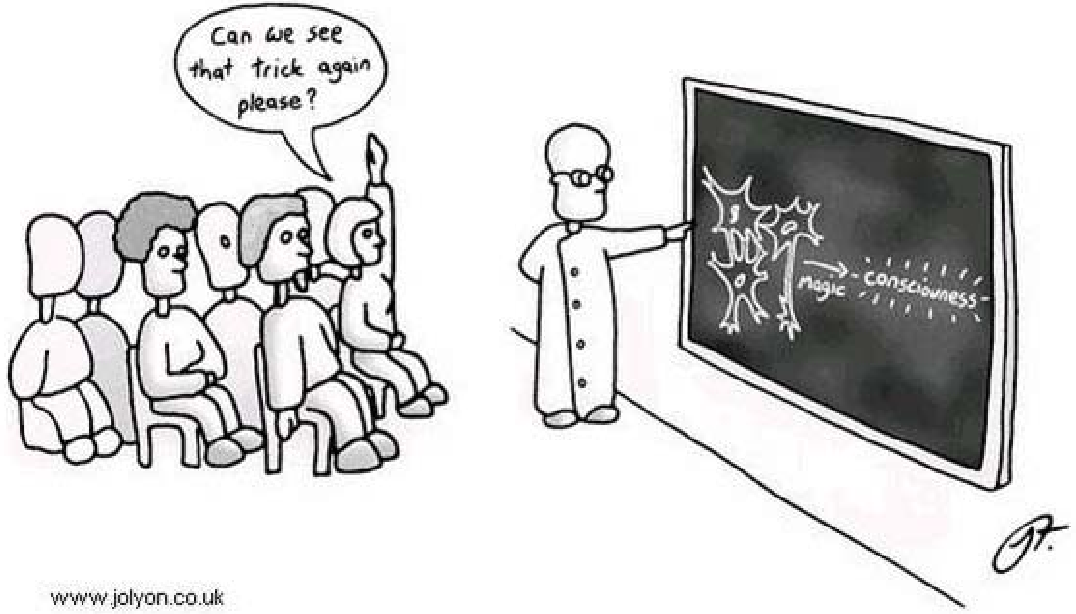
Global Workspace Theory

(Baars 1988++, Dehaene 2003++)

- Bottleneck of conscious processing
- Selected item is broadcast, stored in short-term memory, conditions perception and action
- System 2-like sequential processing, conscious reasoning & planning & imagination



ML FOR CONSCIOUSNESS & CONSCIOUSNESS FOR ML



- Formalize and test **specific hypothesized functionalities of consciousness**
- Get the magic out of consciousness
- Understand evolutionary advantage of consciousness: computational and statistical (e.g. systematic generalization)
- Provide these advantages to learning agents

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THOUGHTS, CONSCIOUSNESS, LANGUAGE

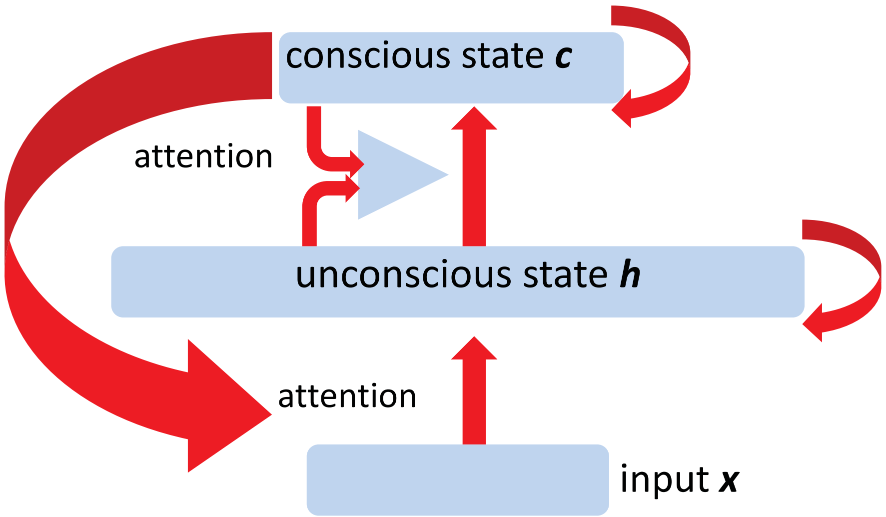
- Consciousness: from humans reporting
- High-level representations ⟺ language
- High-level concepts: meaning anchored in low-level perception and action → **tie system 1 & 2**
- Grounded high-level concepts

  → better natural language understanding

  - Grounded language learning, BabyAI: *(Chevalier-Boisvert and al ICLR 2019)*

THE CONSCIOUSNESS PRIOR: SPARSE FACTOR GRAPH

CONSCIOUSNESS PRIOR



Different kinds of attention in the brain

Bengio 2017, arXiv:1709.08568

- **Attention: to form conscious state, thought**
- **A thought is a low-dimensional object**, few selected aspects of the unconscious state
- Need 2 high-level states:
  - Large unconscious state
  - Tiny conscious state
- Part of inference mechanism wrt joint distribution of high-level variables

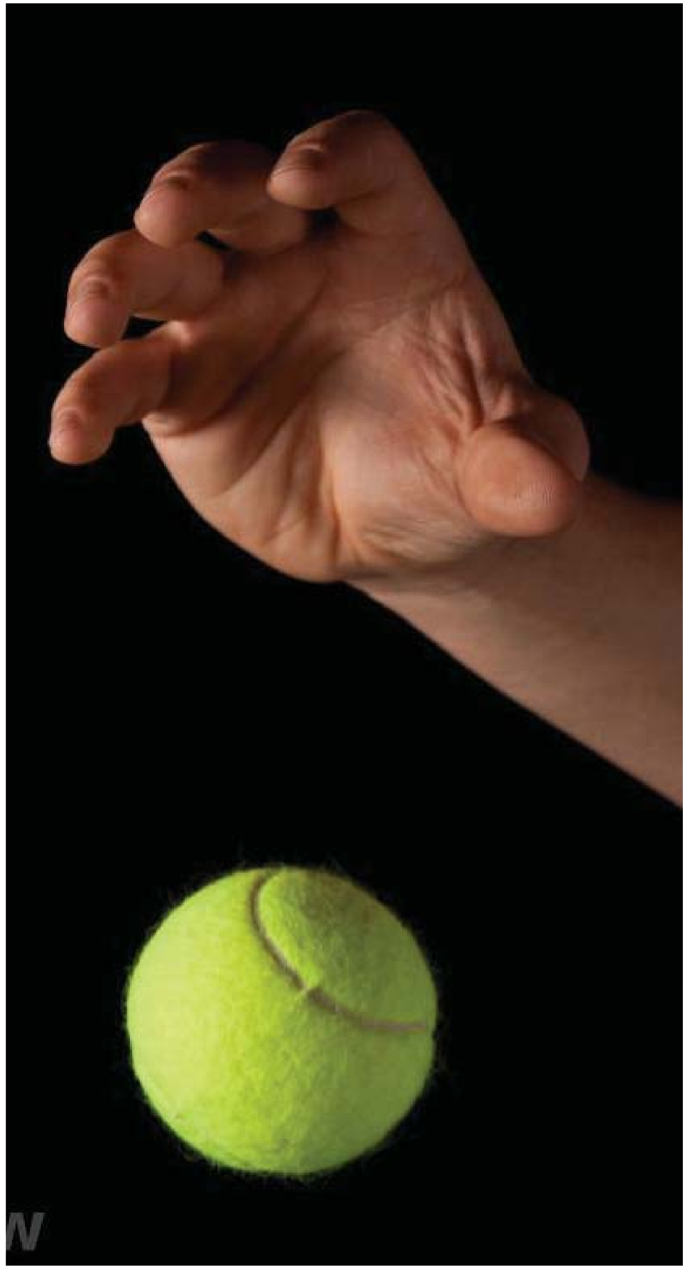
CONSCIOUSNESS **PRIOR**
➔ SPARSE FACTOR GRAPH

Bengio 2017, arXiv:1709.08568

- Property 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"

- **Disentangled factors** != marginally independent,
  e.g. ball & hand

- **Prior**: sparse factor graph join distribution between high-level variables



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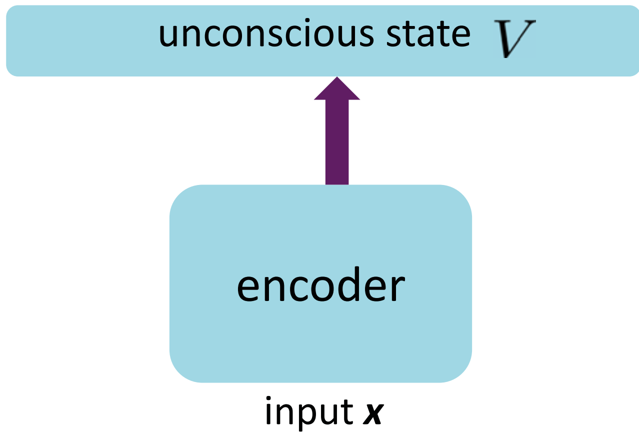
CONSCIOUSNESS **PRIOR → SPARSE FACTOR GRAPH**

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

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

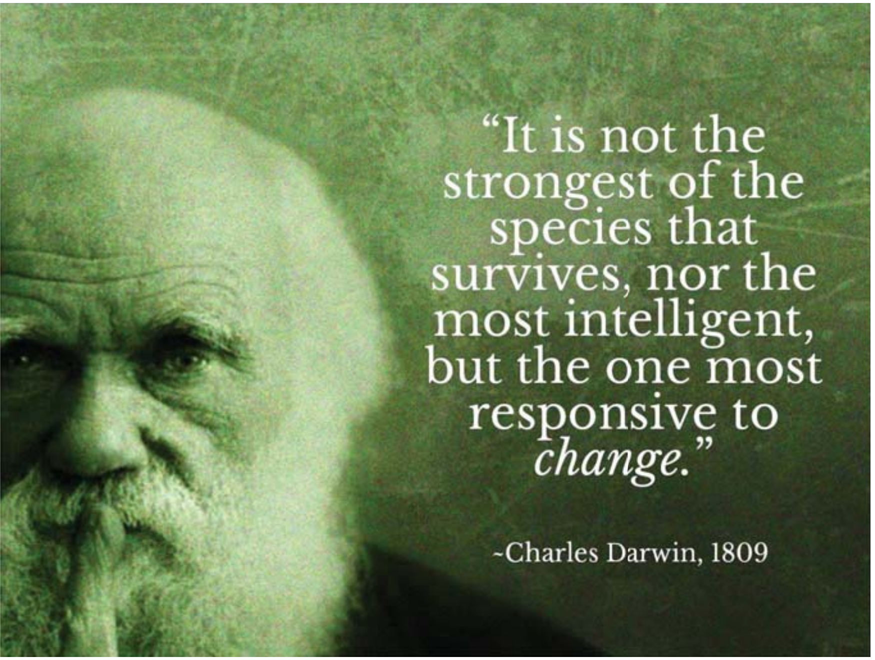
Prior puts pressure on encoder computing implicitly P(V|observations ***x***)



Bengio 2017, arXiv:1709.08568

META-LEARNING: END-TO-END OOD GENERALIZATION, LOCALIZED CHANGE HYPOTHESIS

META-LEARNING FOR TRAINING TOWARDS OOD GENERALIZATION



- Meta-learning or learning to learn
  (Bengio et al 1991; Schmidhuber 1992)
  - Backprop through inner loop or REINFORCE-like estimators
- Bi-level optimization
  - Inner loop (may optimize something) → outer loss
  - Outer loop: optimizes E[outer loss] (over tasks, environments)
- E.g.
  - Evolution ∘ individual learning
  - Lifetime learning ∘ fast adaptation to new environments
- Multiple time-scales of learning
- **End-to-end learning to generalize ood + fast transfer**

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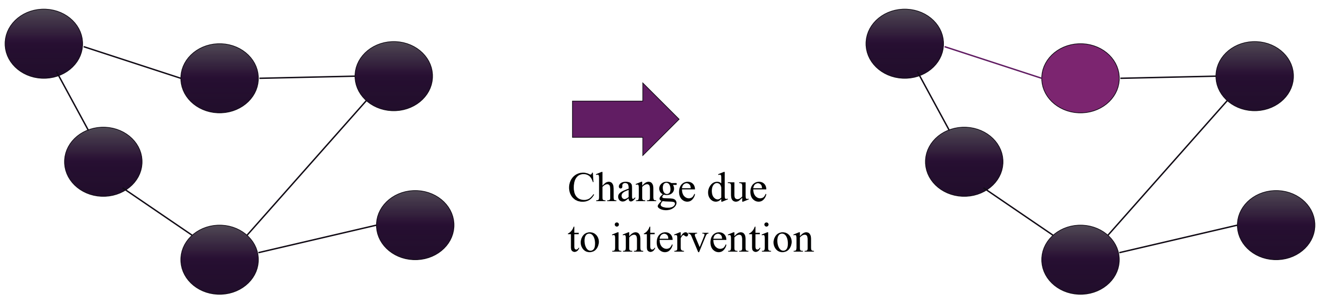
WHAT CAUSES CHANGES IN DISTRIBUTION?

Hypothesis to replace iid assumption: **changes = consequence of an intervention on few causes or mechanisms = local inference or adaptation in the right model**

Extends the (informationally) Independent Mechanisms hypothesis *(Scholkopf et al 2012)*

Underlying physics: actions are localized in space and time.



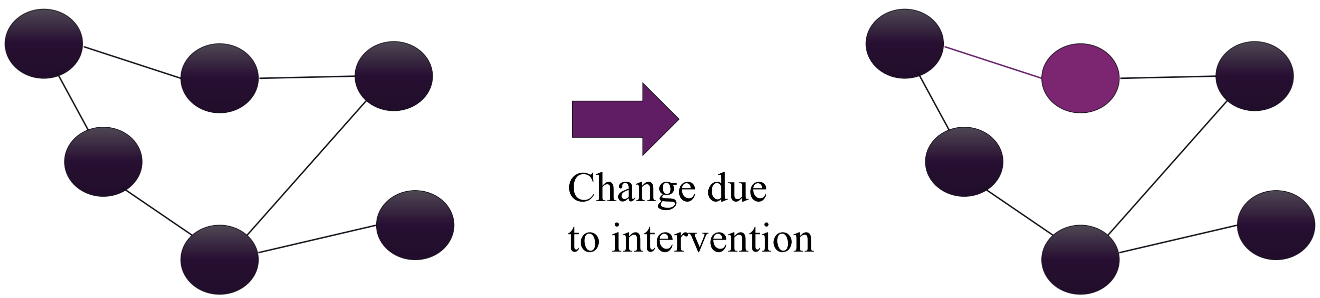
COUNTING ARGUMENT: **LOCALIZED CHANGE→OOD TRANSFER**

Good representation of variables and mechanisms + localized change hypothesis

→ few bits need to be accounted for (by inference or adaptation)

→ few observations (of modified distribution) are required

→ good ood generalization/fast transfer/small ood sample complexity

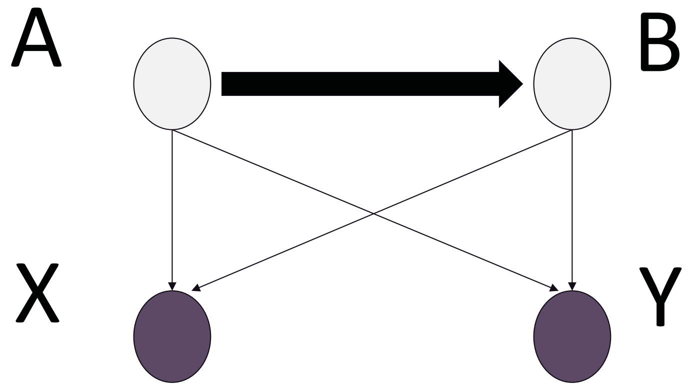


META-LEARNING KNOWLEDGE REPRESENTATION FOR GOOD OOD PERFORMANCE

- Use ood generalization as training objective
- Good knowledge representation ➔ good ood performance
- Good ood performance = training signal

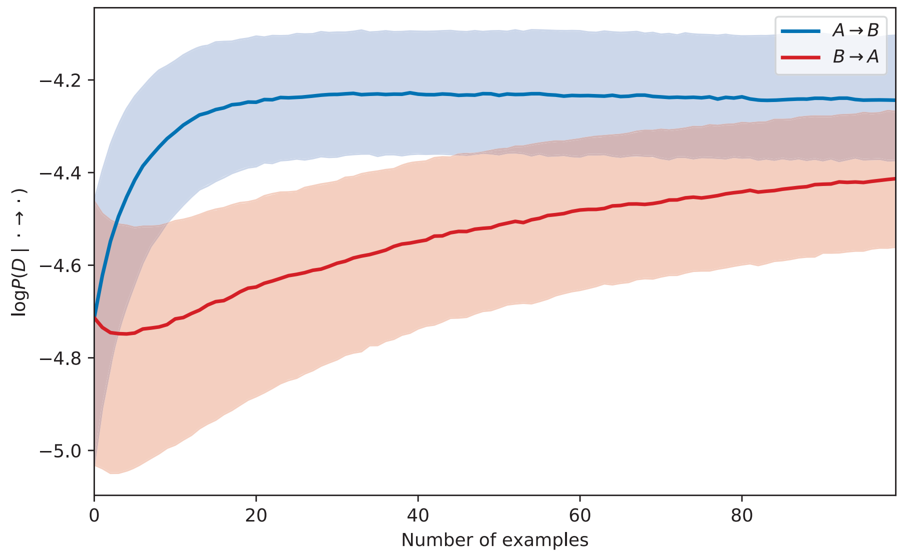
EXAMPLE: DISCOVERING CAUSE AND EFFECT
= **HOW TO FACTORIZE A JOINT DISTRIBUTION?**

A Meta-Transfer Objective for Learning to Disentangle Causal Mechanisms



- Learning whether A causes B or vice-versa
- Learning to disentangle (A,B) from observed (X,Y)
- Exploit changes in distribution and speed of adaptation to guess causal direction

Bengio et al 2019 arXiv:1901.10912



EXAMPLE: DISCOVERING CAUSE AND EFFECT
= **HOW TO FACTORIZE A JOINT DISTRIBUTION?**

Learning Neural Causal Models from Unknown Interventions

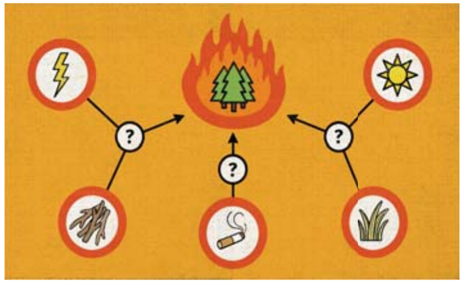
- Learning small causal graphs, avoid exponential explosion of # of graphs by parametrizing factorized distribution over graphs

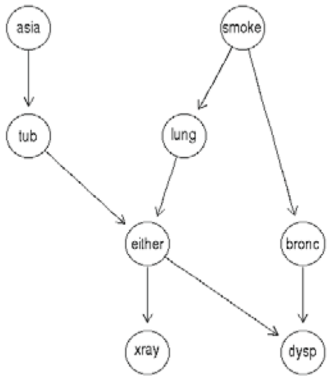
- Inference over the intervention:
  faster causal discovery

Ke et al 2019 arXiv:1910.01075

Asia graph, CE on ground truth edges, comparison against other causal induction methods

Our method	(Eaton & Murphy, 2007a)	(Peters et al., 2016)	(Zheng et al., 2018)
0.0	0.0	10.7	3.1





OPERATING ON SETS OF POINTABLE OBJECTS WITH DYNAMICALLY RECOMBINED MODULES

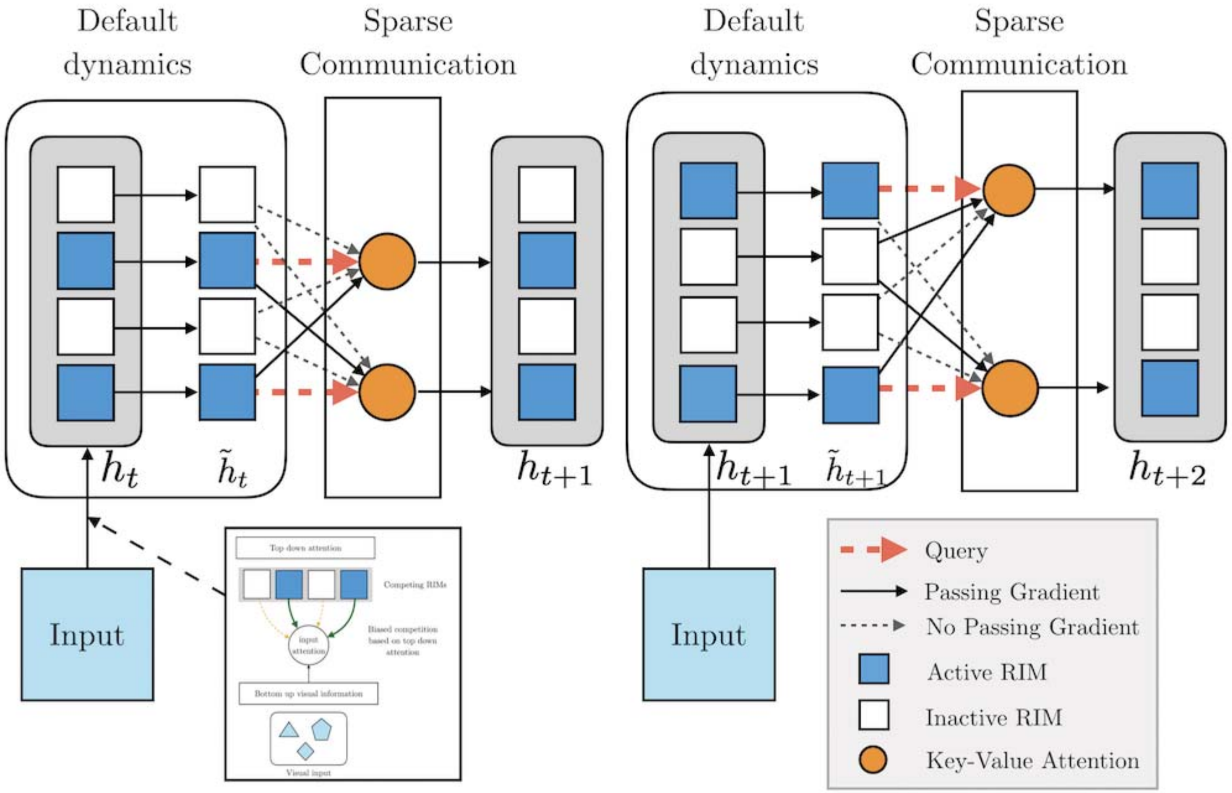
RIMS: MODULARIZE COMPUTATION AND OPERATE ON SETS OF NAMED AND TYPED OBJECTS

Recurrent Independent Mechanisms

Multiple recurrent sparsely interacting modules, each with their own dynamics, with object (key/value pairs) input/outputs selected by multi-head attention

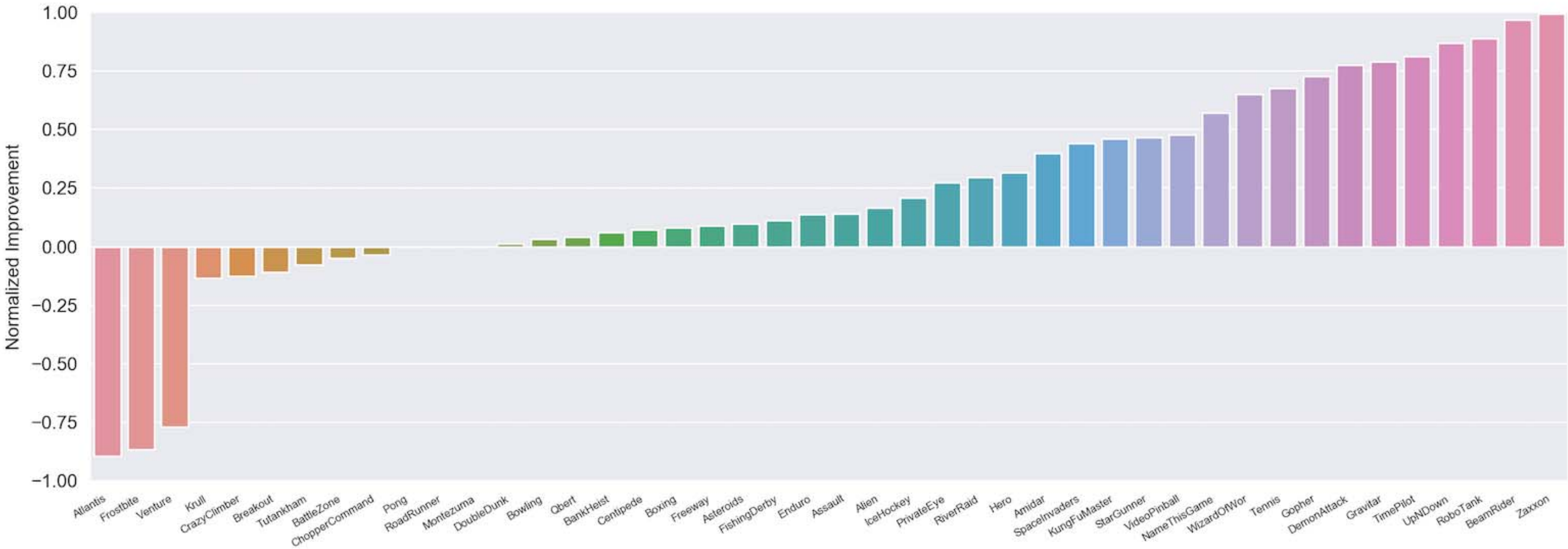
Results: better ood generalization

Goyal et al 2019, arXiv:1909.10893



RESULTS WITH **RECURRENT INDEPENDENT MECHANISMS**

- RIMs drop-in replacement for LSTMs in PPO baseline over all Atari games.
- Above 0 (horizontal axis) = improvement over LSTM.



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HYPOTHESES FOR **CONSCIOUS PROCESSING BY AGENTS, SYSTEMATIC GENERALIZATION**

- Sparse factor graph in space of high-level semantic variables
- Semantic variables are causal: agents, intentions, controllable objects
- Shared ’rules’ across instance tuples (arguments)
- Distributional changes from localized causal interventions (in semantic space)
- Meaning (e.g. grounded by an encoder) stable & robust wrt changes in distribution

CONCLUSIONS

- After cog. neuroscience, time is ripe for ML to explore consciousness
- Could bring new priors to help systematic & ood generalization
- Could benefit cognitive neuroscience too
- Would allow to expand DL from system 1 to system 2
- Hypothesis: need good system 1 functionalities to make system 2 efficient

System 1

System 2

THANK YOU

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