符号逻辑与深度学习的融合

Symbolic Logic & Deep Learning

Hulu Researcher 徐潇然

模型构造

学习动力

未来判断

模型构造 Model Construction

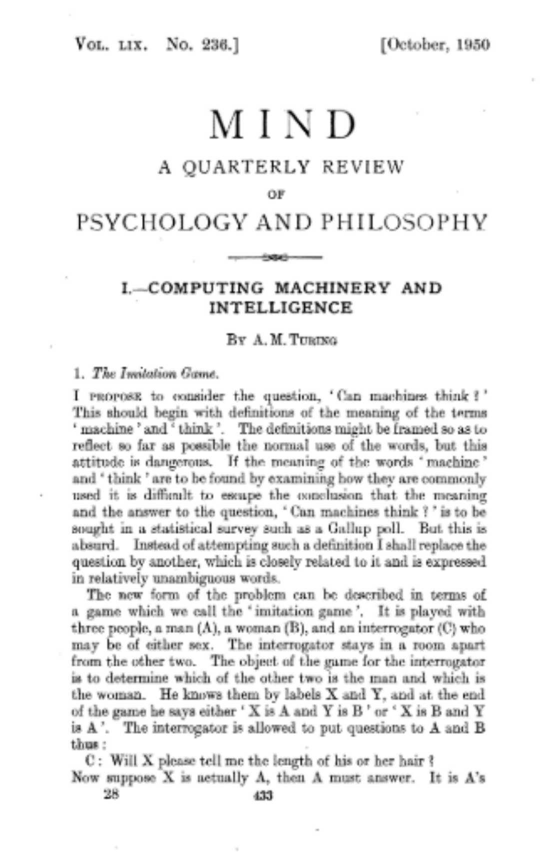
- 除了函数化构造，还需要考虑哪些构造形式？
- 是否要考虑符号化、组合化、关系化等等的构造？
- 实现构造的可学习性，可导固然好，不可导怎么办？
- 如何平衡构造的连续特性和离散特性？
- 意识先验是什么？

hulu

人工智能的历史

- 图灵：发表论文“计算机器与智能”，提出图灵测试
  - *Computing Machinery and Intelligence*, 1950 in *Mind*
- 1956年，达特茅斯会议：正式提出“人工智能”
- 符号逻辑派
  - 认为实现人工智能必须用逻辑和符号系统，试图模拟心智活动
  - 自顶向下看问题，观点偏唯心
- 神经网络派
  - 认为通过仿造大脑可以达到人工智能，试图模拟大脑的神经网络
  - 自底向上看问题，观点偏唯物

功能 v.s. 结构



VOL. LIX. No. 236.] [October, 1950

MIND

A QUARTERLY REVIEW

OF

PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

I PROPOSE to consider the question, 'Can machines think?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

The new form of the problem can be described in terms of a game which we call the 'imitation game'. It is played with three people, a man (A), a woman (B), and an interrogator (C) who may be of either sex. The interrogator stays in a room apart from the other two. The object of the game for the interrogator is to determine which of the other two is the man and which is the woman. He knows them by labels X and Y, and at the end of the game he says either 'X is A and Y is B' or 'X is B and Y is A'. The interrogator is allowed to put questions to A and B thus:

C: Will X please tell me the length of his or her hair?

Now suppose X is actually A, then A must answer. It is A's

28 433

逻辑与符号的发展

- 逻辑主义（罗素）
  - 把数学问题归约到更基本的逻辑问题
  - 命题逻辑，谓词逻辑（一阶逻辑）
- 形式主义（希尔伯特）
  - 把数学形式化，用一套规则不断地变换给定的公式直到显性的形式出现
- 机器定理证明（继承逻辑主义和形式主义的衣钵）
  - 逻辑演算自动化：合一、归结、包含、项重写
  - 名字的变迁：自动定理证明，自动演绎，自动推理
- 专家系统和知识图谱（从一阶逻辑走向描述逻辑）
  - 公理集合 => 知识库，规则库 => 支持集
  - 从纯的逻辑到不纯的逻辑，从语法到语义
  - 知识就是非逻辑的公理

推理 v.s. 知识

莱布尼茨之梦与图灵机

- 通用符号 Universal Character
- 推理演算 Calculus of Reasoning
- 通用真理 Universal Truth

“莱布尼茨梦想对一种普遍的人工数学语言和演算规则进行一种百科全书式的汇编，知识的任何一个方面都可以用这种数学语言表达出来，而演算规则将揭示这些命题之间所有的逻辑关系。最后，他梦想能够制造出完成这些演算的机器，从而使心灵从创造性的思考中解脱出来。”

《逻辑的引擎》第1章 莱布尼茨之梦

“我希望数字计算机能够最终激起人们对符号逻辑的极大兴趣……人与这些机器进行交流的语言……构成了一种符号逻辑。”

图灵在伦敦数学会的演讲

逻辑编程 Logic Programming

- 逻辑编程语言
  - Horn clauses
    - 规则 rules： `H :- B1, ..., B_n.` （H if B1 and … and Bn, H is called the head, Bi is called the body）
    - 事实 facts： `H.` （Without body）
  - Goal-reduction procedures
    - Horn clauses + backward reasoning (searching over an and-or tree)
    - Declarative and procedural representations of knowledge
- Prolog
  - 一阶逻辑编程语言（对比函数式编程语言 LISP）

Algorithm = Logic + Control

（联想“程序=数据结构+算法”）

Facts

```
mother_child(trude, sally).
father_child(tom, sally).
father_child(tom, erica).
father_child(mike, tom).
```

Rues

```
sibling(X, Y) :- parent_child(Z, X), parent_child(Z, Y).
parent_child(X, Y) :- father_child(X, Y).
parent_child(X, Y) :- mother_child(X, Y).
```

Query

```
?- sibling(sally, erica).
Yes
```

概率逻辑编程 Probabilistic Logic Programming

- 思想：
  - Reasoning with uncertainty
  - Inductive logic programming
    - Learning rule weights => parameters
    - Learning rules => relational combinatorial structures

两个关键词：Differentiable，Relational

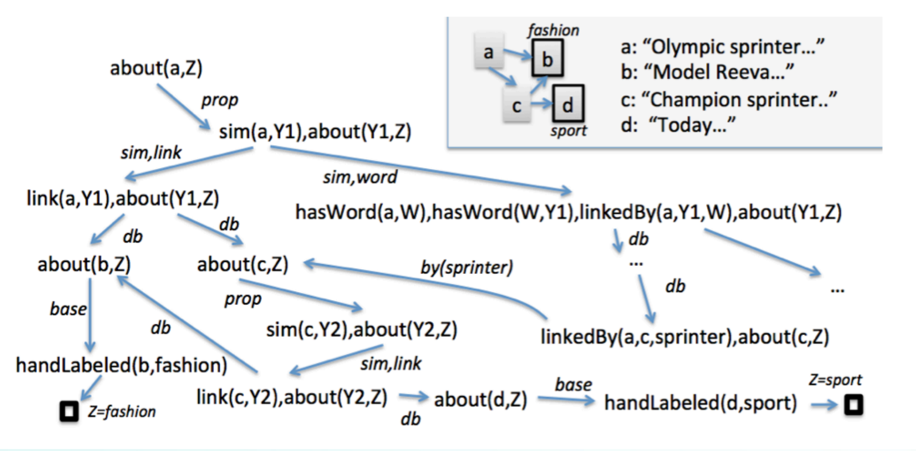
TensorLog: Deep Learning Meets Probabilistic Databases

William W. Cohen Fan Yang Kathryn Rivard Mazaitis
Machine Learning Department
Carnegie Mellon University
5000 Forbes Avenue, Pittsburgh PA 15208

- 方法
  - Markov Logic Networks (2006)
    - *Markov logic networks*, Machine learning 2006, Matthew Richardson and Pedro Domingos.
  - ProPPR (2013)
    - *Programming with personalized pagerank: a locally groundable first-order probabilistic logic*, CIKM 2013, Yang Wang, Kathryn Mazaitis, and William Cohen.
  - TensorLog (2016)
    - *Tensorlog: A differentiable deductive database*, 2016, William W Cohen.
  - Neural LP (2017)
    - *Differentiable Learning of Logical Rules for Knowledge Base Reasoning*, NIPS 2017, Fan Yang, Zhilin Yang, and William Cohen.

推理的图（图搜索、随机游走、消息传递）

ProPPR: Personalized PageRank (aka Random-Walk-With-Reset)



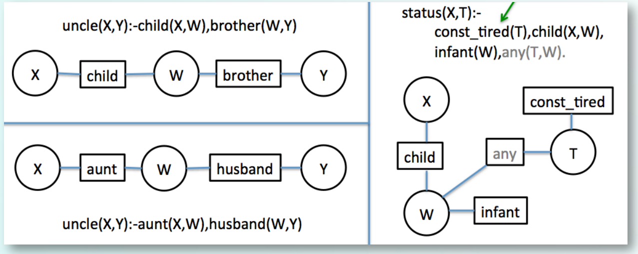
Program + DB + Query define a *proof graph*

```
about(X,Z) :- handLabeled(X,Z)            # base.
about(X,Z) :- sim(X,Y),about(Y,Z)         # prop.
sim(X,Y) :- links(X,Y)                    # sim,link.
sim(X,Y) :-
    hasWord(X,W),hasWord(Y,W),
    linkedBy(X,Y,W)                       # sim,word.
linkedBy(X,Y,W) :- true                   # by(W).
```

Program

Query: about (a,Z)

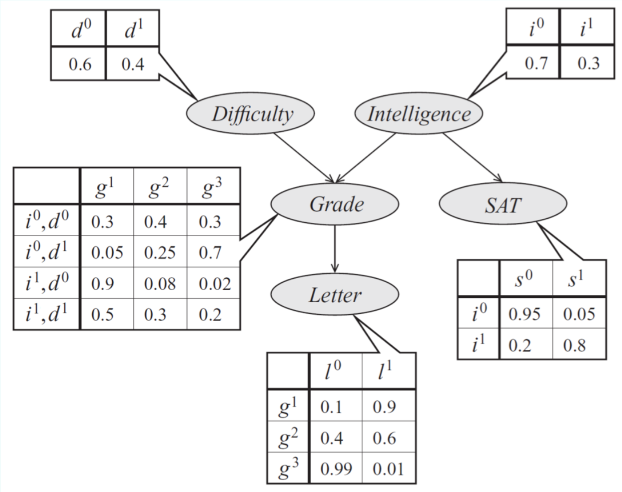
DB:



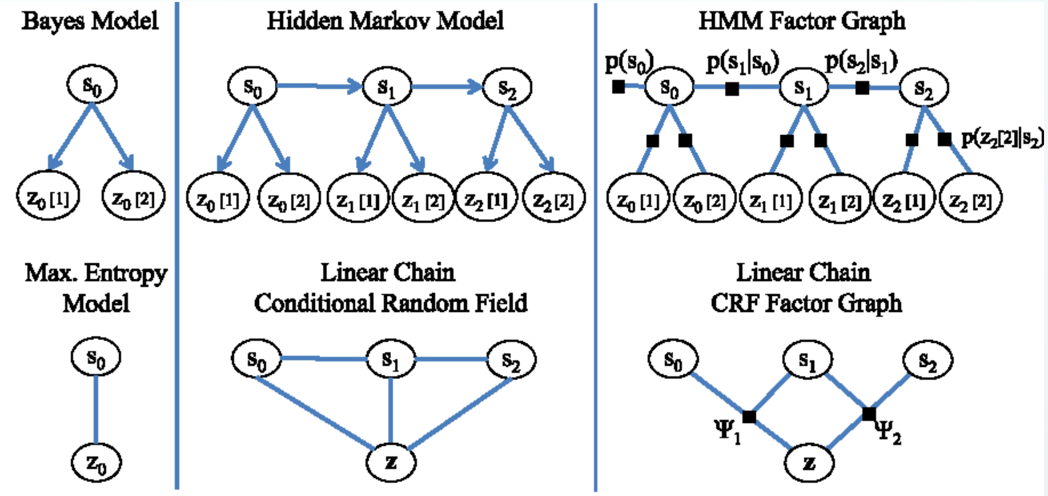
TensorLog: Weighted Proof-Counting

- Message passing over a factor graph
- Learning by backprop

概率图模型的图



贝叶斯网

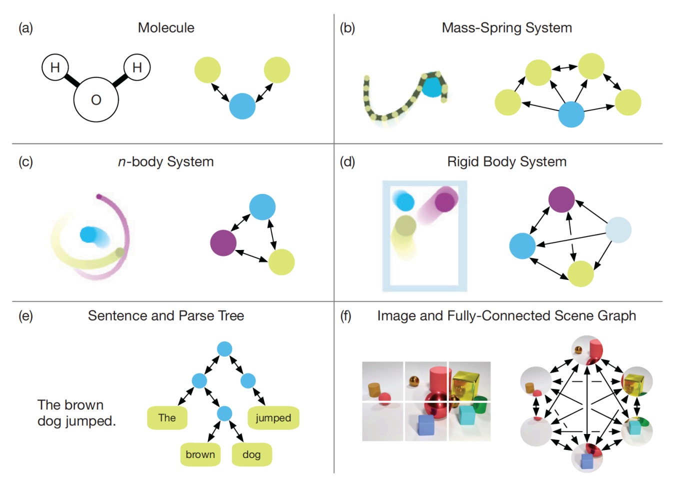


各类含隐变量的概率图模型

深度学习的图

- 图卷积网络（Graph CNN）
- 图神经网络（Graph NN）

"The question of how to build artificial systems which exhibit combinatorial generalization has been at the heart of AI since its origins, and was central to many structured approaches, including logic, grammars, classic planning, graphical models, causal reasoning, Bayesian nonparametrics, and probabilistic programming"



Relational inductive biases, deep learning, and graph networks

Peter W. Battaglia[1*], Jessica B. Hamrick[1], Victor Bapst[1], Alvaro Sanchez-Gonzalez[1], Vinicius Zambaldi[1], Mateusz Malinowski[1], Andrea Tacchetti[1], David Raposo[1], Adam Santoro[1], Ryan Faulkner[1], Caglar Gulcehre[1], Francis Song[1], Andrew Ballard[1], Justin Gilmer[2], George Dahl[2], Ashish Vaswani[2], Kelsey Allen[3], Charles Nash[4], Victoria Langston[1], Chris Dyer[1], Nicolas Heess[1], Daan Wierstra[1], Pushmeet Kohli[1], Matt Botvinick[1], Oriol Vinyals[1], Yujia Li[1], Razvan Pascanu[1]

[1]DeepMind; [2]Google Brain; [3]MIT; [4]University of Edinburgh

Neural Message Passing for Quantum Chemistry

Justin Gilmer[1] Samuel S. Schoenholz[1] Patrick F. Riley[2] Oriol Vinyals[3] George E. Dahl[1]

Non-local Neural Networks

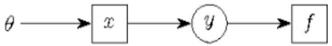
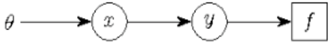
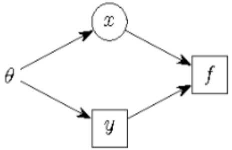
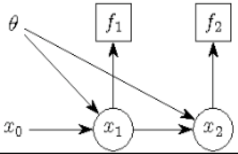
Xiaolong Wang[1,2*] Ross Girshick[2] Abhinav Gupta[1] Kaiming He[2]

[1]Carnegie Mellon University [2]Facebook AI Research

Relational recurrent neural networks

Adam Santoro[*α], Ryan Faulkner[*α], David Raposo[*α], Jack Rae[αβ], Mike Chrzanowski[α], Théophane Weber[α], Daan Wierstra[α], Oriol Vinyals[α], Razvan Pascanu[α], Timothy Lillicrap[αβ]

Stochastic Computation Graphs (SCGs)

Stochastic Computation Graph	Objective	Gradient Estimator
	$\mathbb{E}_y[f(y)]$	$\frac{\partial x}{\partial \theta}\frac{\partial}{\partial x}\log p(y \mid x) f(y)$
	$\mathbb{E}_x[f(y(x))]$	$\frac{\partial}{\partial \theta}\log p(x \mid \theta) f(y(x))$
	$\mathbb{E}_{x,y}[f(y)]$	$\frac{\partial}{\partial \theta}\log p(x \mid \theta) f(y)$
	$\mathbb{E}_x[f(x, y(\theta))]$	$\frac{\partial}{\partial \theta}\log p(x \mid \theta) f(x, y(\theta)) + \frac{\partial y}{\partial \theta}\frac{\partial f}{\partial y}$
	$\mathbb{E}_{x_1,x_2}[f_1(x_1) + f_2(x_2)]$	$\frac{\partial}{\partial \theta}\log p(x_1 \mid \theta, x_0)(f_1(x_1) + f_2(x_2)) + \frac{\partial}{\partial \theta}\log p(x_2 \mid \theta, x_1) f_2(x_2)$

John Schulman
- 提出SCGs的概念
- *Gradient estimation using stochastic computation graphs*, 2015

Stochastic backpropagation的解决方案：
- 基于REINFORCE的方法
  - MuProp
  - Rebar
  - RELAX
- 基于重参数化和松弛化的方法
  - Concrete distribution
  - Gumbel-Softmax distribution

我们的工作！

SCGs上系统化可训练的解决方案：
- *Backprop-Q: Generalized Backpropagation for Stochastic Computation Graphs*, 2018, Hulu
- *Credit Assignment Techniques in Stochastic Computation Graphs*, 2019, DeepMind

模型构造的考虑

逻辑编程
(逻辑演算、概率逻辑编程）

概率图模型
(贝叶斯网、隐变量图模型）

深度学习
(图卷积网络、图神经网络、SCGs）

概率化的构造

函数化的构造

符号化的构造
- 拆解流形表征下相纠缠的因子
- 形成离散化、细粒度的概念表示

组合化的构造
- 构建清晰、可解释的知识结构
- 实施高度非线性的（逻辑）演算（不再是单一的向量演算），进而实现组合泛化

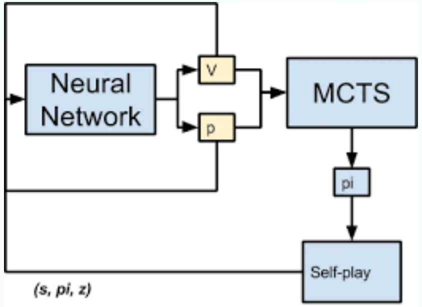
关系化的构造
- 利用关系化归纳偏向
- 图表示方便对世界建模

对连续结构的学习—— Differentiable networks

对离散结构的学习—— Guided search
- Discrete actions by policy or value networks
- Hard attention mechanism

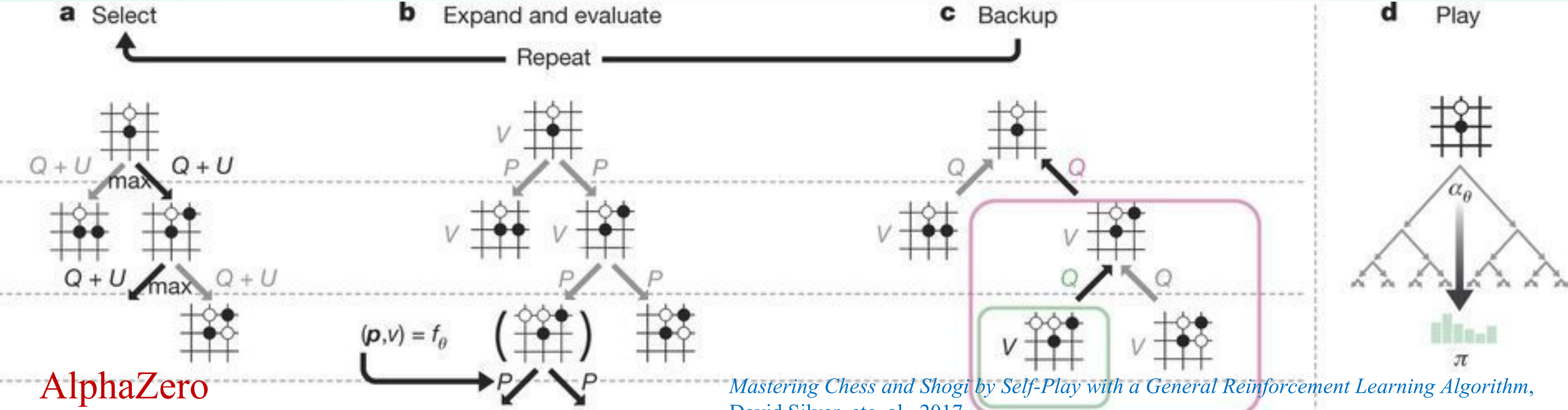
过程式的构造：一次性单趟 v.s. 一步步一轮轮

- 用粗糙的单步模型推演过程一步一步展开
- 综合多轮多步过程的结果来精调单步模型



基于蒙特卡洛树搜索对过程的模拟

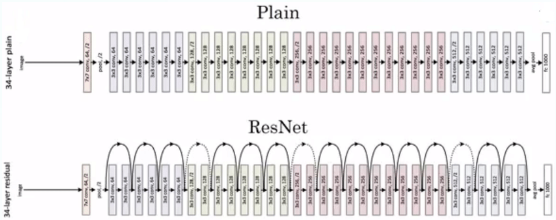
干瞪眼算不出
不如写写划划推一推

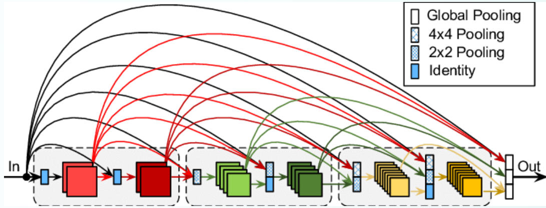


AlphaZero

Mastering Chess and Shogi by Self-Play with a General Reinforcement Learning Algorithm, David Silver, etc. al., 2017

通用性的构造：降低研究者偏好的影响



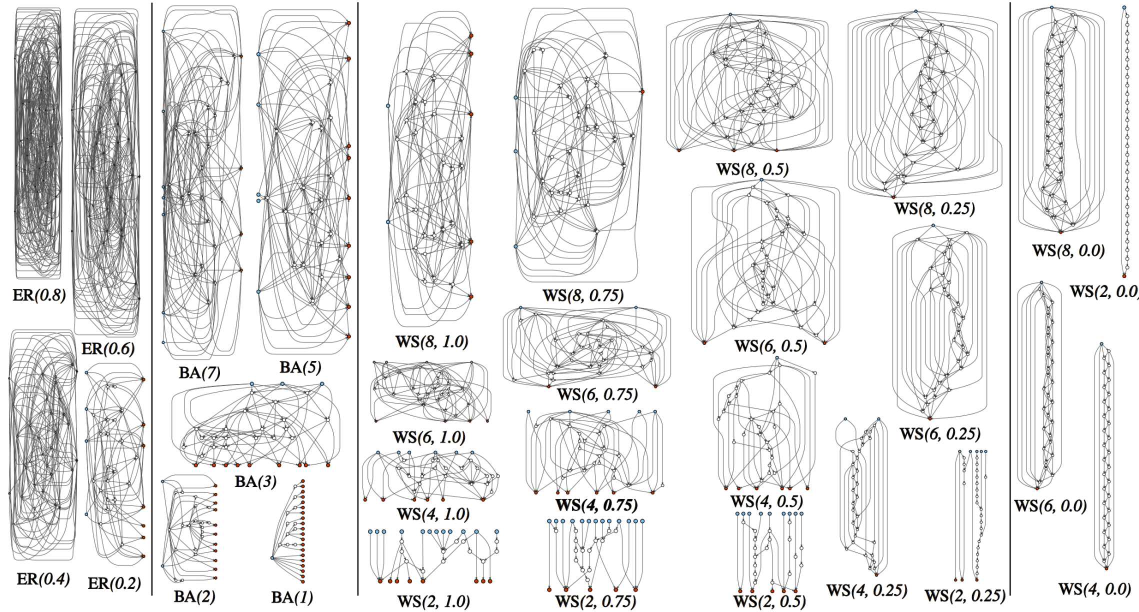


精心设计的计算图

- ResNet
- DenseNet

随机连接的计算图

- 随机图模型
  - Erdos-Renyi (ER)
  - Barabasi-Albert (BA)
  - Watts-Strogatz (WS)
- 调整：有向无环
  - 边：计算流方向
  - 节点：
    - 作输出（多条入边共同计算的结果）
    - 作输入（可参与到多个不同的计算）
- *Exploring Randomly Wired Neural Networks for Image Recognition*, Saining Xie, Alexander Kirillov, Ross Girshick, Kaiming He, 2019



Trade-off：通用性与先验
Solution：通用性先验（元先验）
- 前十年：设计特征 => 设计学习特征的网络
- 近期：设计网络 => 设计网络随机生成器

通用性的构造：依靠算力好于依靠大量先验

"And the human-knowledge approach tends to complicate methods in ways that make them less suited to taking advantage of general methods leveraging computation."

" 1) AI researchers have often tried to build knowledge into their agents, 2) this always helps in the short term, and is personally satisfying to the researcher, but 3) in the long run it plateaus and even inhibits further progress, and 4) breakthrough progress eventually arrives by an opposing approach based on scaling computation by search and learning."

"One thing that should be learned from the bitter lesson is the great power of general purpose methods, of methods that continue to scale with increased computation even as the available computation becomes very great. The two methods that seem to scale arbitrarily in this way are **search** and **learning**."

"... the search for them should be by our methods, not by us." (授之以鱼不如授之以渔)

The Bitter Lesson

Rich Sutton

March 13, 2019

The biggest lesson that can be read from 70 years of AI researc
generalization of continued exponentially falling cost per unit
one of the only ways to improve performance) but, over a sligh
term, researchers seek to leverage their human knowledge of t
Time spent on one is time not spent on the other. There are psy
suited to taking advantage of general methods leveraging com

http://www.incompleteideas.net/IncIdeas/BitterLesson.html

两项重要的运用算力的AI技术：

- Learning - 数值计算
- Search - 离散搜索

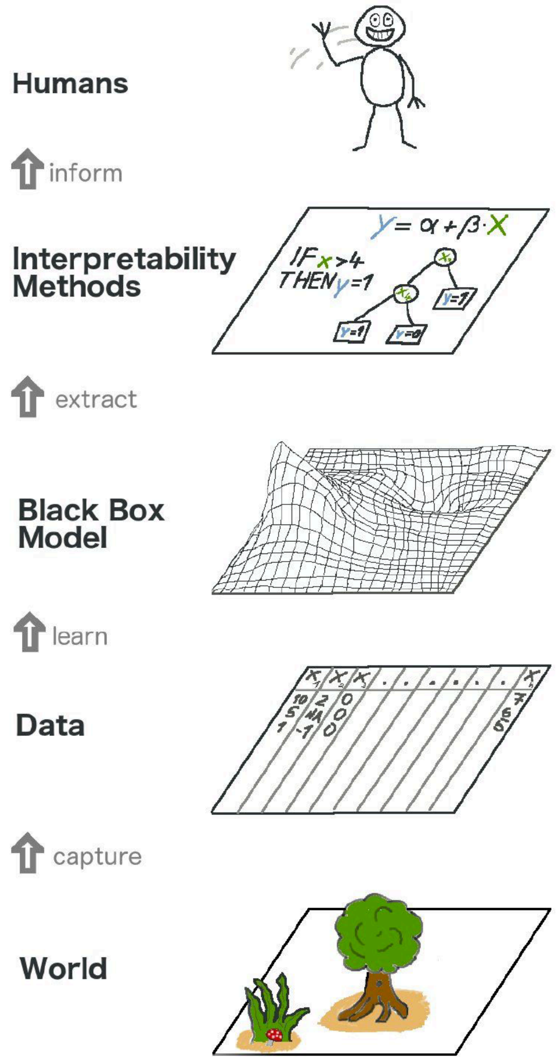
经典的通用先验例子：

- 基于梯度的优化过程
- 卷积计算（各种不变性），循环计算
- Self-Play
- ...

- 比起人类智能，依靠算力构建机器智能是有瑕疵的，但总好于依靠大量规则或特定先验，关键是如何寻找关键性的通用先验与算力完美结合，能随算力增加迸发更大的潜能
- 人类智能的算力体现在life-long和multi-task，更体现在群体智能，从这个角度看人类的算力并不弱

解释性的构造：白盒、灰盒、黑盒

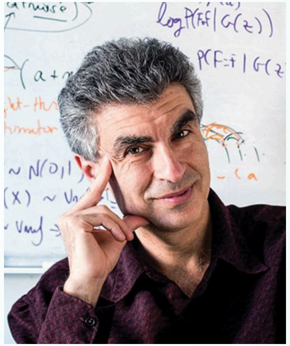
- Discrete reasoning：白盒
  - Discrete relational stucture
  - Logic caculus
  - Knowledge representation
- Differentiable reasoning：灰盒
  - Soft version via weights (continuous)
  - Distributive representation
  - Learnable (via gradient-based optimization)
- Reasoning by GNN：黑盒
  - Neural network-based



解释性的构造：（高维）连续系统 ⇔（低维）离散系统

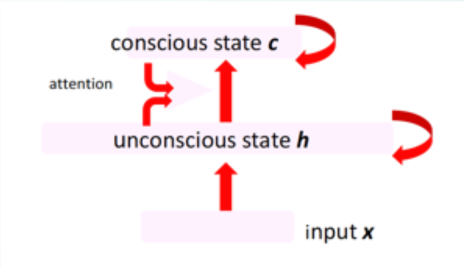
意识先验（Consciousness Prior）

- 解释性是意识的重要特征
- 解释是从大脑高维状态进行低维提取的过程
- *The Consciousness Prior*, Bengio 2017



Bengio关于意识先验的论述：

- 大脑的完全状态是 unconscious 的，包含大量混杂的元素，注意力机制（attention）使得从中剥离出少许合适的元素，形成意识想法
- 意识想法（consious thoughts）是低维化的产物，处于大脑最高层抽象的级别，是对少许因子或概念的组合，紧密关联到短文本表示（如：一个句子、一个短语、一条规则、一个事实），在这个意义上可联系到经典的符号AI和知识表示
- 注意力机制不同于稀疏化，是控制器主动基于条件进行，而且是以 soft-attention 的方式，使得整个过程可用基于梯度的优化算法来训练



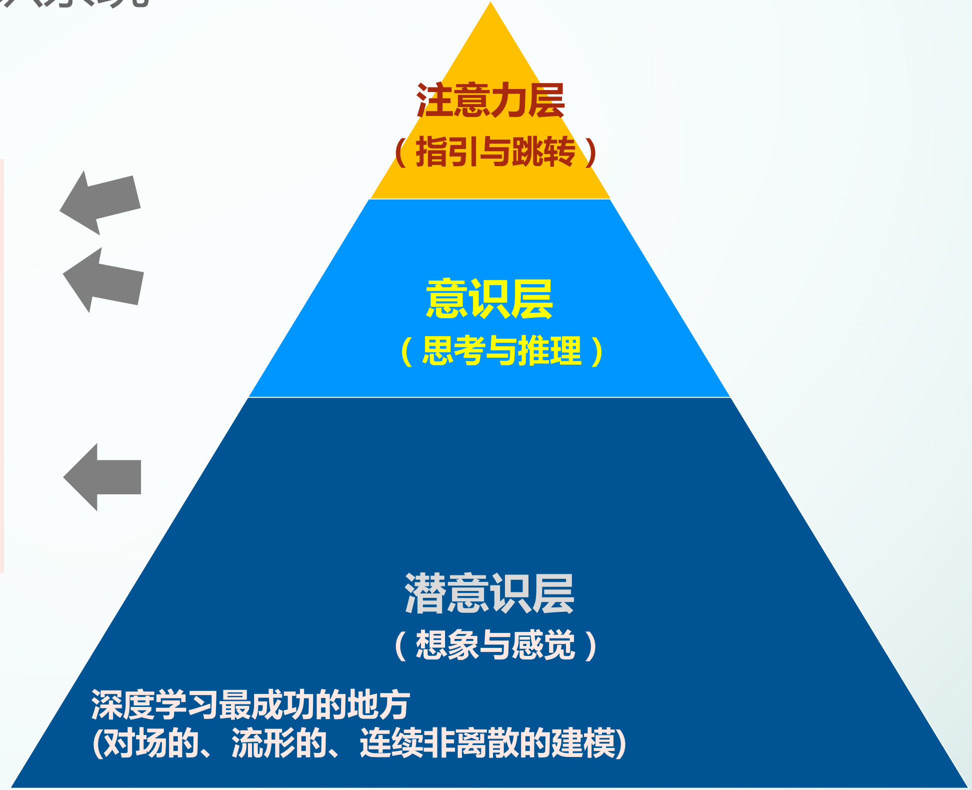
解释性的构造：潜意识系统 ⇔ 意识系统

System 2

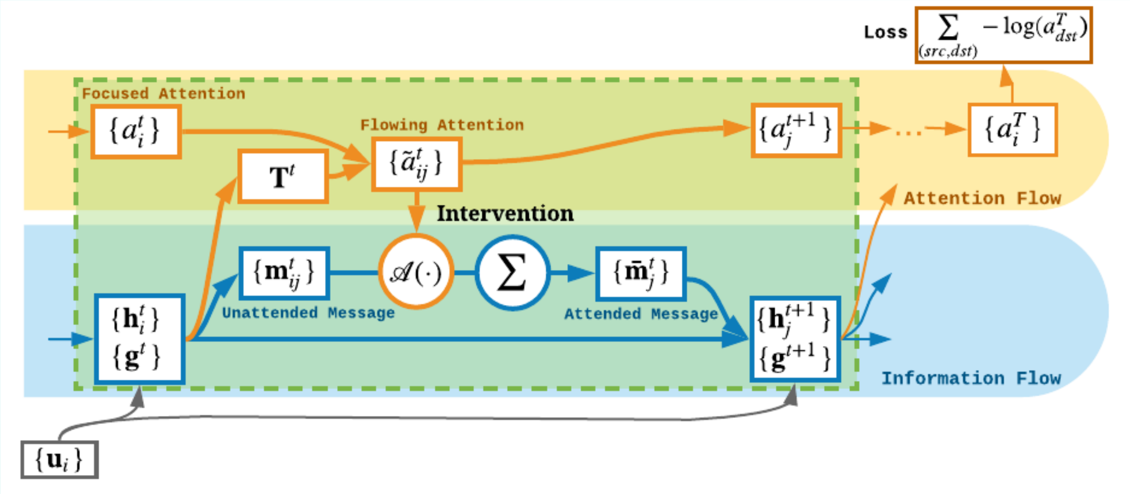
- Slow, logical, sequential, CONSCIOUS, linguistic, algorithmic
- *What **classical symbolic AI** was trying to do*

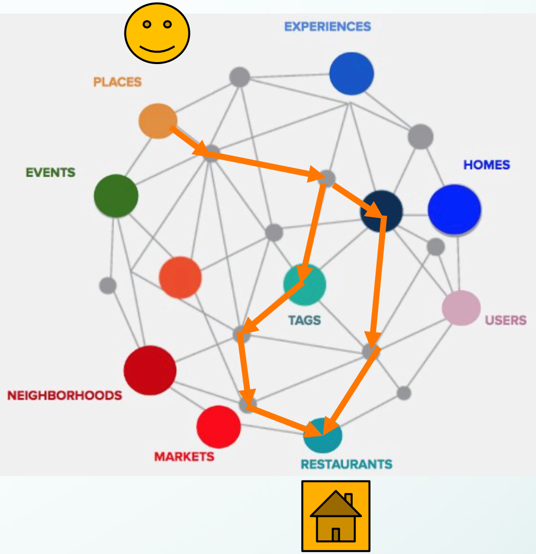
System 1

- Intuitive, fast heuristic, UNCONSCIOUS, non-linguistic
- *What current **deep learning** does quite well*



解释性的构造：（图神经网络）消息传递层 ⇔（可解释）注意力流层





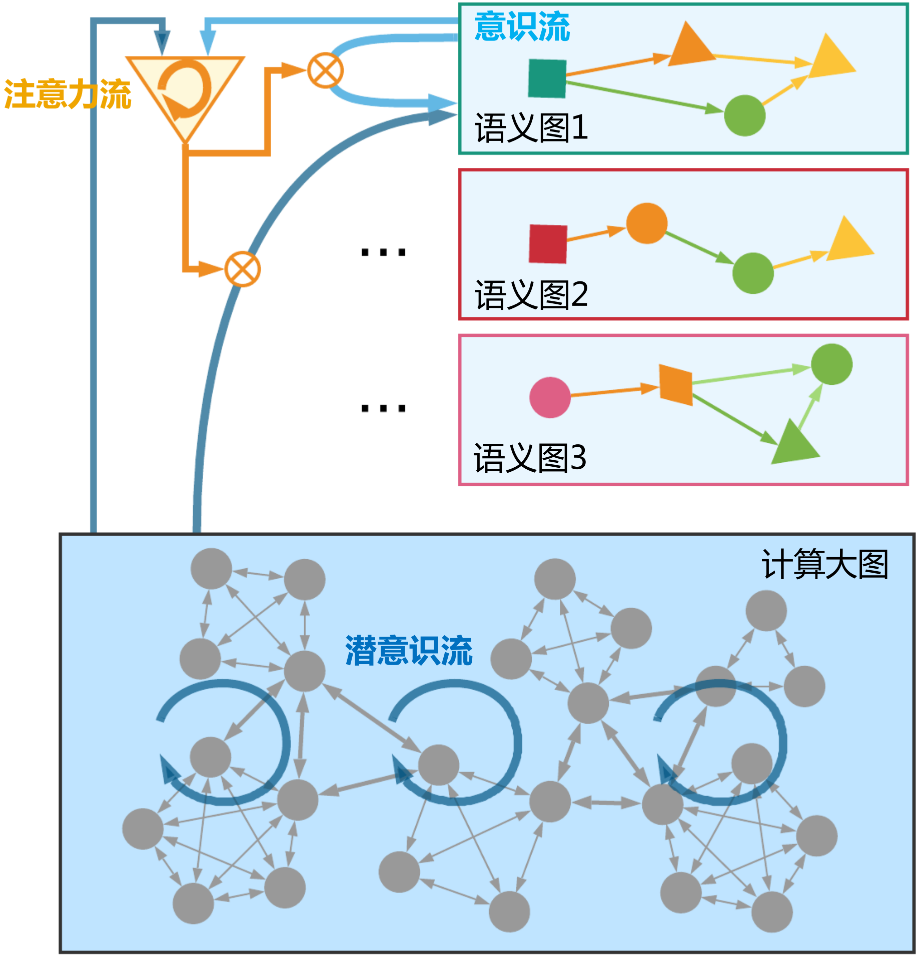
我们的工作！

***Modeling Attention Flow on Graphs*, X Xu, S Zu, C Gao, Y Zhang, W Feng, NeurIPS 2018 R2L Workshop**

连接主义到符号主义的新范式

	计算的自由性	演算的严谨性
神经网络的图	强	弱
概率图模型的图	中	中
符号逻辑的图	弱	强

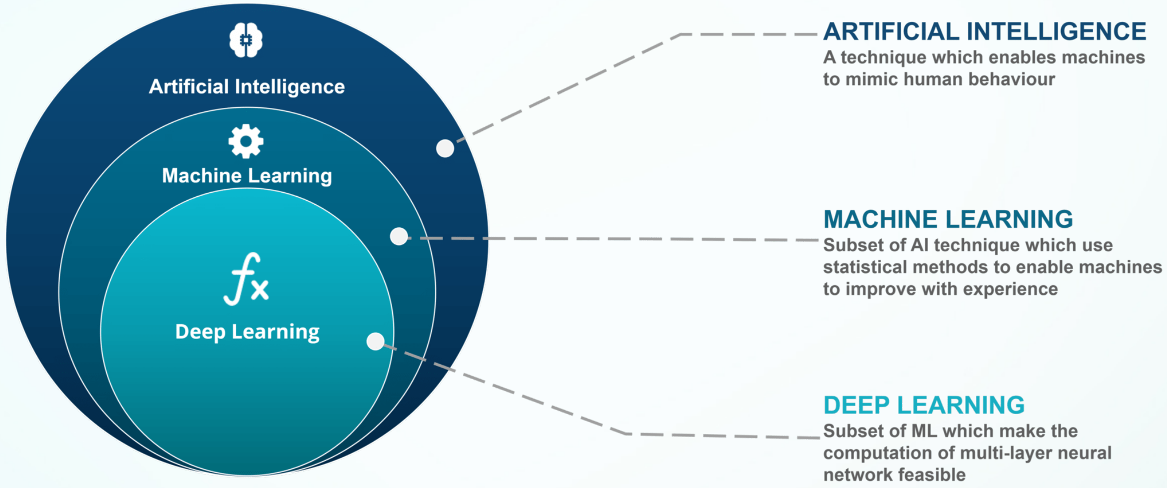
- 从计算图（low-level）到语义图（high-level）的过渡
  1. 潜意识流对应于底层的计算图
  2. 意识流对应高层的语义图
  3. 潜意识流、意识流共同决定注意力流
  4. 潜意识流不受注意力流的干预
  5. 意识流受注意力流的干预
  6. 潜意识流到意识流需经注意力流的干预



学习动力 Learning Dynamics

- 学习的过程是否就是一个数学优化过程？
- 是什么力量在驱动学习的进行？
- 优化的动力源于：优化的目标？优化的对象？优化的方法？优化的场所？
- 学习的动力与世界建模的关系？
- 学习的动力是否必须真实，是否需要可自我解释？

学习与优化 Learning & Optimization



学习问题 Learning Problem $\overset{?}{=}$ 优化问题 Optimization Problem

优化的目标
优化的对象
优化的方法
优化的场所

优化的目标

- 有监督学习
  - 分类任务 VGG, Inception, ResNet：最小化标签预测的交叉熵损失函数
  - 检测任务 Faster R-CNN, YOLO, SSD：再加上最小化边框预测的 L2 损失函数
  - 序列预测任务 Seq2Seq：最大化序列预测的条件似然概率

对数据上某类信号分布的拟合
（离散、连续；个体、序列）

- 无监督学习
  - 语言模型 word2vec (CBOW, SKip-Gram), ELMo, Bert：给定上下文（或词）最大化目标词的条件似然概率
  - VAE：（最大化边际似然的变分下界）最小化期望下重建误差及一个先后验的正则项
  - GAN：（MiniMax）判别器试图分类生成数据与真实数据，生成器试图逼近真实数据分布

对数据自身分布的拟合

- 强化学习
  - Critic-only，Actor-only，Actor-Critic：最大化长期总奖励值

对环境的奖励信号的自适应

优化的对象和方法

优化的对象

- 函数（或函数参数）
  - 优化的搜索空间：函数空间 => 参数空间
  - $\mathbf{output} = \boldsymbol{f}(\mathbf{input};\ \mathbf{params})$ ，如：分类函数、embedding 函数、value 函数、policy 函数
  - 组织结构（人工设计）：函数并函数，函数接函数

优化的方法

- 基于梯度的方法：SGD、Adam 等
- 基于策略梯度的方法：REINFORCE 等
- 基于类动态规划的方法：TD learning (Q-learning) 等
- 其他方法：遗传算法、EM 算法等

优化的目标
优化的对象
优化的方法

深度学习 = 函数拟合！
学习的本质 = 函数拟合？

学习过程不只是函数拟合

现有学习方法的类别：

- Supervised Learning, Unsupervised Learning
- Reinforcement Learning
- Meta-Learning, Few-Shot Learning
- Transfer Learning, Multitask Learning
- Continual Learning, Life-Long Learning
- Adversarial Learning
- Active Learning
- Imitation Learning
- Bayesian Learning
- Causal Learning
- ... Learning

- 学习信号的强弱
  - Supervised signal
  - Reward signal
  - Goal-directed
- 学习信号的范围
  - Immediate
  - Delayed
  - Cross-task/domain
- 学习信号的产生
  - Pre-defined
  - Learned dynamically
- 与学习信号无关的

还不够！

对信号的拟合
对信号的自适应

↓

对信号的解释
对信号背后规律的主动作为

学出的规律不只是函数参数

对规律的被动拟合或自适应 ➡ 对规律的主动作为：

- 从无到有：探索规律
- 从少到多：构建规律
- 从简到繁：组合规律
- 从散到聚：整合规律
- 从乱到序：组织规律
- 从混到析：分析规律
- 从弱到强：利用规律
- 从死到活：推演规律

有监督学习：拟合

强化学习：探索和利用

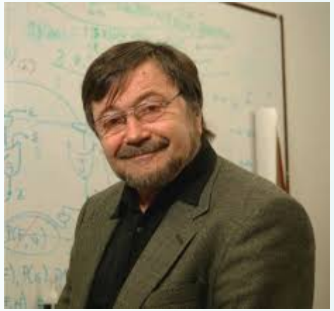
当前的困境：

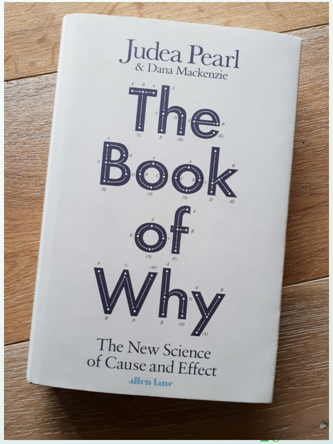
1. 对信号的依赖过于直接，缺乏为探索和构建复杂规律留出的自由度
   - 信号蕴含规律？
   - 信号触发规律（规律蕴含在信号之外）？
2. 缺乏有效的模型工具来表征和构建规律
   - 向量化表征是不够的
   - 表征规律还应考虑：
     - 符号化（symbolic）表征
     - 组合化（combinatorial）表征
     - 关系化（relational）表征
   - 规律要有内在的演绎规则（如：逻辑运算、概率推断）

对深度学习的批评与反思

Judea Pearl

- 批评
  - "All the impressive achievements of deep learning amount to just curve fitting."
  - 认为当前方法只不过是过去方法的升级版: find hidden regularities in a large set of data
- 主张
  - 认为虽做到了 reasoning with uncertainty，但有挑战的是 reasoning with cause and effect
  - 认为思维的重要特征是通过反事实和干预进行因果推理、发现因果关系
  - "We have to equip machines with a model of the environment. If a machine does not have a model of reality, you cannot expect the machine to behave intelligently in that reality."
  - "The first step, one that will take place in maybe 10 years, is that conceptual models of reality will be programmed by humans. The next step will be that machines will postulate such models on their own and will verify and refine them based on empirical evidence."
  - *Theoretical Impediments to Machine Learning With Seven Sparks from the Causal Revolution*, 2018, Judea Pearl

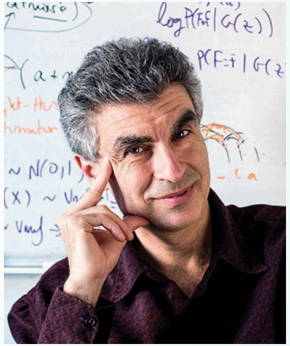




对深度学习的批评与反思

Yoshua Bengio

- 批评
  - CNN 没有传说中的那么神奇，只是学出大量的 low level regularities，这点上与 Fourier filters 没有本质区别，仅仅在图片上施加一个蒙版就造成测试集上泛化能力大幅下降（large generalization gap），而人对图片的认知没有受到丝毫的影响
  - "Deep CNNs have a tendency to learn superficial statistical regularities in the database rather than high level abstract concepts"
  - *Measuring the Tendency of CNNs to Learn Surface Statistical Regularities*, 2017, Jason Jo and Yoshua Bengio
- 主张
  - "Humans generalize better than other animals thanks to a more accurate internal model of the underlying casual relationships"
  - "To predict future situatoins (e.g., the effect of planned actions) far from anything seen before while involving known concepts, an essential component of reasoning, intelligence and science



Consciousness prior

- 空间邻近（CNN）和时间邻近（RNN）的跨度
- Factors 间的独立性和依赖性（非全连接）

Causal mechanism

- 可控的factors
- Mechanism 间的独立性

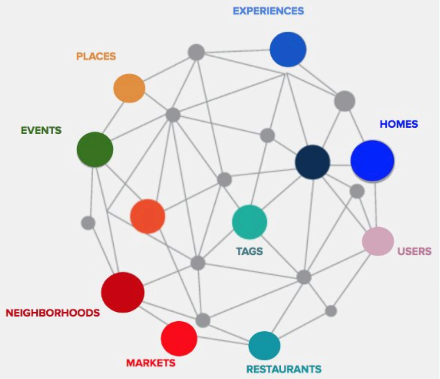
世界建模 —— 什么是世界？

- 优化的目标
- 优化的对象
- 优化的方法
- **优化的场所**

Dataset v.s. World

数据集：MNIST, CIFAR, ImageNet, ...

世界：Atari, Go, StarCraft, ...



脑中的知识地图

Step I	Step II	Step III
数据集 => 世界	真实世界 => 想象世界 像素世界 => 文字世界 具象世界 => 抽象世界 物理世界 => 概念世界	因果推理 反事实、干预

世界建模 —— 数据模型？世界模型？

问：假设在真实世界中，你眼前有座大楼，问它有多高？

数据模型的工作

- 当前模型的方案：先给我一批训练集

80 m

150 m

230 m

世界模型的工作

- 普通方案：先数一数楼的层数，再随机找几层量一量平均层高
- 学霸方案：能否上到楼顶，还要有一个气压计
- 懒人方案：这个世界是否有搜索引擎

为什么需要世界建模？

Kenneth Craik：英国心理学家，1940年提出心智模型的概念

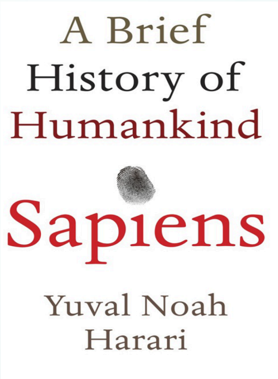
Kenneth Craik's "The Nature of Explanation" (1943), connects the compositional structure of the world to how our internal mental models are organized:

> …[a human mental model] has a similar relation-structure to that of the process it imitates. By 'relation-structure' I do not mean some obscure non-physical entity which attends the model, but the fact that it is a working physical model which works in the same way as the process it parallels… physical reality is built up, apparently, from a few fundamental types of units whose properties determine many of the properties of the most complicated phenomena, and this seems to afford a sufficient explanation of the emergence of analogies between mechanisms and similarities of relation-structure among these combinations without the necessity of any theory of objective universals.* (Craik, 1943, page 51-55)

世界建模的作用：

- 扮演平行于真实世界的物理模型
- 基于关系结构的构建
- 满足（自我）解释即可

《人类简史》认知革命：The ability of the human mind to imagine things that do not really exist (人类想象真实世界中不存在事物的思维能力)



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对世界建模的看法

Yann LeCun

- 认为应基于自我监督的学习能力，学习对世界的基本预测模型（Predictive Models of the World），习得基本常识，并朝着更复杂的推理和规划前进
- 认为在 agent 大脑里需要有一个世界模拟器（World Simulator），使得 agent 在真实世界作出动作前，先在自己的世界模拟器中演练一下

Jurgen Schmidhuber

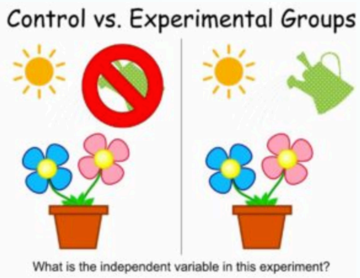
- "Humans develop a mental model of the world based on what they are able to perceive with their limited senses. The decisions and actions we make are based on this internal model."
- 认为基于 RNN 的世界预测模型可以帮助强化学习的 RNN 控制器
- *World Models*, 2018, David Ha and Jurgen Schmidhuber
- *One Big Net For Everything*, 2018, Jurgen Schmidhuber

知识图谱的世界观

- 是训练数据？还是训练场所？
  - 数据的视角（图中的样本）：Graph / Knowledge Graph Embedding
    - 独立的三元组样本：TransE 系列, NTN, DistMult, HolE, ComplEx 等
    - 从图抽出的序列样本：DeepWalk, LINE, node2vec 等
  - 场所的视角（图上的环境）：Graph CNN, GNN
    - 图上的卷积操作
    - 图上的消息传递（message passing）
- 概念化、网络化的世界呈现
  - 交互与推演的方式
    - 信息的传播与反馈
    - 路径的搜索与选取
    - 图结构的构建与修改

知识图谱的世界观

- 因果性学习
  - 机器学习：（被动地）Learning from data
  - 因果性学习：
    - 干预
      - 科学实验：实验组 / 控制组，A/B Test
      - 婴儿学习：与环境时刻交互，不断干预环境并观察结果是否符合预期
    - 反事实：想象世界
- 想象中的“干预”
  - 动作 => 注意力
  - 动作序列 => 注意力流



Attention V.S. Action

未来判断

- 对想象世界的建模方法
- 因果关系的表示及学习
- 充分利用关系化归纳偏向
- 意识先验的技术实现方式
- 学习符号化/组合化的结构
- 设计新任务支持和验证上述方法论

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THANK YOU