"Easy" presentation

The logic route to strong AI

YKY

March 21, 2021

Table of contents

- 1 The success of CNN in computer vision
- 3 Symmetry and inductive bias
- 4 Richard Sutton's view
- 6 Doubts about logicism
- 7 Reinforcement learning
- 8 Structure of logic
- 9 Symmetric neural networks
- 11 For example: symmetric NN for object recognition
- 12 Logicalization of BERT
- 13 Advantages of logical AI (1)
- 14 Advantages of logical AI (2)
- 15 AGI 理论的突破

CNN 在机器视觉中的成功

• 在几何学上, 视觉 具有 平移 不变性:



• Convolution 是一种具有平移不变性的运算:

$$(T_x \circ f) * q = T_x \circ (f * q) \tag{2}$$

(2)

(1)

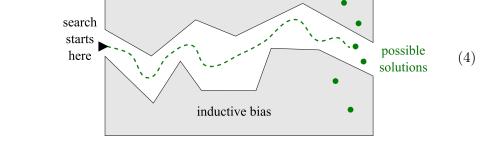
● Yann LeCun 等人 利用 CNN 的 **对称性** 加快了学习速度,成功地解决了机器视觉 的问题



(3)

Symmetry and inductive bias

- 在数学上,对称性 经常能简化计算,所以数学家 特别喜欢 对称
- 在机器学习中,经常要引入 归纳偏好 (inductive bias),缩小 搜寻空间:



• 往往如果 归纳偏好 选对了,可以在短时间内找到答案,否则问题是不可解的 (intractable)

Richard Sutton 的观点

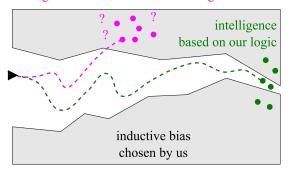
● Richard Sutton 认为,我们只需在 强化学习 的框架下 增加计算力,就可以找到 strong AI



(5)

• 我們選擇的只是众多 形式逻辑 之中可能的一种:

intelligence based on "alternative" logics



(6)

• 这不只是一个「空想」的问题;事实上,世界各地的实验室 已经开始了对 AGI 不同形式的搜索!

对 逻辑主义 的质疑

- 很多人怀疑: 人脑真的用 形式逻辑 思考吗?
- We tend to think there are "little models" inside our heads from which we draw inferences.
- If we're given a description: "woman finds new lover, murders husband":

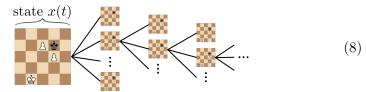


We may not know: Is the woman blonde? What is she wearing?

- In other words, the "model" is devoid of details and our representation seems to be just a sequence of symbols.
- 其实人脑比我们想像中更接近逻辑

Reinforcement learning

• Think of the "state" in reinforcement learning like a board positon in a chess game:



• Reinforcement learning seeks to maximize the total **rewards** accrued over a (possibly infinite) **time horizon**:

$$\text{maximize } S = \int_0^\infty L \, dt \tag{9}$$

- Such maximization gives the AI **intelligence** because it is often beneficial to **delay** rewards, eg: to plot a clever chess move
- But reinforcement learning is a **brute force** approach; we need to give the model some additional **inductive bias**, eg, in the form of **logical structure**

Structure of logic

- 我的想法是:在深度学习中引入 逻辑 的对称性,解决 strong AI 问题
- 因为人的思维 具有 逻辑 的结构,这个 inductive bias 可以帮助我们快速 找到 the solution to strong AI
- 逻辑结构很复杂,但最粗略的 symmetry 是 命题的 可交换律 (commutativity, or permutation invariance):

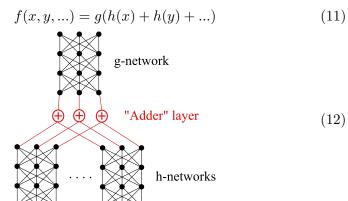
$$A \wedge B \equiv B \wedge A$$

下雨 \wedge 失恋 \equiv 失恋 \wedge 下雨

- 它的重要性类似於 视觉中的 平移不变性
- 另一种讲法是: 它将智能系统的 思维状态 (mental state) 分拆成 一粒粒 独立的 命题 (propositions)

Symmetric neural networks

- \bullet Permutation invariance can be handled by $\mathbf{symmetric}$ neural networks
- 我浪费了两年时间试图解决这问题,却发现在 3 年前已经有两篇论文解决了 [PointNet 2017] [DeepSets 2017],而且数学水平比我高很多
- Any symmetric function can be represented by the following form (a special case of the Kolmogorov-Arnold representation of functions):



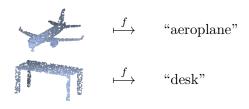
- Sym NN gives a powerful boost in efficiency ∝ n! where n = #inputs
 The code for Sym NN is just a few lines of Tensorflow:

- Very easy to adopt this to existing models such as BERT and reinforcement learning
- I have successfully tested it on the game of TicTacToe: https://github.com/Cybernetic1/policy-gradient

output = q(y)

For example: symmetric NN for object recognition

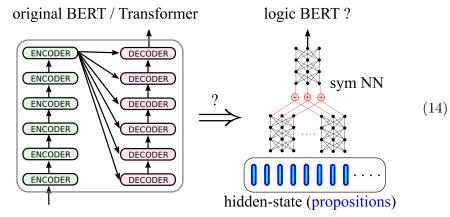
• Imagine objects represented as **point clouds**:



- It does not matter in what order the points are in a sequence; the function $f(x_1,...,x_n)$ is symmetric in its arguments (the points)
- Permutation invariance is **essential** for this to work

BERT 的逻辑化

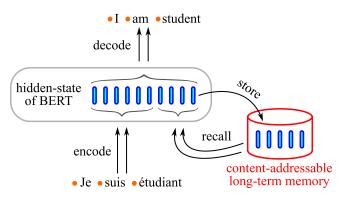
• 类似地,可以将 BERT 的 隐状态 变成 "set of propositions" 的形式,方法是将 原来的 decoder 变成 sym NN:



- 原来的 encoder 可以照旧使用,因为后半部改变了,error propagation 会 令 representation 也改变
- 当然,这个想法有待实验证实 😌

Advantages of logical AI (1)

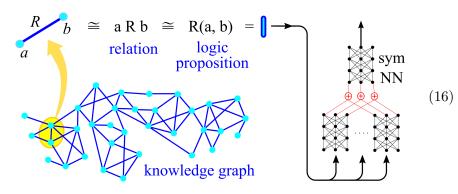
• With logic, it becomes easy to design cognitive architectures, eg: long-term memory module



(15)

Advantages of logical AI (2)

- 知识图谱 不能直接输入神经网络,它必需分拆成很多 edges,每个 edge 是一个关系,也是一个逻辑命题;也可以说 "graphs are isomorphic to logic"
- graphs are made up of edges, edges = relations between nodes = propositions:



AGI 理论的突破

- 最近我成功地描述了 strong AI 和 逻辑之间的数学关系 这种数学关系是永恒不变的,它可以指导日后 AGI 的发展 请参看附件:《再谈一次 AI 的逻辑结构》
- 关於 Logic BERT 与 attention 的详细理论 可参看附件《Logic BERT》

References



Illustration credits:

• Translation invariance, from Udacity Course 730, Deep Learning (L3 Convolutional Neural Networks ▷ Convolutional Networks)