“Easy” presentation

The logic route to strong AI

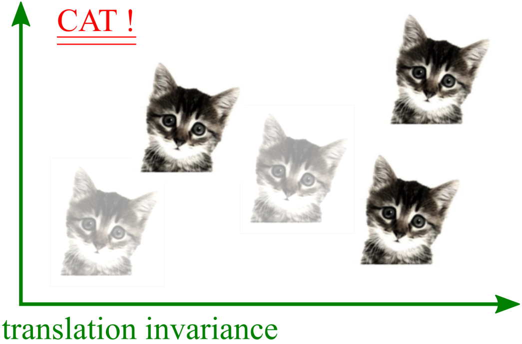
YKY

March 17, 2021

Table of contents

The success of CNN in computer vision

- In geometry, vision is said to possess the property of **translation invariance**:



(1)

- **Convolution** is an operation invariant under translation:

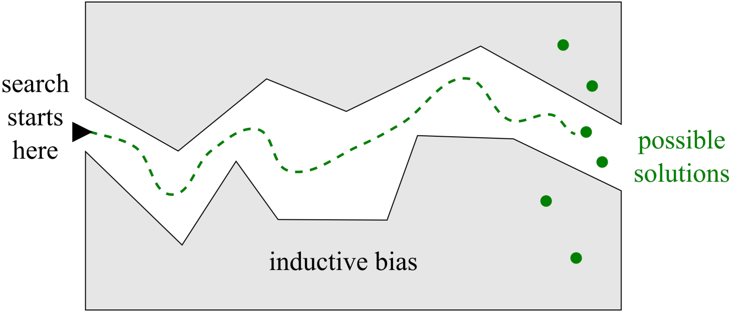
$$(T_x \circ f) * g = T_x \circ (f * g) \tag{2}$$

- Yann LeCun *et al* exploited the symmetry of CNNs to accelerate learning, successfully solved the visual recognition problem

(3)

Symmetry and inductive bias

- In mathematics, symmetry often simplifies computation, which is why mathematicians love to study symmetries
- In machine learning, one introduces inductive bias to narrow down the **search space**:



(4)

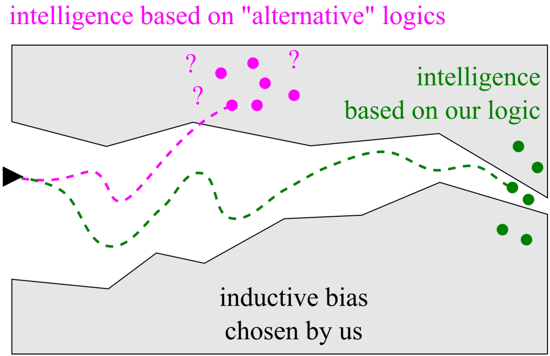
- Oftentimes, if inductive bias is chosen correctly, solution is found quickly, otherwise problem becomes **intractable**

Richard Sutton's view

- Sutton expressed the view that AI can probably be solved merely by **increasing computing power**, under the reinforcement learning framework

(5)

- Our choice is just one out of many possible **forms** of logic:



(6)

- This is not only a theoretical issue;
  Indeed, AI labs around the world had begun the search for AGI with various strategies!

Doubts about logicism

- Many are doubtful: does the human brain really use **formal logic** to think?

(7)

Actually human cognition may be much closer to logic than we've thought

Structure of logic

- The idea is: introduce symmetries of **logic** into deep learning to solve the AGI problem
- Because human cognition has logical structure, this inductive bias may help us find a solution to AGI faster
- Logic is a complicated structure, but its simplest symmetry is the **commutativity** (or permutation invariance) of **propositions**:

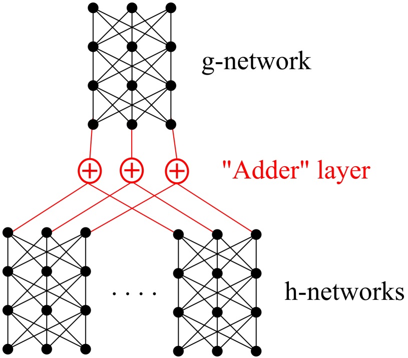
$$\begin{aligned} A \wedge B &\equiv B \wedge A \\ \text{it's raining} \wedge \text{lovesick} &\equiv \text{lovesick} \wedge \text{it's raining} \end{aligned} \tag{8}$$

- Its importance may be analogous to translation invariance in vision
- The significance of commutativity is: it **decomposes** the AI system's mental state into individual propositions

Symmetric neural networks

- Permutation invariance can be handled by symmetric neural networks
- I wasted 2 years trying to solve this problem, and then found out it had been solved 3 years before: [PointNet 2017] and [DeepSets 2017] and their mastery of mathematics is significantly above me!
- Any symmetric function can be represented by the following form (a special case of the Kolmogorov-Arnold representation of functions):

$$f(x, y, ...) = g(h(x) + h(y) + ...) \tag{9}$$



(10)

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

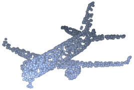
```
h = Dense(3, activation='tanh')
ys = []
for i in range(9):
    ys.append( h(xs[i]) )
y = Keras.stack(ys, axis=1)
Adder = Lambda(lambda x: Keras.sum(x, axis=1))
y = Adder(y)
g = Dense(3)
output = g(y)
```

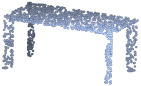
(11)

- 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

For example: symmetric NN for object recognition

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

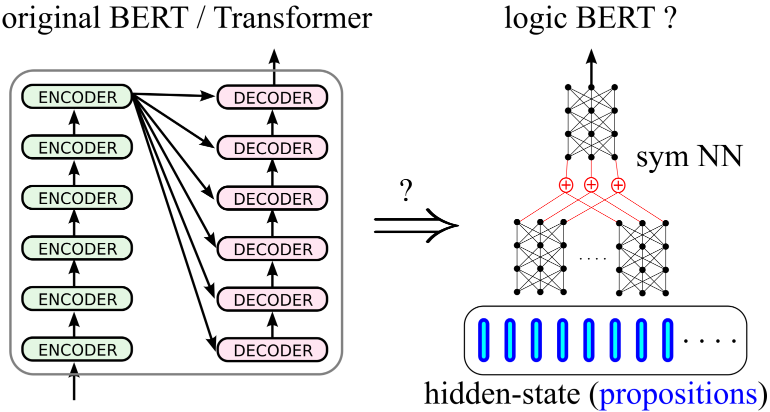
 $\xmapsto{f}$ “aeroplane”

 $\xmapsto{f}$ “desk”

- 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

Logicalization of BERT

- Similarly, we can convert BERT's hidden state into a set of propositions, by replacing the original decoder with a sym NN:

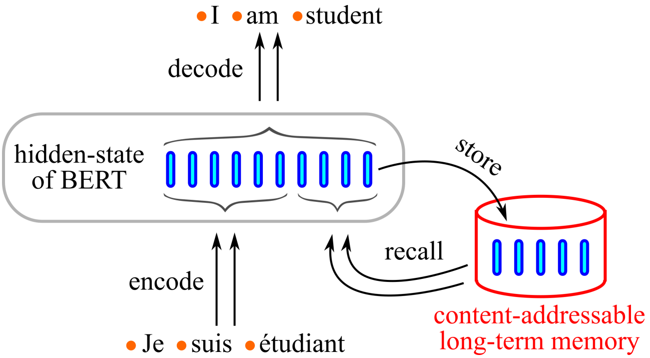


(12)

- The original encoder can be retained. As the decoder imposes symmetry on the hidden state, error propagation is expected to cause its representation to change
- Of course, this remains to be proven by experiment 😊

Application: content-addressable long-term memory

- The original BERT hidden state lacked a logical structure and it was not clear what exactly it contains. After logicalization, propositions inside BERT can be stored into long-term memory:

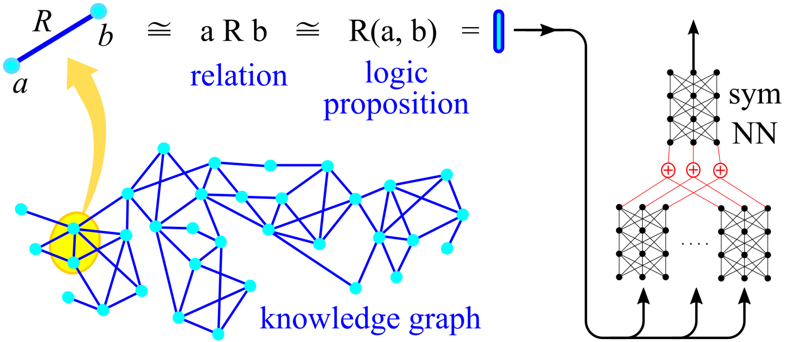


(13)

- These kind of systems are very close to strong AI, and it depends crucially on logicalization
- The content-addressable memory idea came from Alex Graves *et al*'s Neural Turing Machine [2014]

Application: knowledge graphs

- One cannot feed a knowledge graph directly into an NN, as its input must be embedded in vector space. A solution is to break the graph into edges, where each edge is equivalent to a relation or proposition. One could say that graphs are isomorphic to logic



(14)

- Since edges are invariant under permutations, it appears that symmetric NNs are required to process them

AGI

- strong AI
  AGI
  AI
- Logic BERT attention
  Logic BERT

References

Thanks for watching ☺️

[1] Alex Graves, Greg Wayne, and Ivo Danihelka. "Neural Turing Machines". In: *CoRR* abs/1410.5401 (2014). arXiv: 1410.5401. URL: http://arxiv.org/abs/1410.5401.

[2] Qi et al. "Pointnet: Deep Learning on Point Sets for 3D Classification and Segmentation". In: *CVPR* (2017). https://arxiv.org/abs/1612.00593.

[3] Zaheer et al. "Deep sets". In: *Advances in Neural Information Processing Systems* 30 (2017), pp. 3391–3401.

Illustration credits:

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