AGI via Combining Logic and Deep Learning

AGI 2021 Conference

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Part I

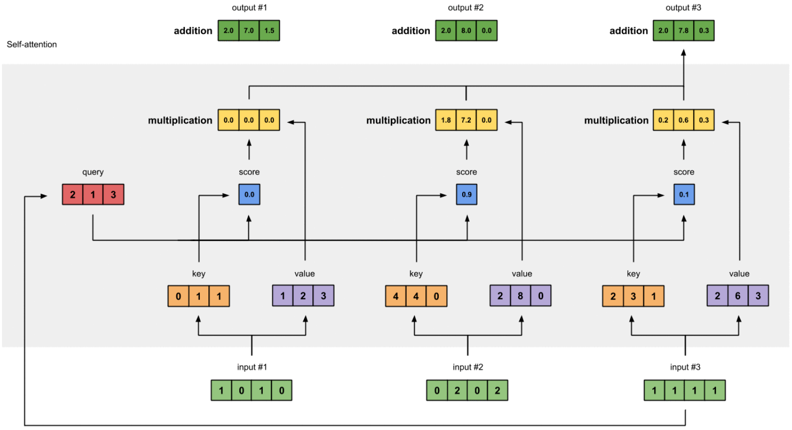
BERT / GPT

BERT is AGI

- BERT can generate texts, answer questions, and even write code
- BERT has learned human knowledge from text corpora
- Therefore, BERT is approximately AGI
- BERT also demonstrates that our computing power is in the **ballpark** of AGI
- I predict that human-level AGI will emerge within 5-6 years

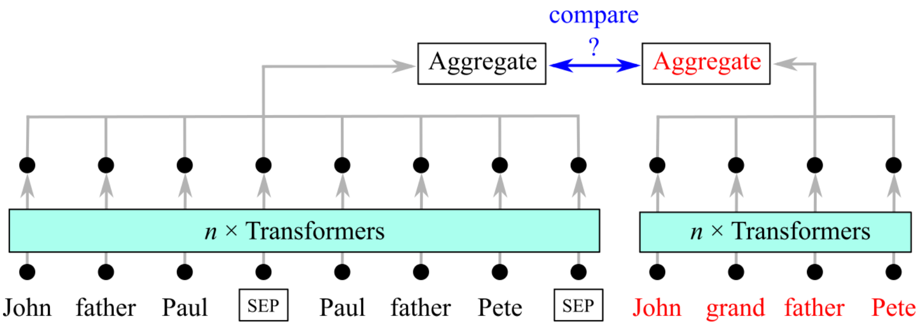
Equivariance of the Transformer

- Many people already know this:
  the Transformer module is **equivariant** in its inputs and outputs:



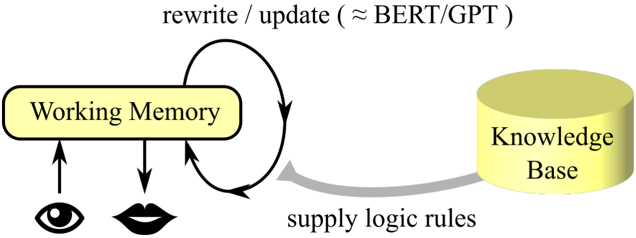
BERT's Hidden Representation

- A simplified view of how BERT performs **question-answering** or **logic deduction**:



BERT compared with AGI architecture

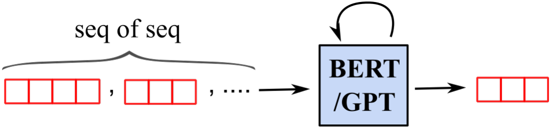
- A minimal AGI architecture is like this:



(1)

AGI as Sequence-to-sequence Rewriter

- The **state** of a logic system is a **set** of propositions
- So state = sequence of sequences,
  The 2nd level represents predicates and terms **inside** a proposition



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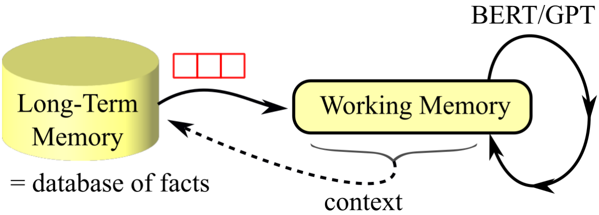
BERT with Long-Term Memory

- With logic, it is easier to design cognitive architectures, eg: long-term memory module



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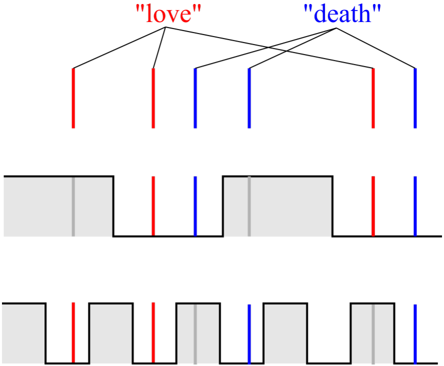
Additivity of Word Embeddings

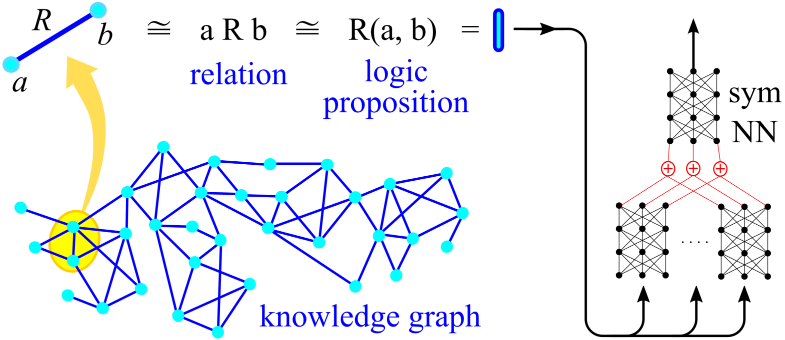
- The sine waves are **Positional Encodings**
- We can see that **Word Embeddings** can co-exist if embedding dimension is large enough



- This suggests that word embeddings can be added together to give **composite** meanings

Memory Recall

- Integrate seamlessly with **knowledge graphs**
- Graphs are made up of edges,
  edges = relations between nodes = propositions:



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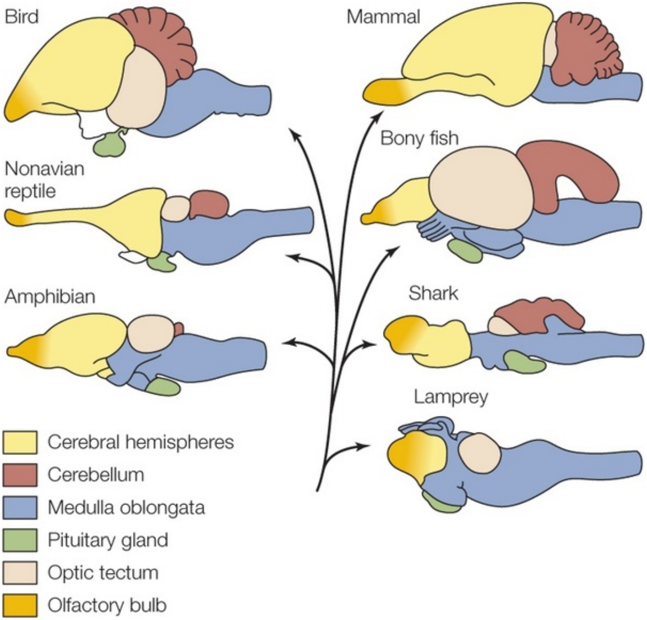
Part II

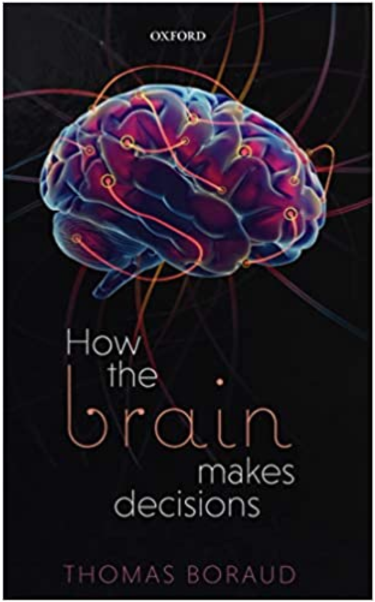
Reinforcement Learning

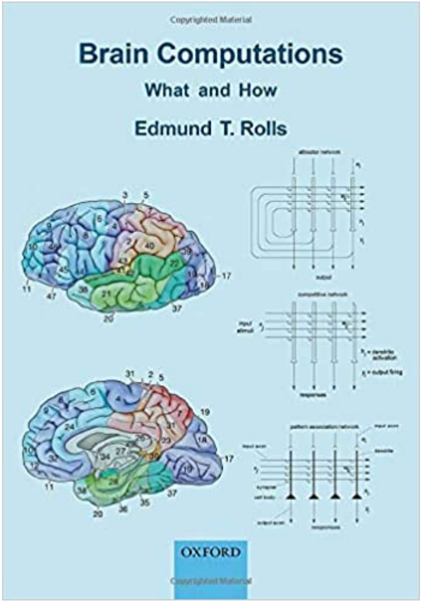
This is a lamprey

Evolution of the Neocortex



Books


OXFORD
How the brain makes decisions
THOMAS BORAUD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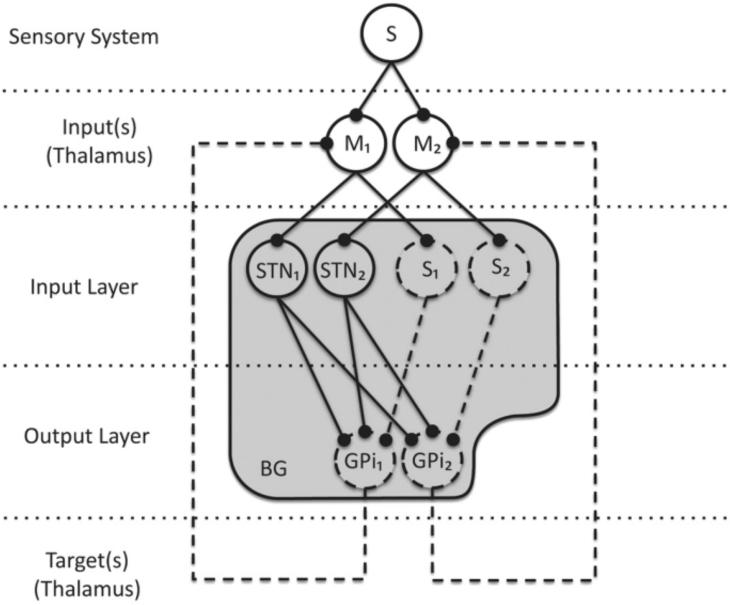
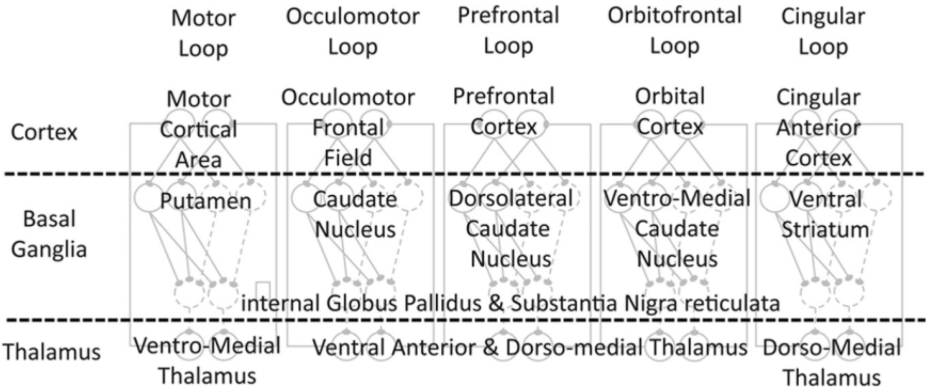
How the Basal Ganglia makes Decisions

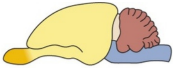


Sub-networks of the Neocortex



Neocortex vs Reinforcement Learning

Neocortical Learning



$+1$ $+100$ $+10$ $\longrightarrow$

food sex money

associations

action_1 action_2 action_3

Reinforcement Learning

reward R_x

$$Q \mathrel{+}= \eta\left[R_x + \gamma \max_{a'} Q' - Q\right]$$

(Q-learning)

action a

Part III

Model-based vs Syntax-based

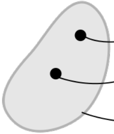
What is a Model?

Syntactic Representation
ie. a set of logic formulas:

```
human (Plato)
human (Aristotle)
∀x. human(x) ⇒ mortal(x)
```

Model theory relates
syntax with semantics

Semantic Representation

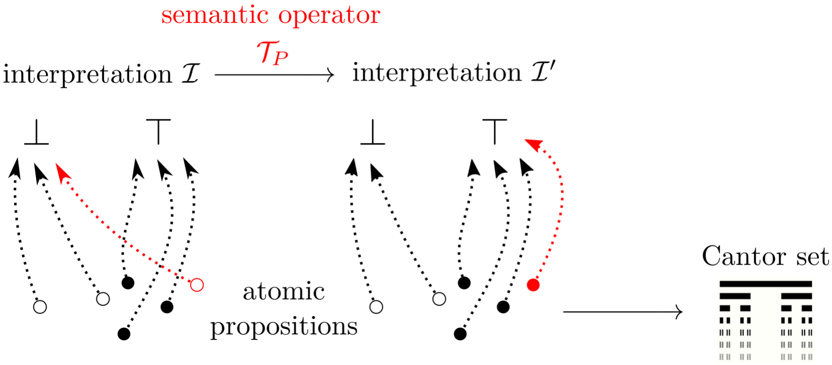


Language **describes** the real world

A **model** is a **representation** of the real world

Hitzler's Core Method

- The **semantic operator** $\mathcal{T}_P$ updates an interpretation to another interpretation:



Hitzler's Core Method

- The **level mapping** ι takes an interpretation to a real number:

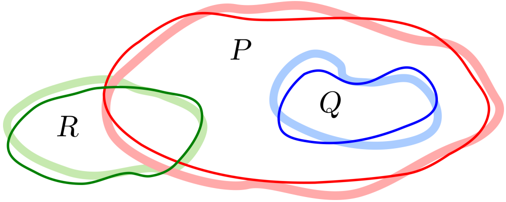
$$\begin{tikzcd} \mathcal{I} \arrow[r, "\mathcal{T}_P"] \arrow[d, "\iota"] & \mathcal{I} \arrow[d, "\iota"] \\ \mathcal{K} \arrow[r, "f_P"] & \mathcal{K} \end{tikzcd}$$

$$\iota(\mathcal{I}) = \sum_{\text{atom} \in \mathcal{I}} b^{-\ell(\text{atom})} \in \mathbb{R}$$

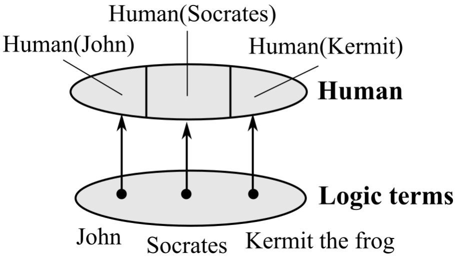
approximated by
neural network

Fibrations

- "Floating" regions and points as models



- "Fibration" structure of predicates

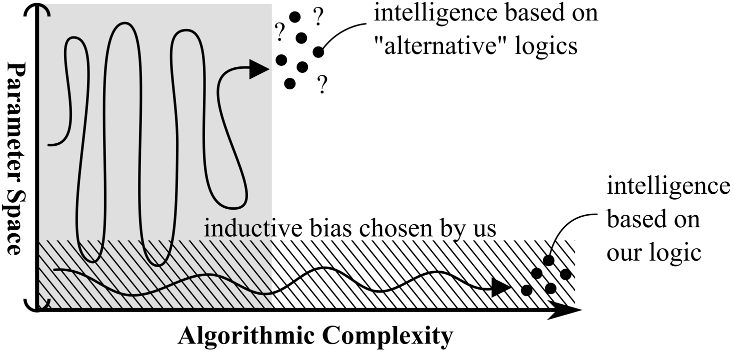


Part IV

No Free Lunch and Inductive Bias

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**:



(5)

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

Richard Sutton's view

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

(6)

References

Thanks for watching ☺️