

AGI from the perspective of categorical logic and geometry

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0 Basics

- The starting point of categorical logic is really the **Curry-Howard isomorphism**, without which you won't be able to understand the sequel.
- Curry-Howard correspondence is the idea of using a mathematical **function** $f : A \rightarrow B$ to simulate or implement the process of logic deduction, specifically $A \Rightarrow B$.
- From this perspective, a logic **proposition** A corresponds to the **domain** A of a function. That is, a proposition is akin to something like a **space**.
- Objects in that space are so-called **proof objects**, we use \blacksquare to denote them.
- It may take a while to get used to, but in fact we see this idea in use almost every day: in **neural networks**.
- A neural network maps certain vectors to vectors. Each vector is a proof.
- The space near a positional vector (under some error margin) ought to represent the **same** concept. So we might as well think of the neighborhood space as a logical proposition.
- This way of doing things is really very obvious and natural.

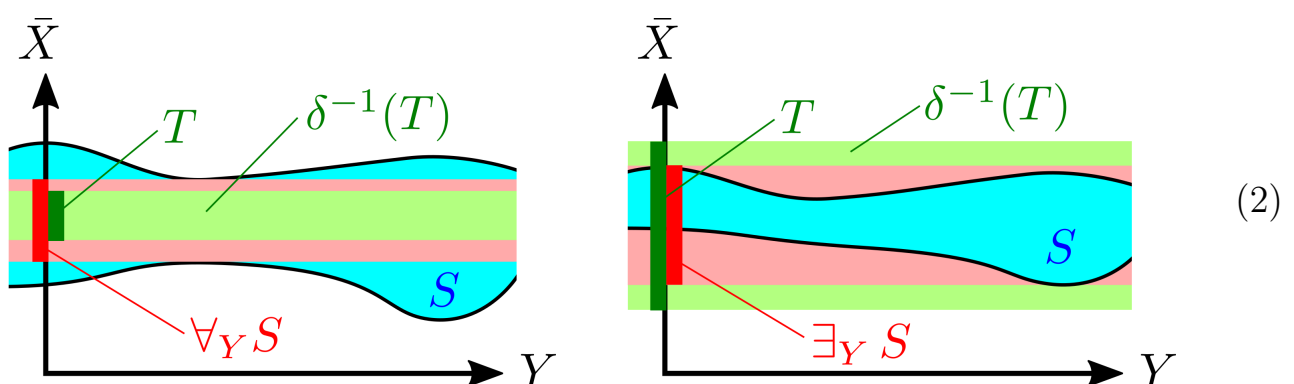
One evidence that this correspondence is on the right track is the truth table of $A \Rightarrow B$, which perfectly matches the cardinalities of the function spaces:

A	B	$A \Rightarrow B$	B^A
0	0	1	$0^0 = 1$
0	1	1	$1^0 = 1$
1	0	0	$0^1 = 0$
1	1	1	$1^1 = 1$

(1)

The goal of categorical logic is to use categorical tools as much as possible, to **describe** the structure of logic.

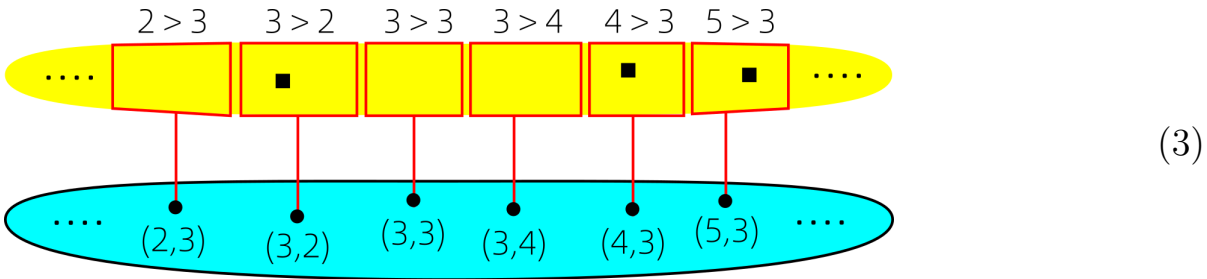
- “Propositions = some kind of spaces” generalizes naturally in category theory to “propositions = **objects** in a category”.
- We use **products** in category theory to express logic \wedge and \vee , and **exponentiations** B^A for $A \Rightarrow B$. The latter are also **morphisms** $A \rightarrow B$ in the category.
- \forall and \exists are described as **adjoints** to certain variable-substitution maps. For example in $\forall x. \phi(x, y)$ the quantifier $\forall x$ projects the space of (x, y) down to (y) only, so the resulting expression is no longer about x .



(This part is a bit complicated, but I have explained it elsewhere. The important thing is to understand the overall concept and not get lost in the details just yet)

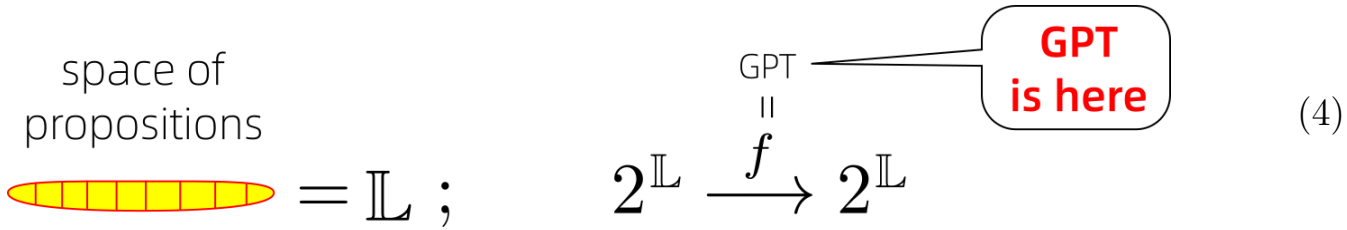
① 1 Where is GPT?

Logic **predicates** are described as **fibrations**, that is, an upper space “indexed” by the base space:



Here we are considering the binary relation “ $>$ ”, so the indexing space consists of pairs of natural numbers $\mathbb{N} \times \mathbb{N}$. We can form relational propositions $> (a,b)$, and because of Curry-Howard, these propositions are “spaces”, ie, yellow squares above. Each square is a proposition, which may or may not have a proof (■).

The union of all the yellow squares above is a **sheaf**, which is the space \mathbb{L} of propositions. **GPT** is a **logic consequence operator** that maps propositions to propositions. But note: GPT is a **set-valued map**. Its domain is not \mathbb{L} but the the power set $2^{\mathbb{L}}$ or $\mathcal{P}(\mathbb{L})$:



Knowing where GPT fits into the scheme of things, provides some clarity. At least for me, because I’m very familiar with **logic-based AI**, I tend to understand the mathematics from this perspective.

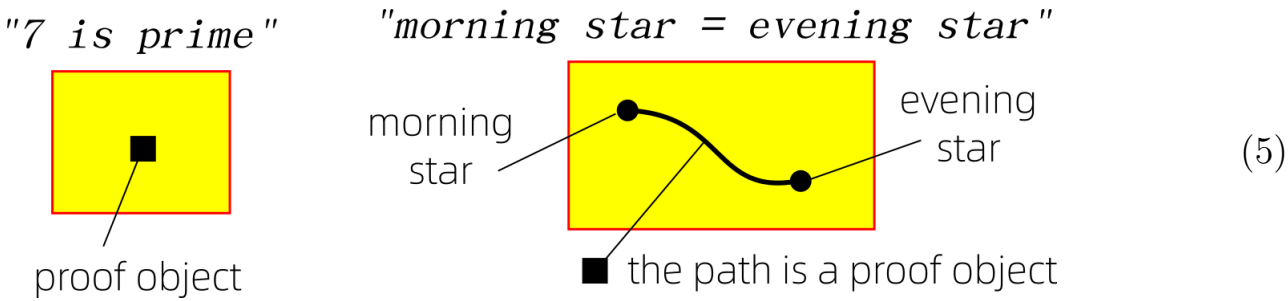
2 What is HoTT?

As Curry-Howard suggest that propositions are some kind of “spaces”, can they have topological structure? This is the original idea of **HoTT** (homotopy type theory) proposed by Voevodsky.



From my limited understanding, a proposition either has a proof or not have a proof. If there is a proof, there is no difference between one proof or another. But HoTT posits that they can differ. In the internal space of a proposition, two **path-connected** points (proofs) are regarded as identical, but there can be regions that are not path-connected in this space, so their proofs are regarded as different.

An example: The ancients regarded Venus as the Morning Star and Evening Star, without knowing that they were actually the same star. This is the difference between intension and extension, which can be handled by **intensional logic**, and can be formulated using **modal logic** and Montague semantics. For details, see this article: <https://plato.stanford.edu/entries/logic-intensional/>



For another example, a group can have different **group presentations**, a situation that seems applicable by HoTT.

These spaces that are not path-connected have a **groupoid** structure, with multiple levels such as 1-groupoid, 2-groupoid, ... up to ∞ -groupoid. I am not familiar with these aspects.

As the reader can see, HoTT is concerned with the interior of “truth” (ie, the yellow square), but AGI is mainly concerned with **inference**, which acts on the proposition space (ie, the entire yellow “banana” space).

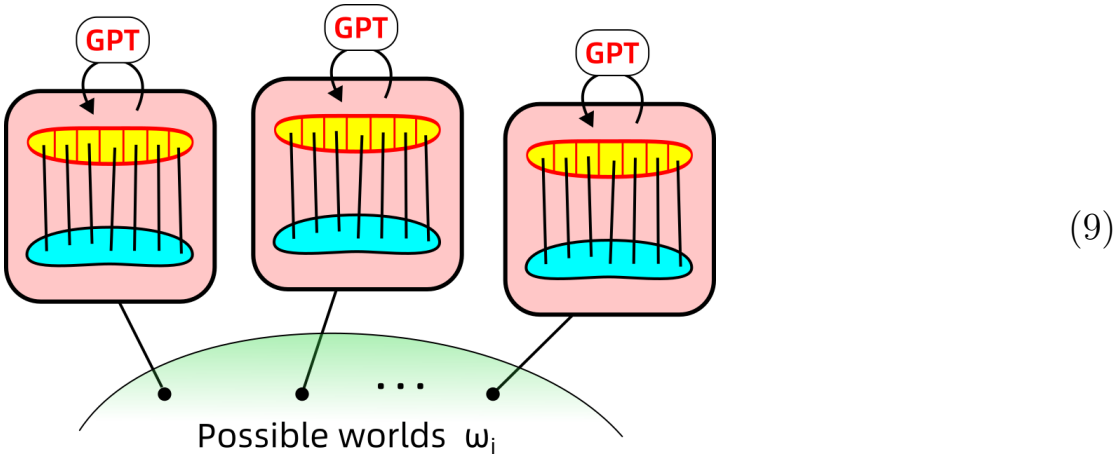
This is not to say that HoTT is useless for AGI, but its impact is subtle and I cannot judge it yet.

In fact, the **Transformer** has the ability to learn very complex syntactic manipulations, that is, it can implicitly learn the derivation steps of various logics such as modal logic. If so, it seems that we be “bypassed” various special logics without the need to explicitly implement them. But it is also plausible that we by imposing certain logical structural constraints that we can accelerate deep learning. These need to be verified experimentally and are promising research directions.

4 Sheaf semantics

The so-called combination seems to be a product, or more simply, lining up the fibers in the direction, which is an addition:

Form a sheaf, and sheaf can also be regarded as topos. The overall image is roughly like this:

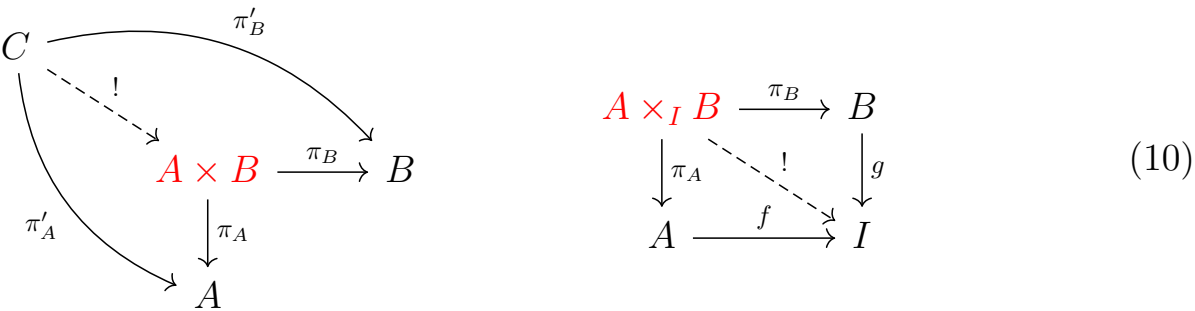


- From the perspective of the human brain, its ability to process “possible worlds” is very limited.
- The most classic example is when playing chess, each predicted move is a possible world. In general, people can usually predict only 3-5 moves.
- Each possible world is actually only one proposition different from the current world. It seems that in practice, there is no need to imagine possible worlds as ”monsters”.
- Possible worlds are generated dynamically when thinking. We cannot quickly train a GPT according to every possible world, so the above GPT’s are copies of the same training results.
- If you want to implement modal logic reasoning, you need to expand the function of the ”little GPT” above so that it can handle reasoning in multiple possible worlds. The method I think of for the time being is purely to follow the idea of classic logical AI, such as tagging each possible world with a specific proposition, and then calculating
- When the number of possible worlds is small, the concept of topological closure / interior does not seem to be very enlightening. From a computer point of view, continuous space is very ”ideal” and is actually very difficult to achieve.

These are quite intuitive. I will look at them in detail when I have time, but now I suddenly feel that this direction may not be too useful...

4.1 Further technical details on sheaves

Note that the categorical product (left) is defined differently from the fiber product (right):



Especially note that in the fiber product, $\pi_A \circ f = ! = \pi_B \circ g$ as the diagram commutes. The upshot is that, in the fiber product, the projection from the product along A or B to I give the same results. For example, we can have the pair $(\text{John}_1, \text{Mary}_1)$ in the fiber product, meaning John from World 1 and Mary from World 1. But we cannot have $(\text{John}_3, \text{Mary}_1)$ in the fiber product; It does not make sense to consider John_3 and Mary_1 together who exist in **different worlds**. Whereas in the categorical (Cartesian) product this is possible.

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5 Algebraic geometry

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6 What's the use of all these to AGI?