

Logic in Hilbert space

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Summary

- It seems possible to construct a model of the **untyped** λ -calculus in Hilbert space, with function application $f(g)$ implemented as $\llbracket g \rrbracket \circ \llbracket f \rrbracket$.
- Doing so allows **self-application** of logic predicates (Curry's paradox can be avoided by the fuzzy truth value “don't know”)
- The notion of **continuous maps** may be advantageous in machine-learning because **generalization** seems to work best with “continuous” domains (as opposed to maps acting on symbolic logic representations which may be discontinuous).
- Elements in the infinite-dimensional \mathcal{H} can be realized on a computer as **neural networks** (which can be seen as functions $\mathbb{R}^n \rightarrow \mathbb{R}^n$ **finitely** generated from sets of weights).

0 Background

In the 1960's Dana Scott constructed a model for untyped λ -calculus, using a domain D_∞ with the property $D_\infty^{D_\infty} \cong D_\infty$. This started off the field known as **domain theory**.

Scott initially believed that such models cannot exist, but later discovered that they can be constructed. In retrospect, this is not surprising because the Church-Rosser theorem demonstrated that the untyped λ -calculus is consistent.

Scott's idea is to begin with an initial domain D_0 and define D_{n+1} to be the function space $D_n \rightarrow D_n$.

Thus it is guaranteed, for any domain $d \in D_\infty$, one can always find a function space $d \rightarrow d$. Therefore the space D_∞ is isomorphic to $D_\infty \rightarrow D_\infty$.

The detailed definition of D_∞ involves building a cumulative hierarchy of infinite sequences, with pairs of operators ψ_n, Ψ_n going up and down levels. For a detailed exposition one may refer to [Stenlund1972], Ch.1 §6.

1 Elements in \mathcal{H}

The structure of D_∞ is reminiscent of Cantor's ordinal number ε_0 :

$$\varepsilon_0 = \omega^{\omega^{\omega^{\dots}}} = \sup\{\omega, \omega^\omega, \omega^{\omega^\omega}, \omega^{\omega^{\omega^\omega}}, \dots\} \quad (1.0.1)$$

and this number is “smaller” than the **continuum**, ie. the real line \mathbb{R} . This led me to think that models of λ -calculus might be found in the Hilbert space of continuous functions.

But such a Hilbert space would be ∞ -dimensional. Next I consider the **neural network** as a function f :

$$\begin{array}{ccc} \mathbb{R}^n & \xrightarrow{f} & \mathbb{R}^n \\ x & \mapsto & y \end{array} \quad (1.0.2)$$

and notice that f and x, y are “unequal” because f can **act on** x, y but not the other way round. This is partly because f is ∞ -dimensional whereas x, y are finite-dimensional. So, what if we increase n to ∞ , then perhaps x, y would become the same kind of objects as f ? In an informal sense \mathcal{H} can be regarded as \mathbb{R}^∞ .

Now we lack the notion of a function **applying** to another function, such as $f(g)$. Since we only need the functions as elements of \mathcal{H} , the domains \mathbb{R}^n is somewhat

“immaterial”. We might as well assume \mathbb{R}^n to be common among all functions, so the function **composition** such as $f \circ g$ always exists. So we define:

$$\llbracket f(g) \rrbracket = \llbracket g \rrbracket \circ \llbracket f \rrbracket \quad (1.0.3)$$

where $\llbracket \cdot \rrbracket$ denotes “model of”.

2 Logical operations in \mathcal{H}

记得在我的 AGI 架构中, \vdash 是用 神经网络 F 实现的。

一般来说, $\Delta \Rightarrow \Gamma$ 就是 \vdash 这个映射 对於 Δ 的一个 **截面** (a restriction of the \vdash map to the domain Δ). 这一点很重要: 一个 map 作用在某些元素上, 但这些元素和那个 map 是「同类」的。这其实是逻辑结构的一个 defining characteristic.

The map \vdash 存在於某 infinite-dimensional Hilbert space \mathcal{H} . 所以 逻辑命题 也应该存在於同一空间内, 而且 空间内的 元素可以 act on 自身。一般来说这是没有可能的, 因为 Cantor's theorem 说 $A \neq A^A$. 但如果符合某些 domain theory 的条件则可以有 $A \cong A^A$.

这个做法有两个问题:

- 如何定义 $f(e)$ where $f, e \in \mathcal{H}$
- given an element $e \in \mathcal{H}$, translate it to a (syntactic) logic formula

Need:

- family of maps that is dense
- self-application: maps can act on maps

$$f(g) \rightsquigarrow \llbracket g \rrbracket \circ \llbracket f \rrbracket \quad (2.0.1)$$

In order to handle tuples like (x, y) , we need to expand our domain to allow functions such as $\mathbb{R}^{2n} \rightarrow \mathbb{R}^n$ with input dimensions $2n, 3n, 4n, \dots$ etc. Then an n -ary function can be implemented via (shown here in the binary case):

$$f(g, h) \rightsquigarrow \left[\begin{array}{c} \llbracket g \rrbracket \\ \llbracket h \rrbracket \end{array} \right] \circ \llbracket f \rrbracket \quad (2.0.2)$$

where f is of type $\mathbb{R}^{2n} \rightarrow \mathbb{R}^n$. With this, we can implement the combinators **S**, **K**, **I** in combinatory logic. The treatment for λ -calculus would be analogous, but I'm too busy to work it out at this time.

Suppose $a \wedge b \Rightarrow c$ and $d \Rightarrow c$, we would like to make the following two definitions of c be consistent with f :

$$\begin{array}{ll} \begin{array}{c} a \\ b \end{array} \begin{array}{l} \searrow \\ \swarrow \end{array} f \longrightarrow c & f(a, b) = c \\ d \longrightarrow f \longrightarrow c & f(d) = c \end{array} \quad (2.0.3)$$

but the arity of f appears different in the two equations. My solution is to adjoin a zero input to the second definition, that is:

$$\begin{array}{c} d \\ \emptyset \end{array} \begin{array}{l} \searrow \\ \swarrow \end{array} f \longrightarrow c \quad f(d, \emptyset) = c \quad (2.0.4)$$

3 Associative attention / recommendation of inference

The word “attention” is used here alternatively, not the same as Attention in BERT or Transformers.

It may be advantageous to use a graph neural network (GNN) as the **state** of our AI system and such that the transition function F maps the current-state GNN to the next-state GNN.

The size of the GNN is the “working memory” size and may be moderately large. So we need an algorithm to select a subset of nodes in the GNN as **candidates** for applying deduction:

$$A_1 \wedge A_2 \wedge \dots A_n \Rightarrow B. \quad (3.0.1)$$

There are $\binom{M}{N}$ ways of choosing a cluster of N nodes from a total of M nodes. Finding such subsets is akin to what **recommendation engines** do, where our problem can be regarded as the recommendation of candidates for logic rules application.

Perhaps an efficient algorithm is to calculate scores of something....

References

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