

See discussions, stats, and author profiles for this publication at: <https://www.researchgate.net/publication/392912389>

Parsimonious Neural Network Abduction

Preprint · June 2025

DOI: 10.13140/RG.2.2.15695.80804

CITATIONS

0

1 author:



Gary Nan Tie

Mu Risk LLC

92 PUBLICATIONS **27 CITATIONS**

SEE PROFILE

Parsimonious Neural Network Abduction

Gary Nan Tie, Jun 22, 2025

Abstract

For hypotheses whose effect is manifested by observations, abduction seeks to explain a given observation by finding a hypothesis whose effect is that observation.

Abductive reasoning has a fibration semantics [1] that can be implemented by neural networks [2]; a step towards artificial general intelligence.

In this note we introduce a parsimonious choice of explanation depending on one's utility function.

An arrow $p: K \rightarrow V$ in a category is said to be a fibration with respect to a class of arrows \mathcal{M} when for any $m \in \mathcal{M}$ and 2-cell $m \xRightarrow{(f,g)} p$, that is solid commutative square

$$\begin{array}{ccc} B & \xrightarrow{f} & K \\ m \downarrow & \nearrow \sigma & \downarrow p \\ Q & \xrightarrow{g} & V \end{array}$$

there exists dotted lifting σ making both triangles commute.

Now let the category arrows be neural networks

on finite data sets. Learn $\tau: V \rightarrow K$ from I/O

$$\{(g(q), \sigma(q))\}_{q \in Q} \text{ subject to } \tau \circ g = \sigma,$$

then $(p \circ \tau) \circ g \approx g$, that is $p \circ \tau|_{g(Q)} \approx 1_{g(Q)}$,

which is to say, on $g(Q) \subseteq V$, effect p is

explained by abduction τ , when p is a fibration,

(and assume lifting σ is learnable).

Let analogies $\mathcal{A}_{p,g}$ be a finite subset of

$$\{ m \xRightarrow{(f,g)} p \mid m \in \mathcal{M}, \text{span}(m,f), p \text{ a fibration wrt } \mathcal{M} \}$$

with corresponding abductions

$$\mathcal{T} = \{ \tau: V \rightarrow K \mid \tau \circ g = \sigma, \sigma \text{ a lifting from } \mathcal{A} \}$$

Let $L: V \times V \rightarrow \mathbb{R}$ be your loss function.

For $\tau \in \mathcal{T}$, let average discrepancy

$$\mu_\tau \triangleq \frac{1}{|g(Q)|} \sum_{v \in g(Q)} L(p(\tau(v)), v)$$

Define $\tau \preceq \tau'$ iff $\mu_\tau \leq \mu_{\tau'}$

With respect to analogies \mathcal{A}

$$\frac{\tau}{\tau} \triangleq \min_{\preceq} \{ \tau \in \mathcal{T} \}$$

is our parsimonious explanation of effect p .

Summary:

For neural networks

$$\begin{array}{ccc}
 & & K \\
 & & \downarrow p \text{ effect} \\
 Q & \longrightarrow & V \\
 & \underset{g}{\text{attention}} &
 \end{array}$$

when p is a fibration with respect to \mathcal{M} ,

learned liftings σ for analogies (2-cells),

induce abductions τ . The abduction with the

least average discrepancy is chosen to our parsimonious

explanation of effect p , according to our utility.

References

[1] 'Fibrations explain all you need!'
- Fibrations, Abduction and Attention
Gary Nan Tie, Mar 4, 2025
DOI: 10.13140/RG.2.2.35984.52488

[2] 'Neural Network Abduction'
Gary Nan Tie, Jun 13, 2025
DOI: 10.13140/RG.2.2.18506.07360/1