C-WARS: THE UNFOLDING ARGUMENT STRIKES BACK - A REPLY TO ‘FALSIFICATION & CONSCIOUSNESS’

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ABSTRACT

The unfolding argument was presented by Doerig et.al. in [1] as an argument to show that causal structure theories (CST) like IIT are either falsified or outside the realm of science. In [2] and then [3], the authors mathematically formalized the process of generating observable data from experiments and using that data to generate inferences and predictions onto an experience space. The resulting substitution argument built on this formal framework was used to show that all existing theories of consciousness were pre-falsified if the inference reports are valid. If this argument is indeed correct, it would have a profound effect on the field of consciousness as a whole indicating extremely fundamental problems that would require radical changes to how consciousness science is performed. However in this note the author identifies the shortcomings in the formulation of the substitution argument and explains why it’s claims about functionalist theories are wrong.

Keywords Consciousness · Falsification · Unfolding Argument · Substitution Argument · IIT · Causal Structure · Krohn-Rhodes Theorem

1 Introduction

The ‘unfolding argument’ presented in [1] made the case that IIT and other causal structure theories (CSTs) are either already falsified or outside the realm of science. This argument was first extended in [2] and a more generalized version was presented as the ‘substitution arguments’ in [3]. The author here will assume that readers are pretty familiar with all 3 papers - [1], [2] and [3]. The focus will be on the last one which we find to be the most general version of the arguments and the most broad in claims. It is very interesting work, accessible and proposes a descriptive mathematical framework that could be very useful moving forward. For the sake of brevity, we will borrow the symbols and terminologies from [3] as much as possible to point out the errors in that model and make suitable corrections. With these corrections incorporated, we should be able see that the substitutions argument does not apply for functionalist theories (or at best have not been proven to do so) in [3].

In this short note, we will start by introducing some relevant concepts and definitions from [3] in section 2. The main contribution of this note is section 3, where we present arguments as to why the results of the substitution argument does not apply for functionalist theories of consciousness by pointing what the formalism missed. The note will conclude in section 4 summarizing the ideas presented here.

2 Understanding the Substitution Argument

We start with the summary of the different parts of the figure from section 2.5 in [3] in detail, since the error stems from these very definitions.
Artificial neural networks. ANNs, particularly those trained using deep learning, have grown increasingly powerful. The authors in [3] then suggest that the unfolding argument against IIT is a special case of the substitution argument, and capable of human-like performance (LeCun et al., 2015; Bojarski et al., 2016). For any ANN, report (output) is functionalist frameworks, we will quote from section 3.4.4 from [3] where this is discussed -

Since the author’s contention in this note is whether the substitution argument has been properly applied with respect to a pretty big claim that all functionalist frameworks have every single inference wrong or have already been falsified. and the latter applies to all known frameworks for the science of consciousness including functionalist frameworks. It is a pretty big claim that all functionalist frameworks have every single inference wrong or have already been falsified. Since the author’s contention in this note is whether the substitution argument has been properly applied with respect to functionalist frameworks, we will quote from section 3.4.4 from [3] where this is discussed -

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**Figure 1:** This picture illustrates substitutions. Assume that some data set \( o \) with inference content \( o_r \) is given. A substitution is a transformation \( T \) of physical systems which leaves the inference content or invariant but which changes the result of the prediction process. Thus whereas \( p \) and \( T(p) \) have the same inference content or, the prediction content of experimental data sets is different. Different in fact to such an extent that the predictions of consciousness based on these datasets are incompatible (illustrated by the non-overlapping circles on the right). Here we have used that by definition of \( P_{o_r} \), every \( p \in P_{o_r} \) yields at least one data set \( o' \) with the same inference content as \( o \) and have identified as \( o \) and \( o' \) in the drawing [3].

1. \( P \) denotes a class of physical systems, each in various different configurations. In most cases, every \( p \in P \) thus describes a physical system in a particular state, dynamical trajectory, or configuration.

2. \( \text{obs} \) is a correspondence which contains all details on how the measurements are set up and what is measured. It describes how measurement results (data sets) are determined by a system configuration under investigation. This correspondence is given, though usually not explicitly known, once a choice of measurement scheme has been made. \( O \) is the class of all possible data sets that can result from observations or measurements of the systems in the class \( P \). Any single experimental trail results in a single data set \( o \in O \), whose data is used for making predictions based on the theory of consciousness and for inference purposes.

3. \( \text{pred} \) describes the process of making predictions by applying some theory of consciousness to a data set \( o \). It is therefore a mapping from \( O \) to \( E \).

4. \( E \) denotes the space of possible experiences specified by the theory under consideration. The result of the prediction is a subset of this space, denoted as \( \text{pred}(o) \). Elements of this subset are denoted by \( e_i \) and describe predicted experiences.

5. \( \text{inf} \) describes the process of inferring a state of experience from some observed data, e.g. verbal reports, button presses or using no-report paradigms. Inferred experiences are denoted by \( e_r \).

Under these definitions for the different components, falsification is defined (Definition 2.1 in [3]) as there is a falsification at \( o \in O \) if we have \( \text{inf}(o) \notin \text{pred}(o) \). A substitution is defined (Definition 3.1) as a \( \phi_r \)-substitution if there is a transformation \( S : P_{o_r} \to P_{o_r} \), such that at least for one \( p \in P_{o_r} \cdot \text{pred} \cdot \text{obs}(p) \cap \text{pred} \cdot \text{obs}(S(p)) = \phi \). The crux of the paper i.e. the substitution argument (represented in the Fig.(1) here) is built using a number of proposition and lemmas, and is given in Theorem 3.10 from [3].

**Theorem 3.10** - If inference and prediction data are independent, either every single inference operation is wrong or the theory under consideration is already falsified.

Inference and prediction data is defined as independent (by Definition 3.8) if for any \( o_r, o'_r \) and \( o_r \), there is a variation \( v : P \to P \) such that \( o_r \in \text{obs}(p), o'_r \in \text{obs}(v(p)) \), but \( o_r \in \text{obs}(v(p)) \) and \( o_r \in \text{obs}(v(p)) \) for some \( p \in P \).

The authors in [3] then suggest that the unfolding argument against IIT is a special case of the substitution argument, and the latter applies to all known frameworks for the science of consciousness including functionalist frameworks. It is a pretty big claim that all functionalist frameworks have every single inference operation is wrong or have already been falsified. Since the author’s contention in this note is whether the substitution argument has been properly applied with respect to functionalist frameworks, we will quote from section 3.4.4 from [3] where this is discussed -
a function of node states. Crucially, this function is non-injective, i.e. some nodes are not part of the output. E.g., in deep learning, the report is typically taken to consist of the last layer of the ANN, while the hidden layers are not taken to be part of the output. Correspondingly, for any given inference data, one can construct a ANN with arbitrary prediction data by adding nodes, changing connections and changing those nodes which are not part of the output. Put differently, one can always substitute a given ANN with another with different internal observables but identical or near-identical reports. From a mathematical perspective it is well-known that both single-layer ANNs and recurrent ANNs can approximate any given function (Hornik et al., 1989; Schäfer and Zimmermann, 2006). Since reports are just some function, there are viable universal substitutions that provably exist.

A special case thereof is the unfolding transformation considered in Doerig et al. (2019) in the context of IIT. The arguments in this paper constitute a proof of the fact that for ANNs, inference and prediction data are independent (Definition 3.8). Crucially, our main theorem shows that this has implications for all minimally informative theories of consciousness. A similar results (using a different characterization of theories of consciousness than minimally informative) has been shown in Kleiner (2019).

While we have introduced the most relevant parts here, we strongly encourage readers to read the full paper in [3]. We will now explore the shortcomings of the substitution argument in the next section and explain why it has not been properly applied to functionalist frameworks.

3 What the Substitution Argument Misses?

The work in [3] is a very interesting base to build from for further formalizing the science of consciousness. However the broad mathematical picture it paints presents a low resolution view of experimental work and modeling methodologies that coarse-grains some very important details. In their paper, Hoel and Kleiner referred to neural networks during their discussion of functionalist frameworks and the equivalence of feedforward and recurrent networks that can produce the same input-output behavior (as utilized in [1]. We will discuss what is missed in their framework using a simple example from a machine state functionalism picture which was used in [2] (A much broader argument equivalent to the unfolding argument was presented in [5] using the Krohn-Rhodes decomposition [6], [7] of finite state automaton). Since neural networks can be decomposed into finite state automata, the work presented here can be extended to cover the cases discussed in [3].

From [4], we have machine state functionalism to be - any creature with a mind can be regarded as a Turing machine (an idealized finite state digital computer), whose operation can be fully specified by a set of instructions (a “machine table” or program) each having the form: If the machine is in state $S_i$, and receives input $I_j$, it will go into state $S_k$ and produce output $O_l$ (for a finite number of states, inputs and outputs).

A machine table of this sort describes the operation of a deterministic automaton, but most machine state functionalists (e.g. Putnam 1967) take the proper model for the mind to be that of a probabilistic automaton: one in which the program specifies, for each state and set of inputs, the probability with which the machine will enter some subsequent state and produce some particular output. On either model, however, the mental states of a creature are to be identified with such “machine table states” $(S_1, S_2, ..., S_n)$. These states are not mere behavioral dispositions, since they are specified in terms of their relations not only to inputs and outputs, but also to the state of the machine at the time.

Let us now set up the machine state functionalism picture under the framework presented in [5]. Consider a physical system $p \in P$ that produces the finite state automaton shown with the corresponding transition table is given in Fig.2(a). The transition table which captures the relationship between the current state, inputs and next state specifies the functional structure. The $\text{pred}$ and $\text{inf}$ functions (correspondences) operate on these automaton states, inputs and outputs to the space of $E$ and generate both $o_i$ and $o_r$ as shown in Fig.2(b).

In our case here, the variation map $T(p)$ is simply a Krohn-Rhodes (KR) decomposition which produces a homomorphic cascaded automaton (that might have a different state space and transition map - we will deal with isomorphic case later) with the same input-output characteristics as shown in Fig.(3). In this figure we have a variation $T(p)$ of the physical system $p$ which produces a different transition table (at the bottom) corresponding to this KR decomposition while maintaining the same input-output characteristics. Since $\text{inf}$ obtained by a verbal report (for example) are functions of the output, the KR-decomposed state machine will produce the same $\text{inf}$. However since this transition table is different, application of the $\text{pred}$ function on the states and their transitions (i.e. functional structure) should produce a different prediction of the experience, hence indicating a successful substitution i.e falsification of machine state functionalism if the inference report is to be believed.

To identify what the argument missed, let’s take another step closer and focus on the $\text{pred}$ function. In the 1st instance when dealing with $p$, we have the $\text{pred}$ function which maps the internal states and inputs (the transitions to the next state are a function of the these two) to an experience in $E$. For example, this might look something like
Figure 2: (a) 2-bit/4 state finite state automaton and its corresponding transition table indicating the next state for every current state and input. (b) A functionalist framework generating a transition table from a physical system $p$ using the $obs$ correspondence. The $pred$ and $inf$ functions act on this state machine to produce model predictions and inference reports on the experience space $E$.

$pred(current - state = 00, input = 1, next - state = 10) = 'happy'$ and inference report of ‘happy’. Now with the inference report being fixed, there would be a substitution $T(p)$ that generates a different transition table as per the KR-decomposition, we have that $pred(current - state = 000, input = 1, next - state = 001) = 'sad'$. Clearly the $pred$ function mapped to different experiences for the same inference report. But we should notice that argument space for the $pred$ function has now changed with respect to the machine states from $\{00, 01, 10, 11\}$ to $\{000, 001, ..., 110, 111\}$. In order to be consistent, we need to have a different prediction function $pred'$ which is properly defined and can act on the new state space to generates maps to $E$. Thus we rewrite $pred(current - state = 000, input = 1, next - state = 001) = 'sad'$ to $pred'(current - state = 000, input = 1, next - state = 001) = 'sad'$. Clearly we can see that for the substitution argument to be successful, we need $pred[obs(p)] \cap pred'[obs(T(p))] = \phi$.

Let us now explore why the substitution argument still does not work even with a modified definition for substitution. Under this new definition, we can have a substitution if $pred[obs(p)] \cap pred'[obs(T(p))] = \phi$ where both $pred, pred' \in \{pred\}_o$. Assume you are a scientist working in the science of consciousness. You generate the datasets from system $p$ and use a state machine functionalist picture to generate the transition table of the 2-bit state machine $A$ (with 4 states). You then proceed to use a prediction function $pred$ that maps these states and inputs to space of experience $E$. Now you are working with the transformed system $T(p)$ which produces data from which you extract the transition table for the 3-bit machine $A'$. We assume that $A$ and $A'$ are related through a KR-decomposition and maintain the same input-output relationships and inference reports. You can use your original $pred$ function only if the new 3-bit state space is suitably coarse-grained to the original 2-bit space (suitably here referring to consistency to be maintained with
Figure 3: A detailed look into the substitution argument using variation $T$ on the physical system $p$, in the case of a machine state functionalist framework. The inference reports $inf$ in both cases are the same while the predictions $pred$ vary on the experience space $E$.
both systems need to be equal to each other - \( F(x, y) = \theta = G(r, \theta) \). For the substitution-like argument to work in this case, you would need all the functions \( F, G \) and \( T \) to be appropriately picked to ensure consistency, and still have \( F(x, y) \neq G(r, \theta) \) which would not be possible by the very definition.

Thus once the finer details in the differences between different prediction functions are accounted for, we can see that for (machine state) functionalist frameworks, the substitution argument would only work under the following bad methodological scenarios -

- Trying to apply the \( \text{pred} \) function on a domain space on which it is not defined i.e. trying to apply \( F \) defined in the \((x, y)\) domain on \((r, \theta)\) and expect to get accurate answers.
- Assuming \( \text{pred} \) and \( \text{pred}^\prime \) are not constrained by each other and the variation map \( T \) i.e. \( F \) and \( M \) constrain \( G \) such that it has to give the same angle \( \theta \). Picking \( \text{pred}^\prime \) arbitrarily is bound to give inaccurate predictions.

The next argument against the author’s objections would be to point towards the case of isomorphic KR-decompositions, in which the number of system states and the global network topology remains consistent and the only difference corresponds to a permutation in the state’s labels [5]. Our original argument rested on the difference between the size of the state space of the different state machines. But what if the KR-decomposition of state machine produces another with the same number of states? This argument once again arises due to the coarse-grained view created by the original framework. To understand this better, let us go back to the case of a scientist working performing these experiments. The scientists uses the observation function \( \text{obs} \) on physical system \( p \) to generate different datasets upon which the transition table is constructed and the \( \text{pred} \) function is defined. Now consider the case where the scientist is operating on an isomorphic KR-transformation \( T(p) \) such that the global topology and number of states remain consistent, while state labels are permuted. In the most straightforward scenario, application of \( \text{obs} \) on \( T(p) \) produces an identical state machine as the earlier case and the application of \( \text{pred} \) produces the same result i.e. there is no substitution or subsequently falsification with \( \text{pred}[\text{obs}(p)] = \text{pred}[\text{obs}(T(p))] \). Moving on to the scenario where application of \( \text{obs} \) on \( T(p) \) produced a state transition table with the same number of states and transition topology but with labels permuted. It seems like the substitution argument wins out here, since the \( \text{pred} \) function can be applied here as well with no change in the state space dimensions but obtaining a different prediction results. However this is once again not the case due to the following reasons - as the scientist applies \( \text{obs} \) to generate the isomorphic machine with permuted labels, it is reasonable to assume that the labeling scheme is contained within \( \text{obs} \) in the manner in which the experiment is setup. Now when the labeling scheme is changed (as required to permute the state symbols) during the process of generating datasets, we can keep track of this change with respect to the original labels and thus understand the label-label map between the two state machines. While the \( \text{pred} \) function can technically be applied on the new state machine, it would be poor practice to directly do so knowing the change in label scheme, without first un-permuting the state symbols. We need to first un-permute the labels and then we can apply the \( \text{pred} \) function on the state machine with the original labels. This would produce the same prediction results as the earlier case. We can think about this as replacing the \( \text{pred} \) once again with a new function \( \text{pred}^\prime = \text{pred} \cdot \text{unpermute} \). With this definition of \( \text{pred}^\prime \), we go back to the case of utilizing \( \text{pred}^\prime \) discussed earlier in this section. We see that with the permutation taken into account, we have \( \text{pred}[\text{obs}(p)] = \text{pred}[\text{unpermute}(\text{obs}(T(p)))] \) and the substitution argument fails. We will make this clear with a simple example - consider running experiments on physical system \( p \), generating a 2-bit (4 state) finite state automaton by picking a labeling scheme by assigning to specific physical observables (like say voltage highs/lows are binary ‘1’/’0’). This simply maps to either changing the state space of the network and/or relabeling the states and thus will not work. While the author here has specifically focussed on state machines and neural networks, we suspect that
objections of the same flavor can be constructed against the other examples of universal computers and intelligences if they are cast under a functionalist picture. We will now conclude this note by summarizing the results in this paper.

4 Summary & Conclusion

The substitution argument presented in [3] would have massive implications in the field of consciousness if it ‘prefalsifies’ all the current major frameworks of consciousness and points towards a new approach in this research area. However the mathematical formalization of the observation-prediction-inference process coarse-grains out some important details which would implicitly invalidate the claims made in the paper with respect to functionalist frameworks. We would need to follow poor experimental and modeling methodologies to allow for the substitution argument to apply on functionalist frameworks and falsify it. Once we take a more fine-grained view and account for the dependencies between these different components, the substitution argument once again simply reinforces the results of the unfolding (like) arguments [1, 5] that the integrated information theory (and causal structures theories) are falsified if the inference report are taken to be valid. The science of consciousness is safe for now and we should not be hasty in abandoning existing frameworks and methodologies to explore phenomenology-first approaches.

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