Can neuroscientists ask the wrong questions? On why etiological considerations are essential when modeling cognition

Abstract: It is common in machine-learning research today for scientists to design and train models to perform cognitive capacities, such as object classification, reinforcement learning, navigation and more. Neuroscientists compare the processes of these models with neuronal activity, with the purpose of learning about computations in the brain. These machine-learning models are constrained only by the task they must perform. Therefore, it is a worthwhile scientific finding that the workings of these models are similar to neuronal activity, as several prominent papers reported. This is a promising method to understanding cognition. However, I argue that, to the extent that this method's aim is to explain how cognitive capacities are performed, it is likely to succeed only when the capacities modelled with machine learning algorithms are the result of a distinct evolutionary or developmental process.

Introduction

As the capabilities of machine-learning algorithms grow, it is becoming increasingly common in the cognitive sciences to utilize the following methodology: identify some cognitive capacity, use machine learning research to build and train algorithms to achieve this capacity, and compare the workings of these algorithms with neuronal activity. When neuronal activity is found to correlate with processes in the machine-learning algorithm, this finding is worthwhile for two reasons - First, we gain a new way to predict neuronal activity, often with better accuracy than previous models. Second, the finding of correlation suggests that computation in the brain is similar in some ways to the machine-learning algorithm. Such work was done for object recognition (Cao and Yamins 2022a; Yamins et al. 2014; Yamins and DiCarlo 2016), reinforcement-learning (Cross et al. 2021), language processing (Goldstein et al. 2022; Schrimpf et al. 2021), navigation[1] (Banino et al. 2018; Cueva and Wei 2018), orientation during self-motion (Mineault et al. 2021) and more.

This methodology closely resembles Marr's (1982) levels of analysis: it begins by describing the performed computation, then it identifies an algorithm which performs this computation, and finally it searches for the algorithm's neuronal correlates. This approach emphasizes the usefulness of top-down constraints in modeling neuronal activity – the model must be able to perform the cognitive function in which the brain area is involved. At least in the step of constructing the algorithm for the cognitive capacity, this approach also minimizes the importance of physical, developmental, or evolutionary constraints – the only constraint on the algorithm is that it achieves high performance on the relevant tasks. For this reason, it is often a pleasant surprise for

[1] Navigation is a slightly different case because neuronal activity is already characterized as representing location in a grid like manner, and therefore neuronal activity is well explained with a simple model. Scientific works show how these representations arise as part of learning navigation-related tasks.

scientists when they discover similarities between the model and neuronal activity. This leads some to suggest that the constraint that the algorithm must perform a specific cognitive capacity may be sufficient to create similarities in the algorithm utilized by the machine-learning algorithm and in cognitive processing (Cao and Yamins 2022a; Yamins and DiCarlo 2016).

Here, I argue that, when this methodology aims to explain how cognitive capacities are performed, it must choose its target capacities carefully. When considering explanandum capacities, the distinction between capacities that the brain has adapted (or developed) to have and capacities that the brain can perform but are not the result of specific evolutionary/developmental pressures is crucial. For when scientists attempt to explain capacities that the brain performs using mechanisms that are adapted for *other* functions, they are unlikely to identify the computation that gives rise to the cognitive capacity. I further argue that identification of neuronal correlates does not imply identification of the right computation, as several scientific publications have shown (Elber-Dorozko and Loewenstein 2018; Jonas and Kording 2017; Marom et al. 2009). Many various computations will correlate with neuronal activity, and therefore considerations of evolutionary and developmental constraints cannot be completely eliminated, even with much empirical data about neuronal activity. Therefore, putting too much weight on correlational data while ignoring etiological considerations, may lead to erroneous attribution of computation to the brain.

The emphasis this paper suggests on evolutionary considerations is not novel. It has been repeatedly suggested by neuroscientists and philosophers that cognitive scientists should pay mind to evolutionary processes. Cao and Yamins (2022b) write: “we want to find tasks that are good proxies for evolutionary goals that brains were actually selected for achieving.” Cisek and Hayden (2022) write: ‘we think that the consideration of evolutionary history ought to take its place alongside other intellectual tools used to understand the brain’. This paper demonstrates concretely how evolutionary and developmental considerations are relevant when using a specific method to identify neuronal computation. Moreover, this paper emphasizes two novel aspects. First, the identification of neuronal correlates cannot be taken as a sufficient indication that scientists accurately describe a capacity or its underlying computation. Instead, decisions about computations in the brain are likely to depend on an interplay of assumptions and data about etiology together with empirical data about brain activity, brain structure and behavior. Second, this paper emphasizes that scientists should be more careful about the capacities they take the brain to have adapted for. The fact that having a capacity increases an organism’s fitness does not mean this is a capacity the organism has adapted to have a specific computation for.

1. An example for performance-based modeling – object classification

The case of object classification is one well-known example for the use of performance-constrained models to explain neuronal activity. In their famous paper, Yamins et al. (2014) train a model that can perform an object classification task at near human performance; The model can classify objects from various perspectives into one of eight categories: animals, boats, cars, faces, etc.

The architecture of the model is inspired by the structure of the visual ‘ventral stream’ in the brain (the areas associated with object recognition) in that it includes several feedforward ‘layers’ where activity in each layer is determined according to the ‘Linear-Non Linear’ (LN) posit about neuronal processing (the function performed by the neurons is some linear operation on neuronal activity in the previous layer, followed by a non-linear operation). However, the model does not aim to copy neuronal processing, only to use it as an inspiration to successfully perform the task; the model was only trained to perform the task as best as possible, and information about neuronal activity was not used during training.

Yamins et al. (2014) recorded neuronal activity in visual areas of monkeys and discovered that the activity of simulated neurons in the highest layer in their computational model was able to predict activity in the inferior temporal cortex (IT) - a 'high' area in the ventral stream, which receives inputs after several stages of neuronal processing, and can support object categorization for a variety of object positions over a wide range of tasks. They were able to predict 48.5 ±1.3% of the variance in activity in individual neuronal sites across the presentation of 1600 different photos. This is a two-fold improvement in prediction over the other, non-performance-optimized, models they tested. Moreover, Yamins et al. (2014) discovered that intermediate layers in their model were able to predict 51.7± 2.3% of the variance of neuronal activity in the intermediate brain area V4, while the first and last layer in the model predicted a much smaller fraction of the variance. Thus, they found strong correlates between neuronal activity and simulated activity in their model, which fitted with the processing stages in the model and in the brain.

Yamins et al. conclude: "[the paper presents] a top-down perspective characterizing IT as the product of an evolutionary/developmental process that selected for high performance on recognition on tasks like those used in our optimization... This type of explanation is qualitatively different from more traditional approaches that seek explicit descriptions of neural responses in terms of particular geometrical primitives".

In a follow-up paper, they demonstrate how they view machine learning algorithms as models for neuronal processing in the ventral pathway (Fig. 1). They write: “HCNNs are good candidates for models of the ventral visual pathway. By definition, they are image computable, meaning that they generate responses for arbitrary input images; they are also mappable, meaning that they can be naturally identified in a component-wise fashion with observable structures in the ventral pathway; and, when their parameters are chosen correctly, they are predictive...” (Yamins and DiCarlo 2016).

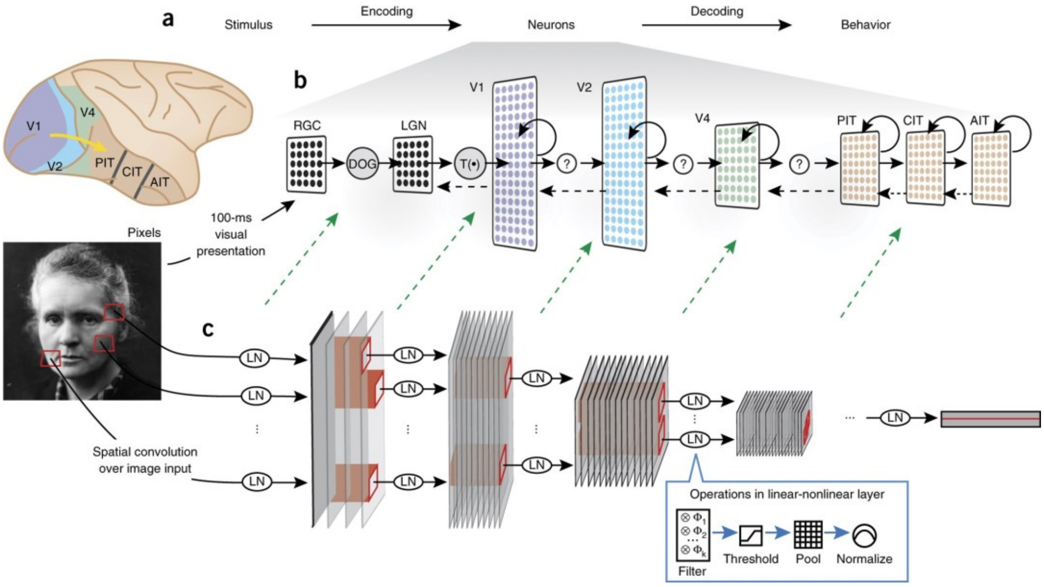

Fig. 1, from (Yamins and DiCarlo 2016)

Machine learning algorithms as means to predict neuronal activity is a useful shift from the ‘explicit descriptions … in terms of particular geometrical primitives’ Yamins et al. (2014) talk about, because it allows scientists to describe neuronal activity even when it does not resemble a known concept. These approaches have been fruitful in a variety of domains, including reinforcement-learning (Cross et al. 2021) - where brain activity of participants playing video games was found to correlate with activity in deep layers of a model that was trained to play the same games from inputs of images to outputs of actions, and language processing (Goldstein et al. 2022) – where neuronal activity while listening to a podcast could be predicted from representations created by language models, to name a few. It has even been suggested that such computational models whose simulated activity maps onto neuronal activity according to specific criteria, met by the model in Yamins et al. (2014), are mechanistic explanations of how the brain performs the capacity (Cao and Yamins 2022a).[2]

Following the impressive results from a variety of papers (Banino et al. 2018; Cross et al. 2021; Cueva and Wei 2018; Mineault et al. 2021; Schrimpf et al. 2021; Yamins et al. 2014) it may seem that this methodology can yield new understanding of the underlying mechanisms for any capacity of our choosing. However, in the next section I point out that this methodology is likely to yield explanation and understanding of cognition only when it attempts to explain capacities that the brain has adapted/developed for. Without such etiological considerations, although simulated activity may show some mapping to neuronal activity, the computational models compared to neuronal activity are likely to be different in important ways from the ones employed by the brain. My argument is that it matters whether a modeled cognitive capacity is one that the brain has historically come to have because of its own effects, rather than a side effect or partial description of the brain's adaptation to other functions. I elaborate in the next section.

2. How evolutionary considerations matter

Biological functions have been extensively discussed in philosophy (Wouters 2005). The major question has been what differentiates the *functions* of the system from other things the system does. To give the oft used example, the heart both pumps blood and makes thumping sounds, but we usually only take the former to be its

[2] See (Craver 2007; Kaplan and Craver 2011; Piccinini 2015) for detailed frameworks of mechanistic explanations

function. On perspectivalist views of function, the functions of the system are not an objective matter, but rather depend on the interests of the observers (Craver 2013). On such views the heart's function may well be to make thumping sounds if the observer is interested in building stethoscopes. This observer may also be interested in explaining the underlying mechanism that is responsible for the thumping sounds.

Another set of views take functions to be an objective matter. One such popular view of functions is the 'selected-effects' view. This view describes functions by reference to their evolutionary history; the function of a system is to bring about effects that in the past were relevant to its selection (Millikan 1989; Neander 1991). Hence, hearts have the function of pumping blood but not the function of making thumping sounds, because only their ability to pump blood was causally relevant to the existence of the organism today. Therefore, there is a difference between functions the system has because they were previously relevant for its selection, and functions the system can perform, i.e., side-effects.

It is not my intention to make an argument in favor of one view or other of function. Nonetheless, I would like to argue that the distinction between 'selected-effects' and other capacities is relevant to the epistemological practice of building computational models for cognitive tasks. This, because the performance-based methodology of computational modeling, described in the previous section, is unlikely to succeed when attempting to model 'side effects'. For capacities that are considered side-effects according to the selected-effects view are unlikely to be given a computational model that is similar to the computation that takes place in the brain.

As a thought experiment, consider a scientist who encounters for the first time a lightbulb. The scientist has no idea what the function of the light bulb is, or if it even has one. She notices that the lightbulb emits heat and tries to explain how it does so.

She comes up with a model for a heat emitting device – a radiator. The radiator is just as good at emitting heat as the lightbulb. Therefore, according to the performance-based methodology it is a model that can be compared with the activity of the light bulb, and correlations between the activities of the two may even be identified, as I also argue in the next section. For example, both heat up when connected to electricity. Nonetheless, there is some deep sense in which the scientist missed how the lightbulb emits heat – it does so via a mechanism that was designed to emit light. The lightbulb emits heat, but it *has* the function of emitting light, and this puts specific constraints on its mechanism for emitting heat, which models constructed specifically to emit heat are likely to miss. Similar scenarios will occur if someone tries to explain how a coffee machine emits such a strong noise, using a performance constrained approach; the issue isn't that the models they come up with do not create coffee, but rather that they are very unlikely to suggest the right answers for the source of the noise – grinding coffee beans and foaming milk. Therefore, they are very unlikely to come up with a mechanism that is similar to how the coffee machine produces noise.

In relation to human cognition, we can consider chess playing. The performance-based methodology would build a machine learning algorithm that can play chess and compare its activity with brain activity. Such chess-playing models have already been created and rivaled human champions. However, according to the selected-effects view, people *can* play chess, but they do not *have* the function of playing chess. Brains were not adapted for chess playing so it would be astonishing to discover that neuronal computation is similar to algorithms designed specifically for chess playing, such as deep blue (Campbell, Hoane, and Hsu 2002). An accurate computational model of human chess playing will take into account that this capacity utilizes mechanisms that were adapted for other purposes.[3] Similar points can be made with regard to driving, baking a cake and drawing paintings.

A similar, but more nuanced, claim is relevant to object recognition. Clearly, identifying objects is beneficial for survival. However, when delving into the details, it is questionable that the brain has adapted specifically to classify a restricted set of objects from a variety of photos where objects are places on unmatching backgrounds (see Fig. 2).

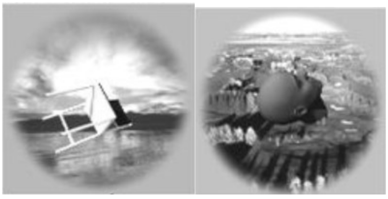

Fig. 2. Example of two test images from (Yamins et al. 2014). Left – a chair. Right - a face.

This, although primates certainly can *perform* this function. More likely, perception has adapted for actively extracting relevant information from moving, natural visual scenes, in a specific environmental context into a wide and complex array of categories. Moreover, proponents of embodied cognition have suggested that it is likely that perception has adapted to support actions that contribute to fitness rather than to accurately represent the environment (Proffitt 2006) and other alternatives to maximizing classification accuracy have been suggested as selection pressures on the

[3] One may suggest that chess experts develop specific mechanisms that are not constrained by other tasks, to support chess playing. This is not impossible, but does not fit with what is known about neuronal processing or about how acquisition of skills in chess affect the brain (Mayeli, Rahmani, and Aarabi 2018), and at any rate novice chess players are very unlikely to have such a module.

ventral visual stream (Bowers et al. 2022). Similar claims can be made regarding other cognitive capacities. For example, models for reinforcement learning from visual inputs are generally trained and tested in video game environments (Cross et al. 2021) which substantially differ from natural environments in various elements, including a simple and discrete structure of states and actions, and explicit relatively immediate rewards.

Moreover, not every capacity that is considered a function according to the selected effects view should be considered a capacity the brain has adapted for. Some cognitive functions may only be partial descriptions of the capacities that brains have adapted to have. The fact that our ancestors were able to distinguish fruits and stones increased their fitness, and this capacity would be considered a function according to the selected effects view, but we do not think ancestral brains have adapted for this specific task, independently of other perceptual tasks. When considering capacities that are the result of evolution, it is useful to consider what evolutionary psychologists call 'Darwinian modules' (not to be confused with Fodor's modules, which are characterized differently) – capacities that are the result of a distinct evolutionary process (Machery 2007b, 2007a).

Evolutionary psychology has been heavily criticized for its attempts to describe practically any behavior as an adaptation (Gould and Lewontin 1979) and on a variety of additional philosophical and methodological grounds (Huneman and Machery 2017). Nonetheless, the argument in the previous section demonstrates that, despite all the pitfalls one may fall into when considering evolution, considerations of the etiology of a cognitive capacity are essential when attempting to explain it. That history for biological functions is often evolutionary. The success of computational models in explaining cognition depends also on whether these models aim to perform capacities that can be characterized as separate from an evolutionary perspective. If they do not, the models are likely to miss pressures and constraints on the way this capacity is performed in the brain.

There is debate on the extent to which cognition can be characterized as evolutionary modular – the extent to which selection pressures can be separated for different cognitive capacities. Moreover, even if scientists correctly identify specific selection pressures, there is no guaranty that adaptation will lead to a capacity that is well-designed to perform the specific task. Nonetheless, it is evident that some capacities are clearly not evolutionary modules, even though they are often tested in experiments. Such capacities include classifying object categories from images with mismatched backgrounds (see Fig. 2) or repeatedly choosing between two options with different reward probabilities, known as the two-armed bandit task (Fox et al. 2020). Moreover, the work of evolutionary psychologists on modules seems to coincide with neuroscientific work when searching for neuronal correlates. As Machery (2007b) writes: "evolutionary psychologists are adamant that many competences, such as reading, programming in C++, and piloting an airbus, are not underwritten by dedicated modules. There is no module whose evolved function is, say, to read, since, obviously, reading is a recent cultural invention. Rather, reading is underwritten by a collection of modules that evolved for other reasons." Indeed, like in the chess-playing example described before, rarely will neuroscientists build computational models for reading, programming, or piloting and compare them with neuronal activity. I suggest that this is because there is no expectation that the brain includes a dedicated module for them. It will be useful to bring in such considerations even when the answer to whether a capacity is an evolutionary module is not so obvious, because being more accurate on this question can aid in building better models for cognition.

It is not impossible to suggest the right computational model without etiological considerations, but etiological considerations aid in constraining the models that scientists consider. It seems that scientists would be very lucky to come up with the right model for how the brain performs a capacity, when their model is optimized specifically for this capacity, while the brain has adapted to have a different capacity. The closer the capacity considered by scientists and the capacity the brain has adapted to have, the more similar we can expect the scientific model and neuronal computation to be.

In the next section I present some objections to the claim that without etiological considerations scientists may be supporting the wrong models.

3. Some objections

a. Neuronal correlates can fully support a specific computation

One evident objection to the claim that computational modeling requires considerations of adaptation, is to note that this argument completely ignores the neuronal data. The described scientific projects in previous section identified correlations between neuronal activity and simulated activity in the model. Is this not evidence that these are the models implemented in the brain?

Although this claim seems obviously true, several scientific publications have demonstrated that it is entirely possible to identify correlations and causal relations that map with one computational model, when the system is designed to perform a completely different computation (Elber-Dorozko and Loewenstein 2018; Jonas and Kording 2017; Marom et al. 2009). Famously, Jonas and Kording (2017) utilized standard neuroscientific methods to understand the workings of a microprocessor that performed a simple task of booting one of three video games. They arrived at ridiculous results such as a “Donkey Kong transistor or a Space Invaders transistor.” – transistors that are taken to have a function that relates only to one specific game, when it is well-known that this is not how microprocessors are designed.

Elber-Dorozko and Loewenstein (2018) analyzed the case of ‘action-value representations’. Many previous scientific findings reported brain representation of a variable called action-value, leading many scientists to believe that the computation of this variable is essential to decision-making. Elber-Dorozko and Loewenstein (2018) specifically designed a model for decision making which does not include any implicit or explicit representation of ‘action-value’, and discovered that standard analyses performed on this model still erroneously identified significant representation of ‘action-value’.

These results demonstrate that correlation does not imply computation (and, for the same reason, neither do mapping of causal relations). It is more understandable why this is so when we consider that when performing a correlation analysis, the null hypothesis is that the neuronal activity is *completely* orthogonal to the computational variable. Any other case with enough data will result in a significant correlation. Thus, identification of a correlation between neuronal activity and some variable is not an indication that this variable is computed, but only that neuronal activity is not completely orthogonal to this variable. Given that any computational variable that performs some capacity is likely to correlate with properties of the inputs and the outputs of the capacity to some magnitude, it would seem that there are many possible computational models that correlate with neuronal activity without being identical to neuronal computation.

Of course, even though scientific results of correlation to neuronal activity cannot imply a specific computational model, still much can be learned from them. First, as long as they are not taken as the sole relevant evidence, they can be invaluable in comparing suggested models. Schrimpf et al. (2020) built a platform for comparison of various computational models with neuronal data in a variety of visual tasks. Such comparisons can certainly assist in determining what computational properties lead to closer resemblance to neuronal processing (but see (Bowers et al. 2022) on the domains in which such evidence should be sought). Relatedly, correlates with neuronal activity is also evidence for the etiology of capacity. If a 'performance-constrained' computational model could predict 99% of neuronal variance (which is currently not likely due to individual heterogeneity, [Cao and Yamins 2022a]), this would be strong evidence also for the etiology of the capacity – this is the computation the brain has historically come to perform. However, etiological considerations never disappear entirely, even a 99% prediction of neuronal activity would not convince us that the brain is calculating the location of Mars relative to Neptune. Thus, there is reciprocity between considerations of etiology and considerations of similarity to neuronal activity, and one should be careful not to put too much weight on the latter.

b. The determinants of computation are not etiological

The reader may have noticed that the argument made in section 3 moved quickly when discussing what is the 'right' and what is the 'wrong' computational model for the computation performed in a system. The examples in section 3 and the scientific papers described in 4a, refer either to adaptation or to design as the determinant of the computation the system performs; that is, conclusions about computation are erroneous because they do not fit with what the system was designed to do or with our intuitions about what the system has adapted to do. There are no 'donkey-kong' transistors because no transistors were designed as such, and there is no chess playing module because the brain has not adapted or developed for chess-playing. This notion fits with the philosophical view that the question of what a physical system computes depends on its etiology. One could adopt such a view if one takes computing systems to be systems that have the function to perform some computation and this function is defined according to the history of the system.

One could, of course, deny that etiological considerations are relevant when considering what the brain, and other systems, compute. There are several popular views of computation that do just that. Shagrir (2022) argues that the individuation of a computation depends on its semantic content (this would be a non-etiological view only if we take semantic content to not be determined etiologically). Piccinini's (2015) framework of physical computation describes computing systems as mechanisms that have the function of performing a specific computation. He is explicit, however, that the functions he refers to are not defined by their evolutionary history, but rather by their current causal contributions (2015, chap. 6).

Such views are worthwhile alternatives to the etiological view. Moreover, there are several criticisms of etiological views of function, most notably that in biological systems the etiology is often unknown, and this does not stop scientists from assigning functions to systems nor does it intuitively seem that etiology should be relevant to determine what a system is currently computing (Craver 2013; Piccinini 2015).

As an answer to the latter criticism, I note that this debate often centers on rare cases where etiology and computation come apart. The case of a swamp-person miraculously created de-novo, or the case of a major first mutation which turns out to be beneficial. While it may certainly be true that in these cases what the system computes comes apart from its history, they are too rare to merit overlooking history in general. For swamp-people practically never happen, and first mutations tend to be small and to build upon previous states. Moreover, attempting to analyze a swamp-person from a scientific perspective seems a nearly hopeless endeavor. For if scientists will try to explain chess playing the same way they explain sound localization (Ashida and Carr 2011), as a unique module, they will have a very hard time making any progress. Thus, ontologically it may be true that etiological considerations are irrelevant for questions about what a system computes. However, empirically, for practically all systems we view as computing, their etiology is relevant and useful for understanding how they perform the computations – organisms have evolutionary histories and computers are designed.

Another challenge to the claim that etiological considerations are essential is that it is very difficult to know the etiology of various capacities, so it is difficult to see how they can be taken into account in determining computation. One answer to this is that while it is challenging to know the exact etiology of capacities, some general properties are quite easily considered, as can be seen in the work of evolutionary psychologists and implicitly in the choices of neuroscientists. To illustrate, we know that brains have not adapted for chess-playing or for stock-trading, or that they adapted for a specific mechanism for telling stones and fruit apart. Considering various organisms can also be telling about the etiology of capacities. Moreover, as described in section 3, models that are built to perform etiologically relevant capacities are also more likely to be similar to behavior and to neuronal activity. Therefore, while etiological considerations are not perfect, they are an important part of building more realistic models and being more explicit and clear about them can help scientists in explaining cognition.

Finally, it is not clear what epistemological alternative non-etiological views of computation suggest. Without constraints on mapping between computational and physical states an incredibly large variety of computations can be considered to be implemented in a system, as demonstrated in the 'triviality arguments about computational implementation' (Sprevak 2018). Therefore, views that deny that etiological considerations are relevant for computation, describe other constraints on the computations implemented in a system. The challenge to these views is to explicate the implications of these constraints to scientific practice. Without such implications to neuroscientific practice, although what a system computes may be well-defined ontologically, it is not clear how questions about what a system computes can be answered. Etiological considerations at least offer some advancement in this regard for the vast majority of computing systems.

c. Current models are a good approximation of cognitive capacities

There is worry that my criticism of the functions neuroscientists model is too harsh. Surely, they are limited, but they are still a great improvement relative to earlier simpler models and they are making effortful attempts to be realistic. To this I answer that this paper does not aim to invalidate the progress that is achieved with this practice, these performance-based models are certainly a step forward towards more accurate models of cognitive capacities. However, I do suggest that as they are they cannot yet provide a realistic model of these capacities and it is useful to keep this mind. Moreover, if neuroscientists wish to claim that their models aim to capture a specific capacity which was created with independent etiological pressures, it would be beneficial if they would do so explicitly. To illustrate, Yamins et al. (2014) may claim that their model describes the first forward pass in the ventral stream where only feedforward connections are relevant and an object is recognized quickly from a single snapshot. This is different from arguing that their model is a model of ‘the ventral steam’ and may be much more plausible. Then the question shifts to the question of whether it is reasonable to this the this quick classification in the forward pass is the result of specific evolutionary pressures.

Furthermore, there is worry that this criticism is the result of assimilating models and experiments. It is common to conduct simple experiments in the lab as proxies for more complex behaviors as it is often reasonable to think that people recruit the same mechanisms in lab settings and in real-life settings (e.g., when choosing between two options in the lab and many different ones in real life). But this cannot be said of machine learning models, training them on simple problems is likely to lead to different models than when training them on complex problem. We cannot say about a model trained on video games that it utilizes complex mechanisms appropriate for real-life setting with unclear states, actions, and rewards.

Finally, if one is convinced by the argument in this paper then it paints a path forward for existing models, rather than aiming to account for more neuronal variance, or improve performance on pre-existing tasks, we should focus on trying to model capacities with specific, independent, etiologies.

d. Even when ignoring considerations of adaptation, we may still identify the right computation

Cao and Yamins (2022b) write: “…given a challenging task, we should take seriously the possibility that two systems that solve it share deep explanatory similarities … difficult tasks are more constraining tasks, and success at difficult tasks justifies mechanistic/causal interpretations of our successful model”. Thus, they suggest that for difficult enough tasks the realm of possible solutions may be constrained enough that any two algorithms that can solve this task are likely to exhibit 'deep explanatory similarities'." Therefore, even without etiological considerations, scientists may suggest the 'right' model. This is an interesting suggestion. But it seems to me that it is motivated by empirical results of correlations between simulated and neuronal activity that are related to object classification tasks. As I argued in 4a, however, such results do not imply that the same computation is taking place in those two systems. Moreover, some counterexamples come to mind. Chess-playing seems like a difficult enough task, yet it is believed that 'deep-blue' solves it in a different manner than people. Finally, the argument in this paper is exactly that the functions the brain and the model are optimized to perform are different, while the latter is optimized for the function, the former may only *perform* it, without being optimized for it specifically. Therefore, the computations performed are likely to differ between the brain and the model. It still may be that for certain tasks the possible solutions are constrained enough, but this seems like an open, empirical question.

4. Some concluding remarks

This paper argued that scientists must take etiological considerations into account when using a performance-based methodology to model neuronal computation. This is because the history of how a computation came to be determines the mechanism that was created to perform it. Two main issues are worth emphasizing. First, although neuronal data can certainly be used to guide scientific search for the computations the brain performs, it is not a deciding factor. For neuronal correlations and causal relations can be identified for a variety of competing hypotheses about computations. Instead more weight should be given to etiological considerations.

Second, the fact that a function increases or increased the fitness of an organism does not mean that this is the right description of the function it has adapted to have, as demonstrated for the cases of object recognition. In general, to discover what the brain computes, scientists should be sensitive to the manner in which the computations became possible. Without such sensitivity, discovering computations in the brain is not impossible, but vastly more difficult.

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