The Consciousness Prior

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First posted October 15th 2017; revised, December 1, 2019

Abstract

A new prior is proposed for learning representations of high-level concepts of the kind we manipulate with language. This prior can be combined with other priors in order to help disentangling abstract factors from each other. It is inspired by cognitive neuroscience theories of consciousness, seen as a bottleneck through which just a few elements, after having been selected by attention from a broader pool, are then broadcast and condition further processing, both in perception and decision-making. The set of recently selected elements one becomes aware of is seen as forming a low-dimensional conscious state. This conscious state is combining the few concepts constituting a conscious thought, i.e., what one is immediately conscious of at a particular moment. We claim that this architectural and information-processing constraint corresponds to assumptions about the joint distribution between high-level concepts. To the extent that these assumptions are generally true (and the form of natural language seems consistent with them), they can form a useful prior for representation learning. A low-dimensional thought or conscious state is analogous to a sentence: it involves only a few variables and yet can make a statement with very high probability of being true. This is consistent with a joint distribution (over high-level concepts) which has the form of a sparse factor graph, i.e., where the dependencies captured by each factor of the factor graph involve only very few variables while creating a strong dip in the overall energy function. Instead of making predictions in the sensory (e.g. pixel) space, one can thus make predictions in this high-level abstract space, which do not have to be limited to just the next time step but can relate events far away from each other in time. The consciousness prior also makes it natural to map conscious states to natural language utterances or to express classical AI knowledge in a form similar to facts and rules, albeit capturing uncertainty as well as efficient search mechanisms implemented by attention mechanisms.

1 Introduction

We propose here a new kind of prior for top-level abstract representations of concepts of the kind humans manipulate with natural language, inspired by modern theories of consciousness such as the global workspace theory [Baars, 1988, 1997, 2002, Dehaene and Naccache, 2001, Dehaene et al., 2017] as a form of awareness [van Gulick, 2004], i.e., as defined by Locke, consciousness is “the perception of what passes in a man’s own mind”, or awareness of an external object or something within oneself (Wikipedia definition). The main contribution of this paper is proposing a machine learning justification for an aspect of this theory, stipulating that elements of a conscious thought are selected through an attention mechanism (such as the content-based attention mechanism we introduced in [Bahdanau et al., 2015]) and then broadcast to the rest of the brain, strongly influencing downstream perception and action as well as the content of the next conscious thought. The paper sees this as a computational mechanism which is consistent with a hypothesis about the form of the joint distribution between the type of high-level variables which can form a conscious thought. Since a conscious thought only refers to very few variables at a time, we suggest that this corresponds to a form of knowledge representation which is factored into pieces involving a few variables at a time. From a probabilistic modeling point of view, this corresponds to a sparse factor graph. Each “factor” captures the possibly strong dependency between a few variables. Although a variable can participate in many such factors, each factor links very few variables, similarly to words or concepts linked together in a sentence in natural language.

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2 System 2 Processing and Global Workspace Theory of Consciousness

For lack of a generally accepted definition of consciousness - because there are still many competing theories - we consider conscious aspects of cognition as those which humans can report about through language. We closely associate conscious processing to Kahneman’s system 2 cognitive abilities [Kahneman, 2011]. System 1 tasks align well with the current successful applications of deep learning, e.g., low-level perception (and to a lesser extent low-level action) and intuitive knowledge (e.g. knowing that a particular Go move is good or that a given picture contains the image of a dog), i.e., knowledge which is difficult to verbalize, and which can typically be applied very quickly (in less than a second). On the other hand, system 2 cognitive abilities are those which can can be described verbally, and thus includes the part of our cognitive abilities which we can communicate explicitly to a computer (typically as a sequence of computational steps), and include things like reasoning, planning and imagination. Typical system 2 tasks require a sequence of conscious steps, which also means that they tend to take more time than system 1 tasks. By this definition, system 2 abilities are closely related to consciousness.

Cognitive neuroscience has been investigating consciousness for several decades and a dominant family of theories on which this paper is anchored are those based on the Global Workspace Theory [Baars, 1988, 1997, 2002, Dehaene and Naccache, 2001, Dehaene et al., 2017]. This theory posits that we become aware of specific pieces of information which will momentarily form the content of working memory. A conscious thought is thus a set of these elements of which we have become aware, joined together and made globally available to other computational processes taking place in the brain at an unconscious level. Consciousness thus provides a form of bottleneck for information which has a strong influence on decision-making (voluntary action), memory (we tend to very quickly forget what we have not been consciously aware of) and perception (we may be blind to elements of our sensory input which may distract us from the current focus of conscious attention).

There are other aspects of consciousness which the global workspace theory does not directly address, such as the notion of self and that of subjective perception, and we do not study them here. Instead, we are interested in the use of machine learning ideas and experiments as ways to formalize theories of consciousness (particularly the global workspace theory), identify advantages which they can bring to a learning agent (e.g. as a useful prior for specific aspects of the world), and as a way to test these theories via machine learning experiments measuring for example their effect on sample efficiency (or the speed of learning) and out-of-distribution generalization.

3 Consciousness Prior Theory

We explain a machine learning framework for these ideas in more detail below, and place them in the context of a learning agent with goals (see Sutton and Barto [1998] for basic notions of reinforcement learning).

3.1 Extracting a Conscious State

Let $x_t$ be the observation at time $t$ for a learning agent, and let $h_t$ be the high-level representation derived from $x_t$ (and from past observed values $\{x_{t-k}\}$ in the partially observable case). For example, $h_t$ could be the output of some kind of recurrent neural network (or RNN, with whatever architecture is appropriate) that reads the sequence of $x_t$ as input and produces an output $h_t$ at each time step:

$$h_t = F(x_t, h_{t-1})$$  \hspace{1cm} (1)

where we call $F$ the representation RNN or encoder and $h_t$ the unconscious representation state. We can think of $h_t$ as a very large vector or as a set containing all the possible elements which could be brought to consciousness via an attention mechanism.

A core objective for the learner is to learn good representations in $h_t$, which disentangles abstract explanatory factors, in the sense that there exist a simple transformation of $h_t$ which can select the information about a single factor (its value or uncertainty about it). With $h_t$ seen as a set, we can think of each element $e \in h_t$ as one of the variables over which the learner needs to form a joint distribution in order to make sense of the high-level dependencies. These dependencies do not have to be limited to those between elements in the same $h_t$; they could also relate elements arising at different time steps.

In contrast, we will define the conscious state $c_t$ as a very low-dimensional set which is derived from $h_t$ by a form of attention mechanism applied on $h_t$, taking into account the previous conscious state and
memory as context:

\[ c_t = C(h_t, c_{t-1}, m_{t-1}, z_t) \]  

(2)

where \( z_t \) is a random noise source and \( m_t \) is the content of memory at time \( t \). The memory content gets updated by possibly committing \( c_t \) to memory:

\[ m_t = M(m_{t-1}, c_t). \]  

(3)

We do not explicitly put them in the notation but a realistic agent would also have goals as part of the context which conditions both the selection of unconscious items (in \( F \)) and the update of the conscious state (in \( C \)), then seen as a search mechanism. Also, although we do not explore the architecture of memory mechanisms very much here, it is clear that different kinds of memory mechanisms exist in the brain, starting with short-term memory from which very recently accessed conscious elements can be retrieved, as well as longer-term memory, which contains a subset of the elements stored in short-term memory. The cognitive interpretation of the above equations is that the value of \( c_t \) is a set of consciously accessed elements and corresponds to the content of a thought one is conscious of at time \( t \). The conscious state \( c_t \) is a very small subset of all the information available to us unconsciously, \( h_t \), but which has been brought to our awareness by a particular form of attention which picks several elements or projections from \( h_t \). The function \( C \) is the consciousness process and because of its random noise inputs, produces a random choice of the elements on which the attention gets focused. This is useful if we think of the consciousness process as a tool for exploring interpretations or plans or to sample predictions about the future or simply imagined scenarios. We can also think of the consciousness process as the tool to make a series of associations forming a coherent argument (for reasoning). It isolates particular high-level abstractions and extracts the information about each of them (some identifying information and attributes, a value, and uncertainty about it or even the fact that it is observed or not). This would happen if we think about a single factor, but in general \( C \) will aggregate a few (e.g. a handful) of such factors into a more complex and composed thought.

### 3.2 Sparse Factor Graphs

A factor graph is a way to represent the joint distribution between a set of variables. Let \( S = \{V_1, \ldots, V_n\} \) be that set and \( P(S) \) be their joint distribution. In a factor graph, the joint is represented as a product of potential functions \( f_j \), each of which only depends on a subset \( S_j \subset S \):

\[
P(S) = \frac{\prod_j f_j(S_j)}{Z}
\]

(4)

where \( Z \) is a normalization constant. We call each \( f_j \) a factor and it creates a direct dependency between the variables in \( S_j \). Indirect dependencies exist between variables by following paths in the bipartite graph formed on one hand with the variables \( V_k \) and the factors \( f_j \) (each associated with a subset \( S_j \) of variables).

Translated in probabilistic terms, the consciousness prior amounts to the assumption that the factor graph for the joint distribution between the elements in the set \( h_t \) (or more generally for the set containing all of the elements in \( m_t \) and all those one could think of in the future) is sparse\(^1\). This is because the cardinality of all \( S_j \)’s is small. The motivation for this assumption comes from observing the structure of natural language (broken down into phrases, statements or sentences, each of which involves very few words) as well as the structure of formal knowledge representations such as the sets of facts and rules studied in classical symbolic/logic AI or in ontologies and knowledge graphs [Ehrlinger and Wett, 2016]. In addition to being sparse, we believe that a related assumption can be made: most factors in the graph describe a strong dependency, i.e., one which makes low-entropy predictions (e.g. about some of the variables in \( S_j \) given the others). Since factor graphs are also generally understood as energy-based models (the logarithm of each potential function contributes an additive term in the energy function corresponding to the overall joint distribution), we can also say that each potential function creates a strong dip in the energy function. Otherwise, they would not be worth putting in the factor graph. This is related to the fact that we should think of this joint distribution as a very rough approximation of the world built by learning agents to help them plan, reason, imagine, etc.

An important purpose for the consciousness prior, from a machine learning point of view, is that it should help a learner discover an encoder which captures the kind of high-level variables which humans talk about when they communicate with language, since natural language statements naturally tend to

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\(^1\)and we probably do not want to represent that graph explicitly, and instead use conscious attention to selectively traverse and explore only relevant parts of it, in the context of given goals.
satisfy both the sparsity requirement (each sentence involves few words) and the "strong dip" requirement (otherwise the statement is not worth communicating). In the quest to discover encoding functions which disentangle high-level concepts from each other, we should see the consciousness prior as one of many tools to constrain the learner towards better high-level representations. Please note in passing that by "disentangled" we do not generally mean marginally independent (that would make "all the top-level variables independent of each other), as in recent work on variational autoencoders [Higgins et al., 2017]. Indeed, notice how natural language concepts (like say "fork" and "knife") tend to not be independent of each other, but instead may be combined to form probable statements (like "she was eating with her knife and fork").

The analogy with natural language and with knowledge graphs, ontologies and formal declarative knowledge also suggests that new potential functions can be created as needed. Instead of having a large but fixed set of potential functions, what we have are mechanisms for creating new ones which "make sense" according to observations, reasoning, or imagination. Instead of enumerating all the possible potential functions, the brain may have the ability to instantiate new ones on the fly. This connects the previous section, which was about the attention mechanisms for selecting a small set of variables forming a conscious thought (c_t) with the topic of this section, which is about the declarative knowledge formed by the set of potential functions each linking a few variables together. Whereas the sparse factor graph constraint is about the underlying beliefs about the world (when expressed with the high-level variables), the attention mechanisms used to build conscious thoughts are part of the inference mechanisms used to compute efficiently according to the consciousness prior.

3.3 Training Objectives

To capture the assumption that a conscious thought can encapsulate a statement about the future, we could introduce a verifier network which can match a current representation state h_t with a past conscious state c_{t-k} stored in memory m_{t-1}:

\[ V(h_t, c_{t-k}) \in \mathbb{R} \] (5)

which should be structured so that \( V(h_t, c_{t-k}) \) indicates the consistency of \( c_{t-k} \) with \( h_t \), e.g., estimating the probability of the corresponding statement being true, given \( h_t \).

More generally, we would like to define an objective (or reward) function which embodies the idea that the attended (conscious) elements are useful, in a way which can be quantified and optimized, i.e., that the representation RNN and the attention mechanism which extracts \( c_t \) from \( h_t \) are trained to optimize this objective function. This can be in addition to other objectives such as being able to reconstruct the raw input or any other supervised, RL, or unsupervised objectives which we probably want to throw in.

There are two distinct mechanisms at play which contribute to map the high-level state representation to the objective function: (1) the attention mechanism (e.g., the consciousness RNN) which selects and combines a few elements from the high-level state representation into a low-dimensional "conscious substate" object (the current content of our consciousness), and (2) the predictions or actions which are derived from the sequence of these conscious sub-states. The second mechanism is easy to grasp and frame in standard ML practice, either in deep learning or RL, e.g., for supervised or unsupervised or RL tasks. For example, the attention mechanism could select elements B from the current representation state and choose to make a prediction about future elements A. Then to improve the quality of the prediction mechanism we may just want to maximize \( \log P(A|B) \) or some proxy for it, e.g., using a variational auto-encoder [Kingma and Welling, 2014] objective or a conditional GAN [Mirza and Osindero, 2014] if one wants to sample accurately an A from B. Note again that such an objective function is not just used to learn the mapping from B to A (or to probabilities over the space of A values), but also drives the learning of the representation function itself, i.e., is back-propagated into the representation RNN.

However, this part of the objective function (e.g., predictive value, computed by V above) is not sufficient and in fact is not appropriate to train the attention mechanism itself (which variables A and B should be selected?). Indeed, if that was the driving objective for attention, the learner would always pick a pair \( (A, B) \) such that A is trivially predictable from B (and there are such aspects of reality which are trivially predictable yet do not help us to further understand the world and make sense of it or achieve our goals).

It remains an open question what other objectives would be appropriate for learning how to attend to the most useful elements, but ultimately we should be able to use the actual RL reward of the learning agent using \( c_t \) for taking decisions. Some form of mutual information, entropy or diversity may be needed so that the attention mechanism is stochastic and can choose a very diverse set of possible attended elements, so as to cover widely the possible variables A on which a prediction is made, i.e., the entropy of \( (A, B) \) pairs.
3.4 Naming Variables and Indirection

Content-based soft-attention or hard-attention mechanisms [Bahdanau et al., 2015; Xu et al., 2015] extract a value from a set of elements by taking a convex weighted sum of values from an input set of values. Those weights are the attention weights and they are computed by an attention mechanism which gives a larger weight on the element with the most appropriate “key”, according to some context.

In standard neural networks without attention, a neuron $i$ is identified by its position in its layer and the signal it sends to some other neuron $j$ downstream does not need to be identified as coming from $i$. However, when attention mechanisms such as described above are used to provide an input value to $j$, the input could come from any of the elements over which attention is making a selection. Depending on the computation performed, it could thus be useful for downstream layers with attention mechanisms selecting their input to receive not just the weighted (selected) value but also information about the source of the information. We can think of that information as a variable name (and possibly other attributes which we can interpret as variable type), which complement the variable value. The idea of (key,value) pairs is that the keys can be used to represent a form of type information, to help match the expected argument type of a downstream computation with an appropriate element selected by an attention mechanism. This is important in order to obtain systematic generalization [Lake and Baroni, 2017] and combinatorial properties omnipresent in natural language, making it easier to combine different pieces of neural hardware together dynamically, with keys being used to decide which information should be routed where. We could thus see the conscious state as a bottleneck to route such information across many different modules.

3.5 Connection to Language and Symbolic Knowledge Representation

We hypothesize that conscious processing of the kind described above could thus help the brain (and future machine learning systems) achieve better systematic generalization and combine concepts in fluent and combinatorial ways. The fact that we define consciousness in terms of verbal reporting may be important to note here. All this indeed suggests that there is a fairly simple transformation of conscious states into natural language sentences. Conversely, an externally provided sentence (heard or read) could also elicit an associated conscious state, although we postulate that the conscious state is generally a richer object than the uttered sentence, i.e., mapping from conscious states to sentences loses information (think about visual imagery, or artistic expression, which are difficult to put in words), and the same sentence could thus be interpreted differently depending on context and the particulars of the agent who reads that sentence. Formally, we could use another RNN to map a conscious state to an utterance $u_t$:

$$u_t = U(c_t, u_{t-1}).$$

A learning agent which uses language could thus benefit from an additional regularization effect putting pressure on the encoder: the set of currently consciously attended elements should have a direct two-way mapping with natural language utterances which may be uttered by other agents, such as a human teacher. This would act as a weak form of supervision for the concepts produced by the encoder. A sentence focuses on just a handful of elements and concepts, unlike our full internal state. This imposes soft constraints on the representation function in that its individual elements or dimensions are more likely to correspond to concepts which can typically be expressed by a single word or phrase. Based on these arguments, it is reasonable to hypothesize that language may actually help humans build sharper internal representations (which are better disentangled) as well as facilitate learning – see the arguments around curriculum learning [Bengio et al., 2003] and cultural learning [Bengio, 2014] – and enable collaborative task-solving.

Along the same line, this research opens the door to the possibility of better connecting deep learning with classical symbolic AI and cognitive science, and move deep learning from perception (where
it currently shines) to higher-level cognition and knowledge representation (where many questions re-
main open). For example, declarative knowledge is classically represented by facts and rules: each of 
them is a very sharp statement (true with high probability) about reality involving just a few concepts. 
Such a nugget of information or knowledge seems to fit well as a conscious state. Combining such 
conscious states sequentially in order to make more complex predictions and inferences or actions is ba-
sically what reasoning is about. However, pasting symbolic logic computations on top of a deep learning 
encoder might not succeed for several reasons. This would lose the ability manipulate uncertainty as 
well as represent the context-dependent effect of goals and background knowledge which deep learning 
with content-based attention can provide, in addition to the ability to improve generalization through 
distributed representations. Instead, we envision extensions of deep learning based on attention that im-
plement conscious processing functionalities associated with system 2 tasks in humans. Progress in this 
direction would also address the often expressed concern about obtaining explanations from deep nets, 
since the approach proposed here would make it easier for a trained agent to communicate verbally its 
high-level state.

4 Considerations for Experimenting with the Consciousness Prior

Because this is a novel theory which may be developed in many different ways, it is important to start 
with simple toy experiments allowing one to test and evaluate qualitatively different approaches, such that 
the turnaround time for each experiment is very short and the analysis of the representations learned very 
easy (because we already have a preconceived idea of what concepts would be the most appropriate to 
disentangle).

Although working with natural language input would be likely to help the agent learn better and more 
abstract representations, it might be better to start with experiments with no linguistic input, to make sure 
that it is the training objective and the training framework alone which are leading to the discovery of the 
appropriate high-level concepts. For example, learning some form of intuitive physics is done by babies 
without the need for linguistic guidance. Similarly, although the consciousness prior could be used in 
supervised learning or task-oriented RL, testing its ability alone to discover high-level abstractions would 
be best done in the context of unsupervised RL, e.g., using an intrinsic reward which favours the discovery 
of how the environment works.

It would be more interesting for the learning task to involve meaningful abstractions which have a high 
predictive power. For example, consider predicting whether a pile of blocks will fall on or off a table. It 
involves a high-level discrete outcome which can be predicted easily, even if the details of where the 
blocks will fall is very difficult even for humans to predict. In that case, predicting the future at the pixel 
level would be extremely difficult because future states have high entropy, with a highly multi-modal 
distribution. However, some aspects of the future may have low entropy. If in addition, these aspects 
have a big impact on predicting what will come next (or on taking the right decisions now), then the 
consciousness prior should be very useful.

Acknowledgements

The author wants to thank Philippe Beaudoin, Gerry (Tong) Che, William Fedus, Devon Hjelm and 
Anirudh Goyal for preliminary discussions about the consciousness prior, as well as funding from NSERC, 
CIFAR, the Canada Research Chairs, and the Open Philanthropy Project.

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