The Experiential Space: Neural Binding of Predicates into a Unified Sensory Experience

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Abstract

This work introduces the concept of an "experiential space", a space of all possible sensory experiences. Indeed, an experience is represented as a point in "experiential space" and is given by the output of a "binding function" applied to the solution to a neural network coding equation, introduced in "Predicate Coding" (Bonal, 2025,[3]), for the sensory nervous system at a given time. This work aims to address the "Neural Binding Problem", understood here as explaining the unity of conscious experience yielded through the activity of a distributed system, such as the sensory nervous system. Finally, this model yields testable hypotheses, such as: (i) TMS-induced perturbations to regions responsible for processing a subset of perceivable predicates should selectively distort corresponding dimensions in experiential space ; (ii) The implementation of a Brain-Computer Interface directly interacting with the sensory nervous system, would yield phenomenal representations coming from the interface within the experience's coordinates ; (iii) The presentation of a gradually changing sequence of stimuli with diverse predicate values during a fixed time interval should yield a higher path-average speed within the experiential space, than the presentation of unchanging stimuli during the same fixed time interval ; (iv) The presentation of unchanging stimuli followed by a rapid change in stimuli with diverse predicate values during a fixed time interval should yield a higher distance speed within the experiential space, than the presentation of unchanging stimuli during the same fixed time interval.

Keywords: Binding Problem, Neural Binding, Unity of Consciousness, Predicate Coding

1. Introduction

There is a fundamental difficulty, in the fields of neuroscience, psychology and cognitive science, to describe how different properties of perception, through different sensory modalities, yield a single unified conscious experience. This is often labeled the "Neural Binding Problem".

Such a difficulty, however, comes with nuances. Indeed, Feldman (2012, [10]), divided the issue in the four distinct problems:

1. General Coordination
2. Visual Feature-Binding
3. Variable Binding
4. Subjective Unity of Perception

This work provides a mathematical model aiming to address "4. ", i.e. the "Subjective Unity of Perception", which Revonsuo (1999, [17]) defines as follows: "How are [...] phenomenally unified entities, constructed by the brain as neurally unique entities, considering that the neural mechanisms necessary for creating different phenomenal contents (e.g., color, movement, vision, audition, touch) are distributed all around the cortex." - (Revonsuo, 1999, [17]) .

In order to do address this issue, this work builds upon "Predicate Coding" (Bonal, 2025,[3]), to bind the stimuli-encoded values yielded by the sensory nervous system during a given time interval, to a trajectory in "experiential space", i.e. the space of all possible experiences. In doing so, the model effectively turns a distributed vector of the encoding-neural activity into a singular unified point in experiential "space". This allows to give a formal resolution to neural binding regarding the subjective unity of perception, as it unifies distributed encoding values into a point or trajectory within the space of all possible experiences. It is to be noted, however, that the suggested answer to the "Subjective Unity of Perception" presented here is aiming to resolve a formal issue, i.e. how can such unity be mathematically and computationally assessed, not the mechanistic issue of surrounding such subjective unity.

There have been several approaches aiming to resolve the neural binding problem, including the "synchronization hypothesis" (von der Malsburg and

Schneider, 1986, [14]), feature integration theory (Treisman, 1998, [21]) (Treisman and Gelade, 1980, [22]), and the enhancement of firing rates (Roelfsema, 2023, [18]). However, these approaches mainly address "1-3.", and "4. " is often disregarded as too philosophical and empirically intractable.

Yet, some theories of consciousness, have aimed to address more firmly the problems arising from subjective unity of perception from a distributed neural system. For instance, through Integrated Information Theory, Balduzzi and Tononi (Balduzzi and Tononi, 2009, [1]), have defined a "qualia space", which aims to assess the "quality" of an experience, and thereby also addressing its unity. The "experiential space" introduced in this work is rooted in a Neural Encoding model, not a consciousness model, whereas the "qualia space" (Balduzzi and Tononi, 2009, [1]) is rooted in Integrated Information Theory (Tononi, 2004, [20]), which does not directly address neural encoding.

Finally, when understanding the experiential space as a readout of neural activity it bears similarity to "representational similarity analysis" (Kriegeskorte et al., 2008, [12]) (Dimsdale-Zucker et al., 2018, [9]), "neural population geometry" (Chung et al., 2021,[6]) (Chen et al., 2025, [5]) and "perceptual manifolds" (Seung et al., 2000, [19]) (Chung et al., 2018, [7]), as it aims to translate neural activity into formal descriptions of sensory experience. However, the mapping from neural activity to the "experiential space" is here done through the framework of Predicate Coding (Bonal, 2025, [3]), which holds precise ontological commitments, and assigns predicate values to each neuron at a given time, therefore understanding neural activity through the lens of such predicates, in a deterministic way. Nonetheless, elements of each of those models, appear within the "experiential space": (i) the process relating neural activity to meaningful and computationally tractable values builds upon insights provided by representational similarity analysis (Kriegeskorte et al., 2008, [12]) (Dimsdale-Zucker et al., 2018, [9]), (ii) the concept of an "experiential space", containing all possible experiences yielded by neural activity builds upon insights provided by both neural population geometry (Chung et al., 2021,[6]) (Chen et al., 2025, [5]) and perceptual manifolds (Seung et al., 2000, [19]) (Chung et al., 2018, [7]) . Yet, none of the formalism of any of these models appear in this work, as it borrows its formalism and fundamental ontology from Predicate Coding (Bonal, 2025, [3]).

2. Theory

2.1. Background

The mathematical model introduced in this paper aims to describe how different encoding values, coming from different neurons, yield the unity of sensory experience, In order to do so, the model will rest upon "Predicate coding" (Bonal, 2025, [3]), according to which each neuron is tuned to properties of stimuli which can be represented by many-valued logic predicates with fuzzy logic (Łukasiewicz) semantics.

The model will here first describe the sensory nervous system as a network of interconnected neurons, each tuned to many-valued logic predicates applied to stimuli. Then, the model will describe how sparse and diverse encoding of predicates can yield a unified sensory experience, through the binding function "$\mathcal{B}$".

2.2. Sensory Nervous System Network

Before constructing the experiential space, let us first conceive of a network representing the neurons and interconnections of the whole sensory nervous system.

The sensory nervous system network, at a time interval "$[t, t+k]$", will be denoted "$net_{sensory.[t,t+k]}$". It will be defined through Predicate Coding notation, i.e. as a graph of anatomically connected neurons $neur_{u.[t,t+k]}$, linked by synapses S:

$$net_{sensory.[t,t+k]} = (V_{sensory.[t,t+k]}, E_{sensory.[t,t+k]}) \tag{1}$$

Where the vertices of the graph are all neurons within the sensory nervous system:

$$V_{sensory.[t,t+k]} = \{neur_{u.[t,t+k]} | neur_{u.[t,t+k]} \in \text{SNS}\} \tag{2}$$

Where "SNS" is a set denoting the sensory nervous system.

Such that for all neurons x in $V_{sensory.[t,t+k]}$ there is another neuron y in $V_{sensory.[t,t+k]}$ for which there is a synapse connecting the two, either: (i) a synapse S at time interval $[t, t+k]$ that takes an output (O_x) from x into an input I_y in y, or (ii) a synapse S at time interval $[t, t+k]$ that takes an output (O_y) from y into an input I_x in x:

$$\forall x(x \in V_{sensory.[t,t+k]} \implies \exists y(y \in V_{sensory.[t,t+k]} \wedge x \neq y \wedge [\exists S^{[t,t+k]}_{x \to y}(S^{[t,t+k]}_{x \to y}(O_x) = I_y) \vee (\exists S^{[t,t+k]}_{y \to x}(S^{[t,t+k]}_{y \to x}(O_y) = I_x))])) \tag{3}$$

And where the edges of the graphs are synapses connecting the neurons:

$$E_{sensory.[t,t+k]} = \{S^{[t,t+k]}_{u \to z} | S^{[t,t+k]}_{u \to z}(O_u) = I_z\} \tag{4}$$

2.3. Unified Equations from Predicate Coding

Having now described the sensory nervous system as a network using Predicate coding notation, this subsection will here outline the two unified equations from Predicate Coding (Bonal, 2025, [3]). Indeed, the first equation aims to approximate the predicate value that a neuron encodes and the second equation aims to approximate the tuple of predicate values that a network encodes.

The first equation (Bonal, 2025, [3]), for a given neuron $neur_{u.[t,t+k]}$ and a given stimulus x, yields a value through the sum of all single-neuron codes c_i^{neur} (such as rate code, latency code...) multiplied by their respective weights $w_{c_i^{neur}}$, divided by their respective maximum $\max c_i^{neur}$ given by neuron u during the time interval $[t, t+k]$, and inputted into a non-linearity function ψ:

$$\text{Code}^{(0)}(neur_{u.[t,t+k]}, x) = \psi(\sum_{i=1}^{n} w_{c_i^{neur}} \frac{c_i^{neur}\big(neur_{u.[t,t+k]}, x\big)}{\max c_i^{neur}}) \tag{5}$$

Where ψ needs to yield a value in $[0, 1]$ and the sum of all the weights $w_{c_i^{neur}}$ must be equal to one, and no weight can be negative. Moreover $\max c_i^{neur}$ cannot be zero.

The second equation (Bonal, 2025, [3]), for a given neural network $net_{g.[t,t+k]}$ and a given stimulus x, yields a value through the sum of all network codes c_i^{net} (such as population coding, correlation coding...) applied element-wise to the tuple of $\text{Code}^{(0)}$ values for neurons in the network, multiplied by their respective weights $w_{c_i^{net}}$, divided by their respective maximum $\max c_i^{net}$ throughout the neural network, during the time interval $[t, t+k]$, and inputted into a non-linearity function ψ applied element-wise :

$$\text{Code}^{(1)}(net_{g.[t,t+k]}, x) = \psi(\sum_{i=1}^{n} w_{c_i^{net}} \frac{c_i^{net}(\text{Code}^{(0)}(neur_{u.[t,t+k]}, x))_{neur_{u.[t,t+k]} \in V_{g.[t,t+k]}}}{\max c_i^{net}}) \tag{6}$$

Such that:

$$\text{Code}^{(1)}(net_{g.[t,t+k]}, x) \in [0,1]^{V_{g.[t,t+k]}} \tag{7}$$

And where each network codes c_i^{net} are maps from $[0,1]^{V_{g.[t,t+k]}}$ to $\mathbb{R}^{V_{g.[t,t+k]}}$, ψ needs to yield a value in $[0,1]$ and the sum of all the weights $w_{c_i^{net}}$ must be equal to one, and no weight can be negative. Moreover $\max c_i^{net}$ cannot be zero.

2.4. Experiential Space

Let us consider $\mathcal{X}$ as a function mapping the set of all stimuli $\mathcal{S}$ to $[0,1]^n$, where n is the cardinality (size) of the set of all predicates perceivable by a given sensory nervous system, applied to stimuli "$\mathcal{P}_{set}$":

$$\mathcal{X} : \mathcal{S} \mapsto [0,1]^n \text{ ; such that: } n = |\mathcal{P}_{set}| \tag{8}$$

Where $\mathcal{P}_{set}$ is defined in Predicate Coding (Bonal, 2025,[3]) as the set of all perceivable many-valued predicates $P_{i.j}$ mapping the set of all stimuli $\mathcal{S}$ to [0,1]:

$$\mathcal{P}_{set} = \{P_{i.j} | \textbf{Perceivable } (P_{i.j}) \geq \tau\} \tag{9}$$

Where τ is a psychophysical threshold.

Such that each predicate $P_{i.j}$[1] are those introduced in the "*Framework for a Testable Metaphysical Science*" (Bonal, 2024, [2]) and are ordered as follows :

$$P_{i.j} \leq P_{n.m} \equiv i < n \lor (i = n \land j \leq m) \tag{10}$$

[1]These many-valued predicates, initially introduced in the "*Framework for a Testable Metaphysical Science*" (Bonal, 2024, [2]), were later used for Predicate coding (Bonal, 2025,[3])

The function $\mathcal{X}$ thus yields a tuple, representing coordinates in the experiential space, defined below:

$$\mathcal{X}(x) = (P_{i.j}(x))_{P_{i.j} \in \mathcal{P}_{set}} \tag{11}$$

Such that:

$$\mathcal{X}(x) \in [0,1]^n \tag{12}$$

Moreover, we can define the set $\mathcal{E}^{set}$ of all outputs of the function $\mathcal{X}$, which will be the foundation for our experiential space:

$$\mathcal{E}^{set} = \{\mathcal{X}(x) | x \in S\} \tag{13}$$

The Experiential Space, is the set $\mathcal{E}^{set}$ paired with a distance function d:

$$\mathcal{E}^{\mathbf{space}} = (\mathcal{E}^{set}, d) \tag{14}$$

While the choice of metric d is ultimately up to experimental fit, one of the suggested metrics is the Minkowski metric, which defines the distance between two experience points X and Y in $\mathcal{E}^{\mathbf{space}}$ as :

$$d(X,Y) = (\sum_{i=1}^{n} |x_i - y_i|^z)^{\frac{1}{z}} \tag{15}$$

Where:

- $X = (x_1, ..., x_n)$ and $Y = (y_1, ..., y_n)$, such that each x_i and y_i are predicate values $P_{i.j}(x)$ such that $P_{i.j}$ is in $\mathcal{P}_{set}$ and x is a stimulus in $\mathcal{S}$
- z is the order of the distance, and is an integer in $\mathbb{Z}$ such that $z \geq 1$
- $|x_i - y_i|$ here represents the modulus of $x_i - y_i$ not set cardinality.

This metric has proven successful in modeling "Multidimensional Psychological Spaces" (Micko et al., 1970, [16]) (Wagner, 1985, [25]) and would therefore have potential to support the experiential space $\mathcal{E}^{\mathbf{space}}$.

Moreover, an experience $\mathfrak{E}$ at a time interval $[t_0, t_n]$ is trajectory a through the experiential space. It is defined as a tuple of points within $\mathcal{E}^{\mathbf{space}}$ from t to $t + k$:

$$\mathfrak{E}_{[t_0,t_n]} = (\mathfrak{E}_{t_0}, ..., \mathfrak{E}_{t_n}) \tag{16}$$

Such that all entries in the tuple $(\mathfrak{E}_{t_0}, ..., \mathfrak{E}_{t_n})$ are points in $\mathcal{E}^{\mathbf{space}}$.

Finally, each sensory experience point $\mathfrak{E}_{t_i}$ is equivalent to the output of a binding function $\mathcal{B}$ applied to the solution to the universal coding equation for the sensory nervous system network $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$:

$$\mathfrak{E}_{t_i} = \mathcal{B}(\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)) \tag{17}$$

Such that $\mathcal{B}$ is the defined as the function that maps the tuple in $[0, 1]^{|V_{sensory.[t,t+k]}|}$ yielded by $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$ to an experience point $\mathfrak{E}_{t_i}$, i.e. a function that maps the set all the tuples yielded by $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$ through time, to $\mathcal{E}_{set}$:

$$\mathcal{B} : \bigcup_{t=1}^{n} \{\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)\} \mapsto \mathcal{E}_{set} \tag{18}$$

In order to $\mathcal{B}$ assign an experience point $\mathfrak{E}_{t_i}$ to $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$,$\mathcal{B}$ yields a value for each dimension of $\mathcal{E}_{space}$ (where each dimension corresponds to a predicate in $\mathcal{P}_{set}$) from entries in the tuple yielded by $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$ (where each entry value corresponds to an encoding value for a neuron in the network). Indeed, let us define the output of $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$ as a tuple of values κ_i, each corresponding to a neuron in the vertices set $V_{sensory.[t,t+k]}$ of the sensory nervous system network:

$$\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x) = (\kappa_1, ..., \kappa_{|V_{sensory.[t,t+k]}|}) \tag{19}$$

Where, $|V_{sensory.[t,t+k]}|$ is the cardinality of $V_{sensory.[t,t+k]}$, and each κ_i is the code for neuron $neur_{u.[t,t+k]}$ in $V_{sensory.[t,t+k]}$.

Now let us define a total assignment A from the vertices set of the network to $\mathcal{P}_{set}$:

$$A : V_{sensory.[t,t+k]} \mapsto \mathcal{P}_{set} \tag{20}$$

Such that A is to be assessed experimentally, with neurons $neur_{u.[t,t+k]}$ in $V_{sensory.[t,t+k]}$ significantly correlating ($p < 0.005$) with the presentation of stimuli with high-valued $P_{i.j}$ in $\mathcal{P}_{set}$ ($P_{i.j}(x) \geq 0.8$).

Finally, $\mathcal{B}$ is defined as the tuple of dimensions of experiential space $e_{P_{i.j}}$

where each $P_{i.j}$ is a predicate in $\mathcal{P}_{set}$, such tuple yields an experience point $\mathfrak{E}_{t_i}$:

$$\mathcal{B}(\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)) = (e_{P_{i.j}})_{P_{i.j} \in \mathcal{P}_{set}} = \mathfrak{E}_{t_i} \tag{21}$$

Moreover, in order to ensure that the values from $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$, which are in $[0,1]^{V_{sensory.[t,t+k]}}$, are in the appropriate dimensions for $\mathfrak{E}_{t_i}$ which is in $[0,1]^{|\mathcal{P}_{set}|}$, each $e_{P_{i.j}}$ is defined as 0 if the count of coding units κ_i mapped to the given predicate $P_{i.j}$ is 0, and as the average of each κ_i mapped to the given predicate $P_{i.j}$ otherwise, such that if there is only one coding unit κ_i mapped to $P_{i.j}$ this value will be given for $e_{P_{i.j}}$ and if there is more the average will be taken:

$$e_{P_{i.j}} = \begin{cases} 0 \text{ if } N_{P_{i.j}} = 0 \\ \sum_{\kappa_i \in A^{set}_{P_{i.j}}} \frac{\kappa_i}{N_{P_{i.j}}} \text{ if } N_{P_{i.j}} \geq 1 \end{cases} \tag{22}$$

Such that $N_{P_{i.j}}$ is the number of coding units κ_i mapped to the given predicate $P_{i.j}$, defined as the cardinality of the set of all neurons $neur_{u.[t,t+k]}$ in $V_{sensory.[t,t+k]}$, mapped to $P_{i.j}$ from the assignment function A, denoted $A^{set}_{P_{i.j}}$:

$$N_{P_{i.j}} = |A^{set}_{P_{i.j}}| \tag{23}$$

Where:

$$A^{set}_{P_{i.j}} = \{neur_{u.[t,t+k]} \in V_{sensory.[t,t+k]} | A(neur_{u.[t,t+k]}) = P_{i.j}\} \tag{24}$$

Such that for each neuron $neur_{u.[t,t+k]}$ in $V_{sensory.[t,t+k]}$, there is a code κ_i in $\mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$:

$$\forall neur_{u.[t,t+k]}(neur_{u.[t,t+k]} \in V_{sensory.[t,t+k]} \implies \exists \kappa_i(\kappa_i \in \mathrm{Code}^{(1)}(net_{sensory.[t,t+k]}, x)) \tag{25}$$

This definition $e_{P_{i.j}}$ allows to assess three possible scenarios encountered when aiming to relate neural activity $\text{Code}^{(1)}(net_{sensory.[t,t+k]}, x)$ to sensory experience $\mathfrak{E}_{t_i}$: (i) the case where the sensory nervous system did not perceive or assess all the perceivable predicates[2] applied to the given stimulus, in such a case, corresponding dimensions in experiential space are taken as 0 as if a predicate is not perceived the stimulus will be experienced as not possessing it; (ii) the case where the sensory nervous system perceived and assessed all the perceivable predicates, and each neuron assessed a given predicate, in such case the encoding values are taken as the experiential point values ; (iii) the case where the sensory nervous system more than one neuron to a given predicate, yielding more neural encoding values than they are perceivable predicates, in such a case, the average values of neurons encoding the same predicate are taken as the value for the appropriate dimension in experiential space.

Since an experience trajectory $\mathfrak{E}_{[t_0,t_n]}$ is tuple of experience points $\mathfrak{E}_{t_i}$, it is given by a tuple of $\mathcal{B}$ outputs:

$$\mathfrak{E}_{[t_0,t_n]} = (\mathcal{B}(\text{Code}^{(1)}(net_{sensory.t_0}, x)), ..., \mathcal{B}(\text{Code}^{(1)}(net_{sensory.t_n}, x))) \quad (26)$$

Such that a time t_i in experiential space corresponds to a time interval $[t, t+k]$ for network encodings $\text{Code}^{(1)}$. Hence, the notation $net_{sensory.t_i}$ refers to the network during a given time interval $[t, t+k]$, such that this time interval is mapped to the instant t_i in experiential time.

Let us now define the path length L of an experience $\mathfrak{E}_{[t_0,t_n]}$, i.e. how far did an experience travel through the experiential space, as the sum of all the distances between each consecutive point in the trajectory $\mathfrak{E}_{[t_0,t_n]}$:

$$L(\mathfrak{E}_{[t_0,t_n]}) = \sum_{i=0}^{n-1} d(\mathfrak{E}_{t_{i+1}}, \mathfrak{E}_{t_i}) \quad (27)$$

Moreover, the distance speed s of an experience $\mathfrak{E}_{[t_0,t_n]}$ can be defined as the the distance between the first and last experiential points within it $d(\mathfrak{E}_{t+k}, \mathfrak{E}_t)$, divided by their time difference Δt:

$$s(\mathfrak{E}_{[t_0,t_n]}) = \frac{d(\mathfrak{E}_{t_n}, \mathfrak{E}_{t_0})}{\Delta t} \quad (28)$$

[2]A predicate being perceivable does not necessarily mean that it is always perceived.

Finally, path-average speed L_s of an experience $\mathfrak{E}_{[t_0,t_n]}$ can be defined as the path length L of that experience $\mathfrak{E}_{[t_0,t_n]}$, divided by the temporal duration of the experience Δt:

$$L_s(\mathfrak{E}_{[t_0,t_n]}) = \frac{L(\mathfrak{E}_{[t_0,t_n]})}{\Delta t} \tag{29}$$

The distance and path-average speed equations allow to track how much perceptual changes occurred within an experience.

This formalism allows for complex, multi-sensory processing of different predicates applied to stimuli, to be compressed into a singular, unified trajectory in experiential space: $\mathfrak{E}_{[t_0,t_n]}$.

Indeed, let us consider a visual stimulus, in a toy system which can only represents three predicate P_1, P_2, P_3, such that:

$$P_1(x) \equiv (\text{wavelength}(x) = 560nm)\ ,\ P_2(x) \equiv (\text{width}(x) = 0.2cm)\ ,\ P_3(x) \equiv (\text{orientation}(x) = 90^\circ) \tag{30}$$

P_1 thus expresses how "yellow (green-ish)" a stimulus is, i.e. 0 means not yellow (green-ish) at all, 1 means fully yellow (green-ish) blue ; P_2 expresses how wide in with respect to $0.2cm$ a stimulus is, and P_2 expresses how oriented compared to 90° a stimulus.

Since all predicates P_n are maps from the set of all stimuli to [0,1], i.e. $\forall P_n(P_n : S \mapsto [0,1])$, the experiential metric space associated with a system that processes "P_1, P_2, P_3" is the set $\mathcal{E}^{set}_{p1,2,3}$, containing the outputs of the function $\mathcal{X}_{p1,2,3} : S \mapsto [0,1]^3$:

$$\mathcal{E}^{\mathbf{space}}_{p1,2,3} = (\mathcal{E}^{set}_{p1,2,3}, d) \tag{31}$$

Such that

$$\mathcal{E}^{set}_{p1,2,3} = \{\mathcal{X}_{p1,2,3}(x) | \mathcal{X}_{p1,2,3}(x) = (P_1(x), P_2(x), P_3(x)) \wedge x \in S\} \tag{32}$$

Thus, if the solution to the universal coding equation $\text{Code}^{(1)}$ for the network of the sensory nervous system $net_{(123).t}$ in this toy model yields the following values :

$$\text{Code}^{(1)}(net_{(123).t}) = [0.7, 0.1, 1]\ ,\ \text{Code}^{(1)}(net_{(123).t}) \in [0,1]^3 \tag{33}$$

Then the coordinates of the sensory experience of the system with the experiential space will be:

$$\mathfrak{E}_x = \mathcal{B}([0.7, 0.1, 1]), \mathfrak{E}_x \in \mathcal{E}^{\mathbf{space}}_{p1,2,3} \tag{34}$$

3. Main Hypotheses and Testable Predictions

Having now outlined the mathematical description of theory expressed in this work, this section will posit the main hypotheses and testable predictions of the model, in order to make it experimentally and empirically tractable.

3.1. How to test the model

1. First, one should define a set of stimuli $\mathcal{S}$ to present to participants, as well as a set of perceivable predicates P_{set} applied to these objects. This should be done following the predicate coding methodology (Bonal, 2025, [3]): "Choose level 1 predicates (most "fundamental" and irreducible features of stimuli), then construct higher level predicates through combinations of lower-level predicates. Such higher level predicates can be evaluated through the predicate equation [and Łukasiewicz semantics (Lukasiewicz, 1970, [26]) (Vincenzo, 2013, [15]) (Malinowski, 2007, [13])]:

$$P_{i.j}(x) = \bigcirc_{l=1}^{L} \Phi_{op_l,a_l}\left((P_{i-1.k}(x))_{P_{i-1.k} \in B_{i.j}}\right) \ , \text{ such that } i \neq 1 \tag{35}$$

[Where: x is the given stimulus, $B_{i.j}$ is the set of all the lower-level predicates used to "build" $P_{i.j}$, Φ_{op_l,a_l} assigns the values of lower-order predicates using Łukasiewicz semantics, it assigns the value to every syntactic unit built from lower-level predicates, based on the l-th operator "op" applied to it, and the arity of the argument of the given operator op_l is denoted "a_l"; $\bigcirc_{l=1}^{L} \Phi_{op_l,a_l}$ is the composition of Φ_{op_l,a_l} for every syntactic unit, L is the number of units,] Then choose a psychophysical threshold τ and reduce the assessed predicated to those for which **Perceivable** $(P_{i.j}) \geq \tau$." - (Bonal, 2025, [3])
2. Having constructed S and P_{set}, one should then construct the $\mathcal{X}$ function as well as $\mathcal{E}^{set}$ and $\mathcal{E}^{space}$.
3. Then, while presenting a stimulus x to participants, such that $x \in S$, one should record neural activity (spikes or BOLD signal) and estimate the solution to the universal coding equation for networks $\text{Code}^{(1)}$.
4. Choose the distance function d in $\mathcal{E}^{space} = (\mathcal{E}^{set}, d)$ and compare alternatives.
5. Finally, compare results given by $\mathcal{B}$ and $\mathcal{E}^{space}$ to alternative metrics, such as representational similarity analysis (Kriegeskorte et al., 2008, [12]) (Dimsdale-Zucker et al., 2018, [9]).

3.2. Testable Predictions

H1: TMS-induced perturbations to regions responsible for processing a subset of perceivable predicates should selectively distort corresponding dimensions in $\mathcal{E}_{space}$

- Prediction: TMS-induced perturbations to regions responsible for processing a subset of predicates, should selectively distort the corresponding coordinates of a trajectory $\mathfrak{E}_{[t_0,t_n]}$. For instance, a TMS-induced perturbation to V4 in extrastriate visual cortex, should selectively distort corresponding color coordinates of the experience "$\mathfrak{E}_{[t_0,t_n]}$".

- Construct a set of stimuli $\mathcal{S}$, a set of perceivable predicates $\mathcal{P}_{set}$, a function $\mathcal{X}$ and an experiential space $\mathcal{E}_{space}$ from the guidelines in **section 3.1**. Assess the assignment function A by presenting stimuli with given predicates and associating cells which significantly respond selectively to these predicates $\mathcal{P}_{set}$. Conduct two experimental sessions. In the first session, "session 1", present participant with stimuli in $\mathcal{S}$ and record neural activity in-vivo, through methods such as fMRI, MEG or single-neuron recording. During the second session, "session 2", present participants with the same stimuli as in session 1 and apply TMS-induced perturbations selectively to areas linked to the perception of given predicates of stimuli presented through the A function, and record neural activity in-vivo, through methods such as fMRI, MEG or single-neuron recoding. Compute Code$^{(1)}$ for both sessions, from Code$^{(1)}$ and A compute $\mathcal{B}$ for both sessions, and from $\mathcal{B}$, compute trajectories $\mathfrak{E}_{[t_0,t_n]}$ for both sessions. If $\mathfrak{E}_{[t_0,t_n]}$ for session 1 contains higher values for predicates who were assigned, through A, to neurons in the area where TMS-induced perturbations were applied, than $\mathfrak{E}_{[t_0,t_n]}$ for session 2, the hypothesis is validated, else it is falsified.

H2: The implementation of a Brain-Computer Interface directly interacting with the sensory nervous system, would yield phenomenal representations coming from the interface within the experience coordinates

- Prediction: The implementation of a Brain-Computer Interface directly interacting with the sensory nervous system, would yield representations coming from the interface within the experience coordinates "$\mathfrak{E}_{[t_0,t_n]}$".

- Experimental Design: Construct a set of stimuli $\mathcal{S}$, a set of perceivable predicates $\mathcal{P}_{set}$, a function $\mathcal{X}$ and an experiential space $\mathcal{E}_{space}$ from the guidelines in **section 3.1**. Assess the assignment function A by presenting stimuli with given predicates and associating cells which significantly respond selectively to these predicates $\mathcal{P}_{set}$. Conduct two experimental sessions. In the first session, "session 1", present participant with stimuli in $\mathcal{S}$ and record neural activity in-vivo, through methods such as fMRI, MEG or single-neuron recoding. In the second experimental session, while complying with ethical guidelines, implementation of a Brain-Computer Interface directly interacting with the sensory nervous system, preferably of a neuromorphic type. Such a Brain-Computer Interface should be trained to selectively respond to given predicates and interact with neurons which are assigned, through A, to similar predicates. During the second experimental session, "session 2", present no stimuli but generate activity in the Brain-Computer Interface assessing the presence of a stimuli with given predicates. Compute $\text{Code}^{(1)}$ for both sessions from neural data, from $\text{Code}^{(1)}$ and A compute $\mathcal{B}$ for both sessions, and from $\mathcal{B}$, compute trajectories $\mathfrak{E}_{[t_0,t_n]}$ for both sessions. If $\mathfrak{E}_{[t_0,t_n]}$ from session 2 contains active predicate values, the hypothesis is validated, else it is falsified.

H3: The Path-average speed L_s of an experience trajectory is higher when presenting a gradually changing sequence of stimuli with diverse predicate values than when presenting unchanging stimuli during the same fixed time interval.

- Prediction: The presentation of a gradually changing sequence of stimuli with diverse predicate values during a fixed time interval should yield a higher path-average speed L_s, than the presentation of unchanging stimuli during the same fixed time interval.

- Experimental design: Construct a set of stimuli $\mathcal{S}$, a set of perceivable predicates $\mathcal{P}_{set}$, a function $\mathcal{X}$ and an experiential space $\mathcal{E}_{space}$ from the guidelines in **section 3.1**. Assess the assignment function A by presenting stimuli with given predicates and associating cells which significantly respond selectively to these predicates $\mathcal{P}_{set}$. Conduct one experimental session, "session 1", where participants are presented with a gradually changing sequence of stimuli in $\mathcal{S}$ with diverse predicate values during a fixed time interval. Conduct another experimental session, "session 2", where participants are presented with an unchanging stimulus in $\mathcal{S}$ during the same fixed time interval. Record neural activity in-vivo, through methods such as fMRI, MEG or single-neuron recoding. Compute $\text{Code}^{(1)}$ for both sessions from neural activity, from $\text{Code}^{(1)}$ and A compute $\mathcal{B}$ for both sessions, and from $\mathcal{B}$, compute trajectories $\mathfrak{E}_{[t_0,t_n]}$ for both sessions. Then compute the path-average speed L_s for both sessions. If L_s session $1 > L_s$ session 2, then the hypothesis is validated, else it is falsified.

H4: The distance speed s of an experience trajectory is higher when presenting unchanging stimuli followed by a rapid change in stimuli with diverse predicate than when presenting unchanging stimuli during the same fixed time interval.

- Prediction: The presentation of unchanging stimuli followed by a rapid change in stimuli with diverse predicate values during a fixed time interval should yield a higher distance speed s, than the presentation of unchanging stimuli during the same fixed time interval.

- Experimental design: Construct a set of stimuli $\mathcal{S}$, a set of perceivable predicates $\mathcal{P}_{set}$, a function $\mathcal{X}$ and an experiential space $\mathcal{E}_{space}$ from the guidelines in **section 3.1**. Assess the assignment function A by presenting stimuli with given predicates and associating cells which significantly respond selectively to these predicates $\mathcal{P}_{set}$. Conduct one experimental session, "session 1", where participants are presented with unchanging stimuli followed by a rapid change in stimuli (all stimuli must be in $\mathcal{S}$) with diverse predicate values during a fixed time interval. Conduct another experimental session, "session 2", where participants are presented with an unchanging stimulus in $\mathcal{S}$ during the same fixed time interval. Record neural activity in-vivo, through methods such as fMRI, MEG or single-neuron recoding. Compute $\text{Code}^{(1)}$ for both sessions, from $\text{Code}^{(1)}$ and A compute $\mathcal{B}$ for both sessions, and from $\mathcal{B}$, compute trajectories $\mathfrak{E}_{[t_0,t_n]}$ for both sessions. Then compute the distance speed s for both sessions. If s session $1 > s$ session 2, then the hypothesis is validated, else it is falsified.

4. Discussion

The mathematical model introduced in this work allows for a description of a unified sensory experience, from neural activity analyzed through the lens of Predicate Coding (Bonal, 2025, [3]). Indeed, it aims to provide a mathematical solution to the fourth instance of Feldman's Neural Binding Problem taxonomy (2012, [10]), i.e. the subjective unity of perception, through the unification of diverse neural activity throughout the sensory nervous system, into a coherent unified experience, as a trajectory within "experiential space".

However, while this model gives a mathematical readout from neural activity to phenomenal sensory experience, a major mystery still remains: the causal link between neural activity and phenomenal experience, which can be seen as a instantiation of the philosophical mind-body problem (Chalmers, 1997, [4]) (Descartes, 1641, [8]).

Indeed, one could aim to treat Binding function $\mathcal{B}$ as more than just a readout, and understood as a form of "communicative" link between the sensory nervous system and and an abstract experience, yielding phenomenal perception. However, if one aims to interpret the mathematics presented in this work in such a way, one problem arises: How can such link instantiate itself in an experimentally discoverable manner? For instance, the communicative link between motor neurons in the brain and voluntary somatic control can be traced back to corticospinal tracts (Heffner et al., 2008, [11]) (Ueno et al., 2018, [23]) (Usuda et al., 2022, [24]). Presuming the existence of such a link would either require a complete reductionist approach, reducing phenomenal activity to neural activity, which would partly dismiss the problem rather than answer it, or accepting the existence of a link between a physiological process (neural encoding) and an abstract experiential space, which is empirically challenging and hard to falsify.

Hence, while this model aims to provide a clear mathematically solution to the presence of a unity of phenomenological sensory experience from diverse neural encodings, if one aims to extend the purpose of this readout to serve as "communicative" link, the philosophical mind-body problem arises.

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