

1 Neural Oscillations as Representations

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Abstract

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We explore the contribution made by oscillatory, synchronous neural activity to representation in the brain. We closely examine six prominent examples of brain function in which neural oscillations play a central role, and identify two levels of involvement that these oscillations take in the emergence of representations: enabling (when oscillations help to establish a communication channel between sender and receiver, or are causally involved in triggering a representation) and properly representational (when oscillations are a constitutive part of the representation).

We show that even an idealized informational sender-receiver account of representation makes the representational status of oscillations a non-trivial matter, which depends on rather minute empirical details.

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1 Introduction

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A foundational hypothesis in cognitive science is that cognition progresses through the manipulation of representations: entities that are about, or stand for, other, generally extra-mental entities (Frankish and Ramsey 2012). According to this hypothesis, information about the external world flows through the brain, encoded somehow in its states, modulating behavior in increasingly sophisticated ways. Much cognitive science aims at identifying those brain states, and uncovering their content—what it is that they say about the external world. In its turn, one of the central research programs in the philosophy of cognitive science aims at formulating a metaphysics of representations: what needs to be the case for a certain vehicle to qualify as a representational state? What determines its representational content? (Cummins 1991; Ramsey 2007; Shea 2018)

30 The paragraph above is written in the abstract way characteristic of philo-
31 sophical discussion on representations (e.g. Fodor 1974; Pylyshyn 1984); one
32 that glosses over particular details of implementation. For example, philoso-
33 phers often use the term ‘vehicle’ with the intention that it range over all
34 possibly representational brain states (say, single neurons, populations of neu-
35 rons, or neurotransmitter discharges) and all possible encodings (say, rate-
36 or phase-based). Studying the metaphysics of representation in such non-
37 committal terms is methodologically smart: it allows the resulting theory to
38 apply to vehicles in general, and to capture whatever is common to all in-
39 stances of representation in the brain. On the other hand, this approach tends
40 to neglect the particular way in which representations are implemented, and
41 the keys those particular ways might hold to the more general question of
42 representation—apart from their intrinsic theoretical interest (Craver 2007;
43 Boone and Piccinini 2016).

44 In this paper we redress this situation with respect to one very interesting,
45 philosophically underexplored kind of vehicle. Frequently, brain activity is or-
46 ganized into synchronous, quasi-periodic patterns of activation which appear
47 to contribute to many aspects of cognition, from pre-attentional grouping
48 (Jensen, Kaiser, and Lachaux 2007; Zion Golumbic et al. 2013; Fries 2015;
49 Pritchett et al. 2015) to the construction and modification of spatial maps in
50 the hippocampus (Skaggs et al. 1996; Colgin et al. 2004). The question that
51 will interest us here is whether these contributions are representational: do
52 synchronous, periodic patterns of activity (we will call them ‘neural oscilla-
53 tions’, for brevity) in and of themselves constitute representations?

54 Investigation of these implementational details is not only interesting in
55 its own right; it can also help philosophers reach conclusions about represen-
56 tation in general. In particular, the results of this paper can be used as a
57 response to the ‘trivialization’ objection against naturalistic theories of con-
58 tent: many theorists have recently argued that theories that try to explain
59 the notion of ‘representation’ in terms of functions, information, or causal re-
60 lations (for example, teleosemantic approaches) are too liberal. According to
61 this complain, if representational status merely depended on the presence of
62 these features, almost any brain event would qualify as such (Ramsey 2007;
63 Burge 2010; Schulte 2017; Gładziejewski and Miłkowski 2017; Butlin 2018;
64 Williams and Colling 2018). This outcome would trivialize the notion of ‘rep-
65 resentation’ and would put its explanatory role into question. Partly for this
66 reason, some of these theorists suggest that attribution of representational
67 status should be restricted to relatively sophisticated processes, such as those

68 involving map-like structures or constancy mechanisms.

69 Neural oscillations show this to be a hasty conclusion: as we will see, under
70 an understanding of representations that would certainly count as liberal
71 by those theorists' lights, some forms of simple oscillatory processes qualify
72 as representational, whereas others do not. "Liberal" naturalistic theories of
73 content can draw a meaningful, non-trivial distinction between brain events
74 that are genuinely representational and those that are not.

75 Our paper is structured in six main sections. In section 2 we sketch our
76 preferred general approach to the question of the metaphysics of representa-
77 tion. Our aim in this section is not to offer a fully developed metasemantics
78 but, rather, to identify a common core to which many theorists working on
79 this topic adhere. This common core will be enough to distinguish two roles
80 neural oscillations can play, in the process of generating representations: we
81 call them *enabling* and *properly representational*. We present these roles in
82 section 3. The following two sections consider some scientifically prominent
83 cases of brain function, with the goal of ascertaining which one, if any, of
84 these roles neural oscillations play in them: section 4 discusses neural oscilla-
85 tions that probably play an enabling role; and section 5 deals with what, we
86 argue, are the properly representational cases. This taxonomy exemplifies a
87 second lesson about the usefulness of investigating particular details of imple-
88 mentation for the study of representations in general: while we have arrived
89 at it from the consideration of rather minute such details, it is not unreason-
90 able to think that it will prove helpful in the investigation and description of
91 many other, unrelated representational phenomena. Section 6 wraps up and
92 offers some conclusions.

93 2 The core metaphysics of content

94 In subsequent sections we will ask of certain kinds of brain activity whether
95 they count or not as representations. In order to answer this question, we
96 need a theory of what makes a certain state representational. A substantial
97 discussion of this question is well beyond the scope of this paper; instead,
98 we will present, without argument, two tenets that are widely (though by no
99 means universally) thought to be part of what it is for a representation to be
100 a representation. These tenets are most closely related with so-called *teleose-*
101 *mantic* naturalistic metasemantics (Millikan 1984; Papineau 1987; Neander
102 2017) but they also draw from the partially overlapping *signaling games*

103 framework (Skyrms 2010; Godfrey-Smith 2014).

104 The first tenet is that all representational systems share an architectural
105 motif: in all of them, representational vehicles, or ‘signals’, mediate between
106 a mechanism producing the representation (called ‘sender’ or ‘producer’) and
107 a mechanism using the representation (‘receiver’ or ‘consumer’). For a mech-
108 anism to qualify as a sender or a receiver, it needs to have the right sort of
109 biological function: the sender’s function is, roughly, to emit the above me-
110 diating signals when certain states of affairs obtains, whereas the receiver’s
111 functions is, roughly, to act in certain ways upon reception of the signal.

112 The content of the representation will be fixed, among other things, by
113 the relation it bears to the behavior of the producer/sender and the con-
114 sumer/receiver. Although the specification of these relations vary from ac-
115 count to account, information generated in the external world flowing from
116 producer to the representation, and from the representation to the consumer,
117 is usually taken to play a role: under a first approximation, contents are fixed
118 by the information that representations carry about the world, under some
119 designated set of optimal conditions. What these optimal conditions amount
120 to is somehow fixed by the receiver/consumer’s biological function—this is
121 the second tenet.

122 Putting these two ideas together, our metasemantic sketch says that a
123 certain mental vehicle, V , is a representation if:

- 124 1. V is an intermediate state in a sender-receiver architecture, and
- 125 2. V helps fulfil its consumer/receiver’s biological function by carrying the
126 information that the state of affairs S is the case (information which
127 has flown to V through its producer/sender)

128 In such a situation, moreover, we may say that the content of V is that
129 S is the case. In this paper, though, our main focus will be on establish-
130 ing that certain neural oscillations are representations, and not so much on
131 ascertaining their content.

132 This metasemantic sketch is heavily simplified—Ruth Millikan, and many
133 other theorists after her, have been developing related ideas for the best part
134 of four decades. Still, it is detailed enough to accommodate a number of
135 properties that many associate with, or even take to be necessary for, the ex-
136 istence of representations. First, the possibility of erroneous representation,
137 or misrepresentation: this will happen, among other things, in some cases

138 of sender *malfunction*, the possibility of which is part and parcel of its hav-
139 ing a biological function. Second, the fact that representations ought to be
140 action-guiding—or, at least, somehow contribute to the production of behav-
141 ior: this will fall out of understanding biological functions as contributions
142 to the subsistence of the individual (Mossio, Saborido, and Moreno 2009)
143 or contributions to selection for the functional device in question (Millikan
144 2002). From section 4 onwards we will rely on these ideas in our discussion
145 of the representational status of oscillations. Before that, we will briefly dis-
146 tinguish two possible degrees of involvement for oscillations to have in the
147 generation of representations.

148 3 Enabling and representational roles

149 The taxonomy we are about to present is not a theoretical assumption, but
150 one of the results of the present investigation: after having surveyed many
151 of the relevant empirical cases, it is the classification that suggests itself as
152 most conducive to understanding and organizing the involvement of neu-
153 ral oscillations in the generation of representations. In any event, of course,
154 other useful taxonomies are certainly possible, and our preferred one does
155 not aim at being exhaustive. The two roles under which we will classify the
156 involvement of neural oscillations in representational phenomena are:

157 **Enabling:** Neural oscillations enable or trigger the activation of a represen-
158 tation.

159 **Representational:** Neural oscillations properly are (or are a constitutive
160 part of) a representation.

161 First of all, neural oscillations play an enabling role when their main job
162 is to help set up the communication channel between sender and receiver.
163 To see what this means, we first note that a sender-receiver configuration
164 is just a *point-to-point information-processing pipeline* in the Shannonian
165 tradition (Shannon 1948; El Gamal and Kim 2011, section 3.1). Compare
166 the entirely analogous figures 1 and 2. The sender/producer can be thought
167 of as well as an *encoder*, and the receiver/consumer as a *decoder*. Efficient
168 encoding/decoding is useful in order to get relevant information through in-
169 herently noisy, limited-capacity channels, and some of the time it is coding-
170 related roles that neural oscillations will play: for example, oscillations can

171 help communicate to the encoder/decoder what is the task-relevant informa-
 172 tion they should focus on communicating (this is related to what information
 173 theorists call a *distortion measure*—see Martínez (2019) for details). This is
 174 our interpretation of the phenomena discussed in Subsection 4.1. They can
 175 also constitute the mechanism that allows the brain to move from reading
 176 representations to writing them, and back (Subsection 4.2). A third kind of
 177 enabling role is to help build a representation, without being a proper part
 178 of it (Subsection 4.3). There are probably many other purely representation-
 179 enabling roles that neural oscillation can play.

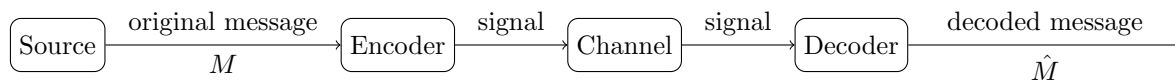


Figure 1: A point-to-point information-processing pipeline



Figure 2: A sender-receiver model

180 The job of neural oscillations, however, is not limited to facilitating (or
 181 disrupting) communication. Sometimes they seem to play a *bona fide* repre-
 182 sentational role. In other words, they are a constitutive part of the vehicle
 183 of communication—of the signals in figure 1. Neural oscillations not only
 184 enable the flow of information, but also convey information themselves. In
 185 Subsections 5.1 and 5.2 we discuss two cases in which oscillatory phenom-
 186 ena not just enable but *are* representations. Finally, in Subsection 5.3 we
 187 take a step back and canvass the general role that oscillations play in the
 188 generation of an important kind of representational vehicle—so-called *neural*
 189 *sequences*—across the brain.

190 4 Enabling oscillations

191 In this section we review cases in which oscillations provide background con-
192 ditions for representations to exist, or are causally involved in the tokening
193 of representations, without being themselves representational.

194 4.1 Attention and Communication Through Coherence

195 Attention is a kind of modulation of sensory processing, whereby incom-
196 ing stimuli are preferentially processed, or ignored, based on their current
197 saliency, or behavioral relevance to the perceiver (Treue 2001; Gilbert and Li
198 2013). Attentional influence helps target finite and expensive computational
199 resources in higher cognition to the treatment of those aspects of the incom-
200 ing sensory stream that most directly affect the perceiver. “As a consequence
201 the perceptual quality of a visual stimulus located within an attended region
202 is improved ... at the expense of the perceptual quality of stimuli located
203 elsewhere ...” (Chalk et al. 2010, p. 114).

204 Attentional influence on sensory processing has been demonstrated to
205 exist as early on as V1 (Posner and Gilbert 1999) but probably not earlier
206 than that (Alilović et al. 2019); this influence increases as we move on to
207 higher visual areas (Maunsell and Cook 2002) although “the magnitude of
208 attentional effects depends on the nature of the task and the configuration
209 of the stimulus” (Gilbert and Li 2013, p. 352).

210 Spatial attention is often directed to concrete spatial areas in the visual
211 field. The once ubiquitous metaphor was that attention is like a ‘spotlight’: it
212 illuminates the attended area and singles it out for further processing (Bre-
213 fczynski and DeYoe 1999; Hurlbert and Poggio 1985) More recent research
214 has uncovered some limitations of this spotlight metaphor. First, the spatial
215 resolution of neurons decreases as we go up in the visual processing hier-
216 archy (that is, the receptive field size of these neurons increases, Dumoulin
217 and Wandell 2008): the higher the visual area, the bigger chunks of the visual
218 fields particular neurons are affected to. This makes intuitive sense: these neu-
219 rons are often, though not always, attuned to global properties of the visual
220 scene—to its gist; and not so much to fine-grained details, say, of texture or
221 color. This means that attention cannot be just a matter of upstream neurons
222 specializing on (directing a spotlight to) smaller, spotlight-sized, visual-field
223 regions. Furthermore, the existence of attentional mechanisms that target
224 objects and features, and not spatial regions, has been amply demonstrated

225 (Maunsell and Treue 2006; O’Craven, Downing, and Kanwisher 1999; Treue
226 and Trujillo 1999). Attentional mechanisms, therefore, somehow are able to
227 single out, from the whole input to a neuron’s receptive field, a relevant
228 subset of activity for further treatment.

229 One of the most widely accepted hypothesis as to how attention ac-
230 complishes this, Pascal Fries’s *communication through coherence* (also CTC
231 henceforth, Fries 2005, 2015), relies on synchronized¹ oscillations in the gamma
232 band (or *gamma oscillation*, for short, Pritchett et al. 2015; Jensen, Kaiser,
233 and Lachaux 2007; Fell et al. 2003; Zion Golumbic et al. 2013; Fries 2009). In
234 this section we first discuss the mechanism by which synchronized oscillatory
235 behavior is accomplished; then how this solves the problem that attention
236 faces; and, finally, whether attention-related gamma oscillation could be plau-
237 sibly regarded as representational.

238 Gamma oscillation depends crucially on the behavior of fast-spiking in-
239 hibitory interneurons (Pritchett et al. 2015; Fries 2009). Simplifying some-
240 what current computational models of the emergence of oscillatory behavior
241 (see, e.g., Börgers, Epstein, and Kopell 2008, for a fuller picture), the main
242 idea is that a stimulus presentation excites a group of interneurons, which in
243 turn inhibit a larger group of excitatory neurons in their vicinity. When the
244 inhibition wears out (after approximately 15ms, hence the gamma frequency
245 of the resulting rhythm, Pritchett et al. 2015, p. 254) there is a window of
246 opportunity for the activity of excitatory neurons, which in turn generate the
247 next cycle of inhibition by interneurons.

248 Attention is hypothesized to work roughly as follows: the stimulus at-
249 tended to by a population of neurons downstream, D , oscillating in the
250 gamma band, is the one encoded by the population upstream, U , also oscil-
251 lating and synchronized with D . The way in which this helps fix attention to
252 the stimulus encoded by U is by enhancing the *effective connectivity* (Friston
253 2011) between D and U (and impeding the connectivity between D and other
254 possible neuronal populations upstream). First, focusing on the downstream
255 neuron population, “input consistently arriving at high-gain phases benefits
256 from enhanced effective connectivity” (Ni et al. 2016, p. 240). Second, focus-
257 ing on the upstream population, “[presynaptic synchronization] . . . ensures
258 that a presynaptic activation pattern arrives at postsynaptic neurons in a
259 temporally coordinated manner” (Fries 2015), which in turn results in much
260 enhanced impact in postsynaptic neurons because of feedforward coincidence

1. Here, by “synchronized” we mean “in (delayed) coherence”, see Fries (2015).

261 detection (Fries 2009). This is, in a nutshell, the mechanism that Fries calls
262 CTC.

263 Our main question is: are attention-related gamma oscillations represen-
264 tational? To be precise, the putative representational vehicle is

265 **Vehicle:** Populations U and D being synchronized in the gamma band.

266 Under the simplified analysis of representations we are working with (as
267 presented in section 2) a representation is, at least, a vehicle that mediates
268 between a sender (or producer) and a receiver (or consumer). Now, on the
269 one hand, it *is* possible to find a sender, or set of senders, for *Vehicle*. First,
270 for saliency-based attention, the most salient stimulus is the one that will
271 drive excitatory neurons most vigorously. This will kick off the process de-
272 scribed above, that results in gamma oscillation for these neurons, which in
273 turns “manages to entrain postsynaptic neurons and thereby achieves the in-
274 crease in input gain at the postsynaptic neurons.” (Fries 2015, p. 226). The
275 sender of the attentional vehicle, according to this picture, would be neural
276 (e.g., retinal) activity vigorous enough to entrain gamma oscillation. For top-
277 down attention, the CTC picture is somewhat less clear. Roughly, whatever
278 volitional processes that result in a mandate to attend to a certain spatial
279 region, feature or object would directly communicate with U (recall, this is
280 the population of upstream, presynaptic neurons), causing them to synchron-
281 ize, and thereby entraining D . The sender, according to this picture, would
282 be something like the neural correlate of an intention to focus one’s attention
283 on the feature encoded by D .

284 But, on the other hand, it is very unlikely that *Vehicle* have a receiver:
285 that D attends to U is not something that needs to be communicated to an-
286 other area of the brain for further treatment. There is no further component
287 that is sensitive to the synchronization and employs it to gather information
288 about some state of the world. Here neural oscillations enable a better com-
289 munication between two brain areas, but they are not supposed to represent
290 or carry information about any particular aspect of the world. Attentional
291 modulation of sensory processing is a very efficient way of optimizing the
292 brain’s limited computational budget, but the information that this opti-
293 mization might carry is of no use to other brain areas.²

2. At least in usual cases, leaving aside comparatively uncommon situations of self-
monitoring of attention (Harris et al. 2005).

294 Note that our claim here is just that *Vehicle* (that is, the actual neural-
295 oscillatory implementation of attention) is not representational. We are not
296 discussing other phenomena in the vicinity, such as, for example, the in-
297 tention to focus our attention on some aspect of the visual field, which, as
298 suggested above, could plausibly trigger an attentional process in some cases.
299 The communication of this intention to neural population *U could*, for all we
300 know, constitute an imperative representation with a content along the lines
301 of “Attend to stimulus S!”. We will not discuss here this possible imperative
302 representation³ among other things because the philosophical treatment of
303 imperative representations is less mature than that of indicative ones. See
304 Butlin (2018) and Artiga (2013) for related discussions.⁴

305 What attention does falls squarely under *channel management*: given the
306 available channel capacity from early vision to the extrastriate cortex, infor-
307 mation relevant to current behavioral goals (top-down attention) or infor-
308 mation that might potentially inform new behavioral goals (saliency-based
309 attention) needs to be prioritized. Attention-related gamma oscillations play
310 a purely enabling, non-representational role.

311 4.2 Retrieval and encoding of cognitive maps

312 Our second example concerns place cells. Research on these neurons began
313 in the 1970s, when O’Keefe and Dostrovsky (1971) discovered that activity in
314 some cells of the rat’s hippocampus (specially in areas CA1 and CA3) were
315 not well correlated with significant events (such as food finding or lever press-
316 ing), but were instead specially sensitive to location. Subsequent research has
317 confirmed that these cells carry information about particular places and many
318 have taken this to suggest that rats possess a cognitive map of the environ-
319 ment (O’Keefe and Nadel 1978; Muller et al. 1994; McNaughton et al. 2006;
320 Hartley et al. 2017).

321 Cognitive maps must be stable enough that they can be re-used whenever
322 the rat needs to navigate the same space. At the same time, in certain circum-
323 stances (e.g. in new environments, or when familiar environments change in
324 significant ways) a new map needs to be created, a process called ‘remapping’

3. A representation which, by the way, would also be possibly mediated by gamma synchrony, this time between the frontal eye field and V4 (Gregoriou et al. 2009). See Baluch and Itti (2011) for a review of top-down influences in attention.

4. We would like to thank an anonymous reviewer for drawing our attention to this point.

325 (Muller and Kubie 1987). The exact circumstances that trigger remapping
326 are not well understood, but it has been extensively shown that this process
327 involves cells changing their place fields and establishing new connections
328 between them. In case of *global* or *complete* remapping, the cell’s new place
329 field does not bear any specific relationship with the previous one (Knierim
330 2003; Latuske et al. 2018).

331 The existence of remapping, however, raises a puzzle. When the rat needs
332 to orient itself in a familiar environment, action needs to be driven by the
333 information stored in the hippocampus and, when it finds itself in a new
334 environment or when the old environment changes in significant ways, the
335 new information needs to be stored. The problem, however, is that some of the
336 very same brain regions containing place cells (e.g. C3, and CA1) are involved
337 in both processes of encoding and retrieval (Leutgeb et al. 2005). How can a
338 system deal with these two different goals? How can the hippocampus *encode*
339 new information without interference from old memories, and *retrieve* an
340 old map without interference from incoming input? One possible mechanism
341 involves the use of neural oscillations.

342 The entorhinal cortex (EC) is one of the main extrahippocampal relays de-
343 livering new information to the hippocampus (Buhl and Whittington 2007).
344 In encoding a new map, activity in the EC and CA1 is synchronized, meaning
345 that cells in both regions tend to fire in-phase, whereas synaptic transmission
346 between CA3 and CA1 is weak, which prevents interference. In contrast, in
347 retrieval there is strong input from CA3 to CA1 and weak input from EC
348 (Hasselmo, Bodelón, and Wyble 2002; Montgomery and Buzsáki 2007). In a
349 nutshell, the idea is that, in encoding, oscillations are used in order to pro-
350 mote the transmission of information between extrahippocampal areas and
351 the hippocampus and inhibit interference from CA3, while, in retrieval, it is
352 information between CA3 and CA1 that is privileged (Hasselmo and Stern
353 2014; Colgin 2016). This seems, again, to be a clear example of communica-
354 tion through coherence.

355 Now, if this hypothesis is on the right track, what role are neural oscilla-
356 tions playing? As in the case of attention reviewed earlier, here synchroniza-
357 tion seems to to be the mechanism used for privileging the transmission of
358 certain kinds of information: it facilitates communication between two neu-
359 ronal assemblies and, at the same time, obstructs possible interferences from
360 other brain areas. Neural oscillations do not seem to provide any new con-
361 tent; they are just the mechanism that opens or closes the channels from two
362 areas that store preexisting information or relay new information.

363 It is important to note that the fact that synchronized oscillation is estab-
364 lished between CA1 and EC (CA3) *does* carry information about the system’s
365 task currently being one of encoding (retrieval). It is sometimes suggested
366 that the kind of metasemantic account sketched in Section 2 has the un-
367 welcome consequence that most any informational connection will come out
368 representational. Encoding/retrieval in the hippocampus shows this to be
369 false: as no other part of the brain is receiving (or consuming, or decoding)
370 this information, the relevant vehicle does not qualify as a representation.
371 Again here, neural oscillations seem to play a merely enabling role.

372 4.3 Theta precession in remapping

373 Neural oscillations can also play a different sort of enabling role: sometimes
374 they are instrumental in building a certain representation, but they are not
375 themselves part of the actual representational vehicle. We offer theta preces-
376 sion as an example of this kind of enabling.

377 The mammal hippocampus presents a very strong pattern of oscillation
378 in the theta frequency band, around 3–10 Hz (Buzsáki 2002). There appears
379 to be a systematic timing relationship between the activities of single place
380 cells in CA1 or CA3 and this background theta rhythm: O’Keefe and Recce
381 (1993) found that as rats move through the place field corresponding to a
382 certain place cell, the phase of spike trains of this cell tend to change their
383 phase with respect to the background theta period: when the rat enters its
384 place field, a place cell starts firing at the end of the first theta cycle, and
385 subsequent spike trains progressively move forward, as the rat progresses
386 through the field. By the time the rats leaves the place field, bursts might
387 have advanced a whole cycle, i.e. almost 360° , but never more, and most of
388 the time the phase precession spans at most about 180° (O’Keefe and Recce
389 1993; Maurer et al. 2006; Schmidt et al. 2009). This process is called ‘theta
390 precession’ (Figure 3).

391 Among the different proposals on offer about the role of theta precession
392 (Jensen and Lisman 2000; Hasselmo 2005; Huxter, Senior, and Allen 2008;
393 Jeewajee et al. 2014), another one of which we will discuss in Subsection 5.1,
394 we will here focus on the relation between precession and remapping (Skaggs
395 et al. 1996). Spatial representation in the hippocampus is not topological, in
396 the sense that two cells that are close together are not more likely to represent
397 adjacent areas than more distant cells. How can a stable map be formed
398 in such a structure? How can distant neurons come to steadily represent

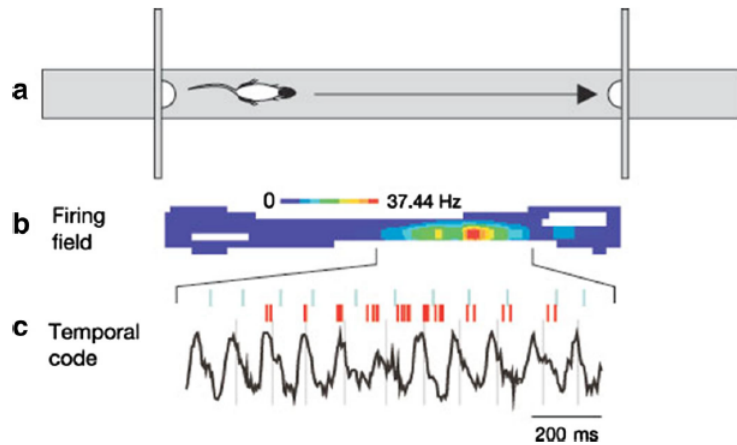


Figure 3: The colored area in b represents the place field of a particular hippocampal place cell when the rat crosses the field represented in a. c shows that place cell spikes (shown in red) precess against the theta oscillations: firings begin near the peak and progressively move earlier in subsequent cycles (from Huxter, Burgess, and O’Keefe 2003).

399 adjacent locations and how are their connections established? William Skaggs
 400 and colleagues suggest that precession plays a key role.

401 In short, the suggestion runs as follows. When the rat initiates a process
 402 of remapping, place cells lose their preferred place fields and gain new fields
 403 that bear no predictable relationship to the old ones. Suppose that a rat
 404 engages in remapping and in the new environment an A-cell fires when the
 405 rat is in location A.⁵ Here precession is to be expected: the first spike train
 406 will take place near the peak of the last gamma cycle within the first theta
 407 cycle,⁶ but in subsequent theta cycles the firing pattern will take place at
 408 earlier phases as the rat traverses the field. At some point the rat will enter
 409 a new place field B and a B-cell (which might be located far away from any
 410 A-cells) will become active. Now, due to precession these two cells will fire

5. In this paper we follow the convention of calling the cell that represents, e.g., location A an “A-cell”; *mutatis mutandis* for other cells and their place fields.

6. For more on the relation between theta and gamma cycles see Lisman and Jensen (2013) and Section 5.3 below.

411 in the order AB and, since place fields partly overlap, this pattern will be
 412 repeated several times as the rat moves (see figure 4).

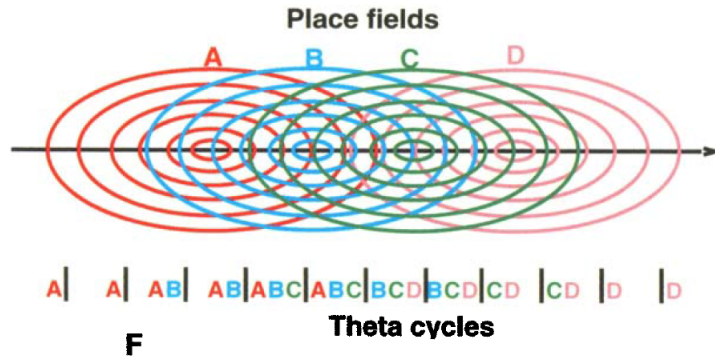


Figure 4: From Skaggs et al. 1996: 169. Explanation in the main text.

413 More generally, as the rat traverses a sequence of places ABCDE, the
 414 following pattern will emerge (vertical lines represent the beginning of a theta
 415 cycle): $\dots |ABC|ABC|BCD|BCD|CDE|CDE \dots$. Note that spike trains in
 416 the A-cell will systematically take place a bit earlier than spike trains in
 417 the B-cell (or vice versa, if the rat is traveling in the contrary direction).
 418 This short time span between the spikes of two cells that represent adjacent
 419 locations A and B is crucial because it will help strengthen the connections
 420 between A- and B-cells through long-term potentiation (LTP).⁷ It has been
 421 suggested that LTP reinforces better the synaptic connections from A-cell to
 422 B-cell when the A-cell fires slightly earlier in time than the B-cell (Larson
 423 and Lynch 1989). If this is true, precession might facilitate LTP between
 424 neurons that carry information about adjacent places and this might explain
 425 how maps can be formed in which cells located at a (relatively) long distance
 426 from each other represent nearby places (Skaggs et al. 1996; Bechtel 2016).

427 Let us suppose that this explanation is on the right track. Do neural oscil-
 428 lations play a representational role here? We lean towards a negative answer:
 429 neural oscillations should be construed as a mechanism that enables the con-
 430 struction of a map-like representation, but are not part of it. Certainly, the
 431 stable time lag between spike bursts of A- and B-cells, afforded by their occu-
 432 pying different phases in the gamma cycle, is sensitive to (carries information

7. Long-term potentiation is a persistent strengthening of synapses caused by co-activation patterns (Cooke and Bliss 2006).

433 about) the adjacency of the related place fields, but we suggest that this is
434 not enough to credit the underlying oscillations with a representational role.
435 There are two main reasons for this.

436 First, LTP occurs whenever there is a particular temporal delay between
437 the activity of two cells, independently of how this delay is produced. In
438 LTP, timing, not phase, is essential: firings of A- and B-cells need to be suf-
439 ficiently close *in time* and, for example, keeping phase-delay constant, LTP
440 will happen if the oscillation is sufficiently fast, but not if it is too slow.
441 Compare this with the cases of communication through coherence in atten-
442 tion reviewed above: there, persistently rhythmic, coincident activity (and
443 not merely a certain time lag) seemed to play an essential role in upstream
444 neurons entraining downstream activity. The second reason is that, in this
445 mechanism, there does not seem to be any receiver sensitive to oscillations as
446 such. There is no internal downstream mechanism sensing this phase delay
447 and using it to gain information that could be used in some computational
448 process.

449 5 Representational oscillations

450 So far we have discussed cases in which neural oscillations play a role in
451 bringing about representational phenomena without being representations
452 themselves, but rather partly constituting the communicative scaffolding nec-
453 essary for representations to emerge. In this section we present cases in which
454 neural oscillations do seem to play a properly representational role.

455 5.1 Theta precession in prediction

456 Apart from its contribution to remapping, theta precession plays a second
457 role that might qualify as genuinely representational. In their seminal paper,
458 O’Keefe and Recce (1993) found that place cells tend to fire more vigor-
459 ously in earlier phases of the background theta wave, as the rat approaches
460 the center of their place field. In fact, they observed that the phase of the
461 background theta wave at which place-cell activity is maximal appears to
462 correlate much better with the exact location of the rat within the place field
463 than with the time it has spent in it, or its velocity. Furthermore, in normal
464 conditions this precession (i.e., the phenomenon by which the phase of pre-
465 dominant place-cell activity moves towards the beginning of the theta wave)

466 vanishes when the rat is in the running wheel (Czurko et al. 1999; Hirase
467 et al. 1999), which lends support to the idea that the relevant connection is
468 not with its speed or the time it has spent in a place field, but with its lo-
469 cation. As a result, some have suggested that theta phase is used to provide
470 a more fine-grained representation of location: whereas activity in a given
471 place cell indicates the broad area in which the rats finds itself (this would
472 be *rate coding*), the degree of precession carries information about the rat’s
473 location within the place field (and this would be *phase coding*). Jensen and
474 Lisman (2000) provided further support for this hypothesis, when they used
475 the activity recorded in 38 pyramidal cells to pinpoint the rats’ place within
476 a linear track, and showed that by including phase information they could
477 improve the accuracy by 43% (p. 2607). They were able to predict the rat’s
478 position within a 2-meter track with a precision of 3 cm.

479 Other, more recent work interprets the same results in a slightly differ-
480 ent way: instead of taking them to support the idea that phase codes for
481 fine-grained location information within one and the same place field, John
482 Lisman and colleagues have claimed that phase coding is actually used to
483 make *predictions* about which place field the rat is moving towards (Lisman
484 and Redish 2009a; Lisman and Jensen 2013). This is, in a sense, a different
485 gloss on the same main idea: you can think of place fields as being compar-
486 atively big, and therefore interpret theta phase as coding for location within
487 that field; or you can think of place fields as comparatively smaller, and then
488 think of theta phase as predicting which place field the rate will be visiting
489 next. Indeed, an important feature of the more recent Lisman and colleagues
490 model is that “the ‘true place field’ . . . is taken to be approximately one-
491 seventh of the apparent place field (the entire field where rate is elevated)”
492 (Lisman and Redish 2009b, p. 1194). Below, though, we will review empirical
493 data that seems to support the prediction interpretation as more than a mere
494 gloss. It is also possible that there be *both* downstream consumers for this
495 phase-coded information that use it as an aid to prediction or as fine-grained
496 information about location (Colgin 2016, p. 245; Maurer and McNaughton
497 2007, p. 325f). In the remainder of this section we will stick to prediction.

498 The predictive role relies on the fact that neural oscillations at different
499 frequencies can be nested, with faster oscillations locked to concrete phases
500 of the slower ones. In particular, within a single theta cycle (called a ‘sweep’),
501 there can be between 5 and 14 gamma cycles (Lisman and Redish 2009a, p.

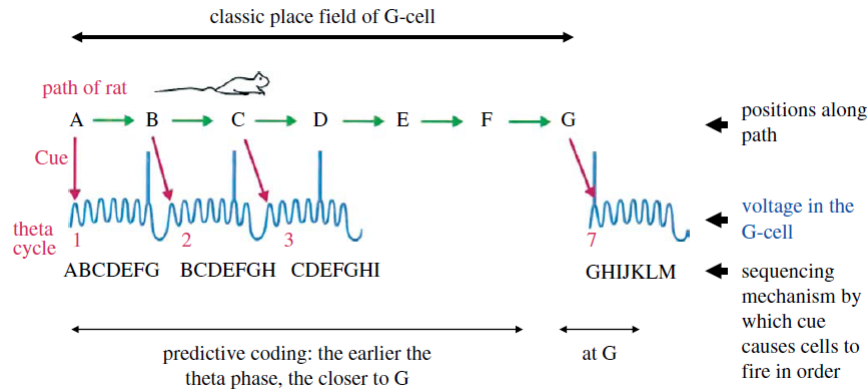


Figure 5: From Lisman and Redish (2009a, p. 1196)

1194).⁸ In the current context, this means that a theta sweep accommodates a sequence of 5 to 14 place-cell gamma bursts. Lisman and colleagues' idea is that this sequence is used for prediction: the order in which place cells fire within a single theta cycle corresponds to the order in which the rat expects to visit their place fields.

Let us consider a particular example. Suppose A, B, C, D, E, F and G are the different sections of a path that leads to a certain goal. When the rat is in A, the A-, B-, C-, D-, E-, F- and G-cells will fire within a single theta cycle, in this order. The A-cell firing early in the theta cycle represents that the rat is *in* A. In contrast, the G-cell firing at the end of the cycle represents that the rat is *moving towards* G. In other words, the order in which cells fire within a sweep represents the location of their place field with respect to each other. A place cell firing early in the theta cycle represents the actual location, whereas firings in later phases of the cycle predict future positions (Jensen and Lisman 1996).

Different kinds of evidence have been presented in support of this hypothesis. First of all, the postulated predictive role coheres very well with accounts of hippocampal memory (Jensen and Lisman 1996; Lenck-Santini, Fenton, and Muller 2008): the idea being that prediction relies on the hippocampus operating in "recall mode" (Jensen and Lisman 1996). There is also more direct evidence for a predictive role: as the rat familiarizes itself with a certain environment, it should be able to predict its future location

8. "Seven to nine", according to Buzsáki (2010, p. 370).

524 earlier; and this is indeed what is observed: as rats becomes more famil-
525 iar with an environment, more gamma cycles are nested within every theta
526 cycle—indicating that prediction starts earlier (Jensen and Lisman 1996).
527 There is also evidence that rats make predictions about future locations be-
528 fore choosing a path, by relying on this phase-coded information. Johnson
529 and Redish (2007) showed that, at bifurcation points in a T-maze, theta
530 sweeps go, successively, through the sequence of place fields corresponding
531 to both arms, which suggests that the rat evaluates available possibilities in
532 advance of deciding.

533 Let us suppose that this phase-coding-as-prediction hypothesis is correct:
534 a G-cell firing at the beginning of the theta cycle represents that the rat is
535 in G, whereas the very same pattern of activity at late stages of the theta
536 cycle would instead represent that the rat is heading towards G. In this case,
537 it seems that oscillations-involving states such as, e.g., *Vehicle* below satisfy
538 all the requirements for qualifying as representational states:

539 **Vehicle:** G-cells firing early in the theta cycle.

540 On the one hand, it is very plausible that *Vehicle* has a sender—that
541 is, an internal mechanism that generates it in response to location-related
542 worldly states of affairs.⁹ There are two main current hypotheses about this
543 mechanism: that it relies on two different oscillators, and that it emerges
544 from asymmetric connections among place cells (Maurer and McNaughton
545 2007). Hybrid models have also been formulated. But our understanding of
546 this mechanism is still in flux and, as Maurer and McNaughton note in their
547 review, it might “turn out to be extraordinary” (p. 332).¹⁰

548 *Vehicle* also has a receiver, as it makes a clear functional difference down-
549 stream (again, assuming that the prediction hypothesis is correct): distin-
550 guishing a representation of the actual location from a representation of a
551 future location the rat will be in. This is made most vivid in the role they

9. Or perhaps we should think of this case as involving two senders: one in charge of the actual place cell that gets activated, and another in charge of the phase in which this activation happens. As far as we know, our current understanding of the relevant mechanistic details does not allow us to adjudicate this question.

10. The asymmetric-connectivity model is related to the facilitation of long-term potentiation discussed in Subsection 4.3. As far as we are aware, the particular details about how the look-ahead role can be made compatible with the remapping role are still unknown. In any event, the provisional consensus appears to be that both roles *are* compatible (*cf.* Colgin 2016).

552 seem to play in navigation-related decision making (see above.) We conclude
553 that here neural oscillations appear to play a representation-constitutive role,
554 rather than just an enabling role. What is their representational content? The
555 most plausible reading, as we have argued, is that a late theta phase modifies
556 a place-cell representation: G-cell firing in early theta-phases represents that
557 the rat *already* is in G, whereas G-cell firing in late theta-phases represents
558 that the rat is moving toward G.

559 It could be objected that, in fact, it is just *G-cell firings* that are properly
560 representational, with the background theta oscillation merely providing a
561 syntactic scaffolding. After all, it is only place cell firings, not oscillations,
562 that carry the relevant information about present and future locations. But
563 theta phase does not have a merely syntactical role. Early (late) phases of
564 the theta wave have something akin to predicative content:

$$\lambda x\{\text{I am currently at (moving towards) } x\}$$

565 Another possible deflationary understanding of the role theta phase plays
566 is that it is merely contextual: its contribution to the meaning of *Vehicle*
567 would be analogous to the contribution time makes to an utterance such as
568 ‘Whiskers is at G *now*’. While the time at which the utterance is made sup-
569 plies the reference for “now”, this is compatible with refraining from claiming
570 that time is literally part of the representation. But this is not a good model
571 for the role theta phases play: time contributes itself to the meaning of “now”,
572 but theta phases are not themselves part of the content—they *stand in for*
573 times, like representations do.

574 Finally, phase differences are as information-carrying as firing rates: if we
575 want to infer where the rat currently is from hippocampal activity, simply
576 focusing on the rate of activation of place cells will not do. We need to take
577 into account the phase of activation as well.¹¹

578 5.2 Feature Binding

579 One of the first modern discussions of the role that synchrony plays in brain
580 function is von der Malsburg (1981). Here, von der Malsburg suggests that
581 the “correlation between two cellular signals” should be defined “in terms
582 of synchrony and asynchrony between spike trains” (we are citing from the

11. We would like to thank an anonymous reviewer for pressing us on these points.

583 4th edition of this paper, von der Malsburg 1994, p. 110). Von der Mals-
584 burg presents his synchronicity-based “correlation theory” of brain function
585 as a way of solving, among others, the problem of detecting specific percep-
586 tual patterns—among the very many possible combinations of colors, shapes,
587 movement, etc. that could make up a visual scene. Postulating the existence
588 of a set of specialized units that differentially respond to each such pattern
589 (the variously called *cardinal*, *gnostic*, *pontifical* or *grandmother* cells, see
590 Quiroga 2013), he claims, will not do, as “the number of [such units] required
591 would . . . be forbidding” (von der Malsburg 1994, p. 101). This is known as
592 the problem of *combinatorial explosion*: if we are to keep track of n simulta-
593 neous features (color, shape, etc.), each of which could take m values (blue,
594 yellow, square, etc.), we would need m^n grandmother cells. Synchronization
595 between cells, on the other hand, can result in dynamically created “synap-
596 tic networks”, in which individual cells respond to rather simple stimuli, but
597 which collectively function as “complex composite feature detectors” (p. 112).

598 Another important early theory of brain function which predicts a role
599 for synchrony in feature binding along these lines is Grossberg’s *Adaptive*
600 *Resonance Theory* [ART]. In a recent review of ART, Grossberg states that

601 Coherent binding of the attended features to the category give
602 them a meaning as a context-sensitive “event” rather than as
603 just isolated pixels. Such coherent states between distributed fea-
604 tures and symbolic categories are often expressed dynamically
605 as synchronously oscillating activations across the bound cells
606 . . . (Grossberg 2013, p. 9)

607 This “coherence between distributed features and symbolic categories” is
608 what we would now call feature binding (of the former features into an object
609 conceptualized under the latter symbolic category).

610 Many experimental results support these ideas: Gray et al. (1989) fa-
611 mously demonstrated that oscillatory responses were evoked by stimuli which
612 showed coherent motion, but not by stimuli which moved in opposite direc-
613 tions (Gray et al. 1989; Gray et al. 1990, p. 335). That is: synchronous activity
614 marks the presence of coherent motion, which (as Gestalt theorists suggested)
615 is in its turn evidence that the two stimuli in question are not in fact separate
616 entities, but belong to one and the same object. Kreiter and Singer (1996)
617 showed that two cells with overlapping receptive fields, but such that each
618 of them is tuned to a different direction of movement, can be driven to fire

619 in synchrony by the movement of a single bar, yet not by two bars each one
620 moving in the preferred direction of one cell—again here, synchronization
621 goes with co-boundedness, even trumping the tuning features of individual
622 neurons. Synchronization appears to be responsive to other Gestalt-grouping
623 principles as well, besides coherent motion (Singer and Gray 1995; Engel et
624 al. 1992; Gray 1999). Tallon-Baudry and Bertrand (1999) review much other
625 relevant evidence. Modeling work also supports the link between oscillations
626 and feature binding (Eckhorn et al. 1990) and suggests that synchroniza-
627 tion can be sufficiently fast in long-range interactions (Yazdanbakhsh and
628 Grossberg 2004).

629 The most ambitious contemporary version of this *binding by synchrony*
630 [BBS] hypothesis claims that synchrony is the main code for feature binding.
631 This seems to be the position taken by proponents of the *temporal binding*
632 *model* (Engel and Singer 2001; Engel, Fries, and Singer 2001, and papers
633 cited therein), who claim that “neural synchrony . . . is crucial for object rep-
634 resentation” (Engel, Fries, and Singer 2001, p. 706). There are good reasons
635 (both theoretical (Shadlen and Movshon 1999; Di Lollo 2012)¹² and empiri-
636 cal (Palanca and DeAngelis 2005)) to think that synchrony is not the only
637 feature-binding code. Still, the results discussed above and many others (in-
638 cluding ones by Palanca and DeAngelis in the critical paper just cited) sug-
639 gest that it does make a contribution to representing the fact that different
640 features are co-bound to the same object (*cf.* Hommel 2004, Box 1).

641 Let us assume that this putative contribution takes the following form:
642 “the mechanism that evaluates temporal relations among responses for per-
643 ceptual grouping interprets synchronous responses as related and segregates
644 them from responses that are temporally offset.” (Singer 1999, p. 51) where,
645 as we have just discussed, “interprets” should not be taken to mean that
646 synchronicity *determines* the status of responses as related or unrelated,
647 but rather that it provides evidence for it, possibly to be combined with
648 other mechanisms such as, e.g., task-dependent alterations in neural tuning
649 (Gilbert and Li 2013, p. 5). Should we interpret this less ambitious version
650 of BBS as vindicating a representational role for synchrony?

651 In a nutshell, the hypothesis is that synchronous activity between two
652 populations that code for two different perceptual features would represent

12. Di Lollo is sceptical about the very existence of a feature-binding problem. He defends that something like gnostic cells are actually available in the brain, but doesn’t explicitly discuss how combinatorial explosion is therefore dealt with.

653 *that these features are co-bound.* Again, we unpack this idea by trying to find
654 occupants for the different roles in our metasemantic sketch. First, there is a
655 plausible occupant for the role of representational vehicle:

656 **Vehicle:** A population of neurons P_1 (that encodes a perceptual feature F_1)
657 and another population P_2 , (that encodes a perceptual feature F_2) firing
658 in synchrony.¹³

659 Now, is there a plausible sender/encoder for *Vehicle*? What this encoder
660 has to do is to subsume populations P_1 and P_2 into a larger coherent assembly,
661 as a reaction to the fact that onset and offset of activity in P_1 and P_2 is more
662 or less simultaneous (which in turn is explained by features F_1 and F_2 being
663 actually co-bound in the world, and therefore appearing and disappearing
664 more or less simultaneously).

665 There are at least two goals that this encoder must meet. First, note that
666 the fact that F_1 and F_2 are reliably co-instantiated is not the same as, nor
667 sufficient for, synchrony. Co-instantiation is indeed sufficient for *sameness*
668 *of onset and end of firing*, but not for the fact that, during the duration
669 of the firing episode, this firing is synchronized, which it is, “over periods
670 ranging from tens to thousands of milliseconds” (Gray 1999, p. 38), more-
671 over showing sophisticated oscillatory structure (Singer and Gray 1995, p.
672 1094). Second, this synchronic firing must start quickly and reliably after
673 stimulus onset if it is to be an ecologically viable way of signaling feature
674 boundedness. This job description is far from computationally trivial, and it
675 is met by a rather specific pattern of lateral interconnections in the relevant
676 neuronal population, with the right mix of excitation and inhibition (Fries
677 2015; Yazdanbakhsh and Grossberg 2004, see Section 4.1 above). This kind
678 of network architecture is a good candidate for our sender/encoder.

679 There is also a plausible receiver for *Vehicle*: the whole point of binding
680 by synchrony is that dynamic assemblies formed by synchronized neurons are
681 treated as a unit. One often proposed mechanism in this connection is that
682 coincidence-sensitive neurons (Engel and Singer 2001, p. 18; Abeles 1982;
683 König, Engel, and Singer 1996) would be specially driven by neurons fir-
684 ing synchronously (see Fries 2015, on *effective connectivity*). We will discuss

13. Shouldn't the vehicle be just the *coinstantiation* of P_1 and P_2 firings, rather than full-blown synchrony? Not according to the defenders of the BBS hypothesis: synchrony (i.e., rhythmic, congruent activity), and not mere coinstantiation, is necessary to entrain postsynaptic activity in a sufficiently vigorous way (Fries 2015; Engel, Fries, and Singer 2001, p. 705).

685 “reader-classifiers” of these neuronal assemblies in more detail in Subsec-
686 tion 5.3.

687 It seems, thus, that in the case of BBS all of the links in our metase-
688 mantic sketch have a plausible occupant. We therefore tentatively conclude
689 that *Vehicle* is a representation. Note that here synchrony is not merely an
690 enabling mechanism: synchronized oscillations are a constitutive part of the
691 representational vehicle. Moreover, and more importantly, these same oscil-
692 lations are directly causally involved in the decoding behavior. That is, it is
693 by virtue of its oscillatory profile that *Vehicle* means what it means.

694 5.3 Sequences

695 An impressive body of work associated mainly (but not only) with György
696 Buzsáki’s lab (Buzsáki 2006; 2010; Buzsáki and Watson 2012, among many
697 others) has aimed at uncovering “syntactical” units in brain processing: how
698 does the brain go about providing vehicles over which computations can be
699 performed? As we will see, neural oscillations play an essential role in the
700 construction of these various syntactical units. It will turn out, though, that
701 there is some, perhaps ineliminable, indeterminacy between taking some cases
702 of neural activity as constituting one such unit (e.g., a “neural word”) or as
703 a process of computation of one unit from another. In our framework, this
704 will translate to indeterminacy in their status as properly representational.

705 Constructing these vehicles is a difficult task, if only because it involves
706 arbitrating between two desiderata that pull in different directions. First,
707 the repertoire of available vehicles needs to be *sensitive* enough: it should
708 be possible to token, reliably, different vehicles in the presence of different,
709 but similar, external conditions. Brains need to keep track of fine-grained
710 differences in external events (say, in the velocity of looming or receding ob-
711 jects, Maier et al. 2004) and this requires provisioning a sufficient number of
712 different vehicles to stand in for each member in a sufficiently fine-grained
713 partition of such events (say, for a sufficiently fine-grained range of differ-
714 ent looming velocities). Note that this sensitivity requirement is not met by
715 simply generating states that count as different under some third-personal
716 criterion: it must be possible for these different states to make a difference
717 to the system itself—they must be possibly *treated as different* downstream.

718 Second, this repertoire needs to be *robust* enough: the vehicles in question
719 need to be somehow resistant to the very noisy environment in which they
720 are tokened (see Faisal, Selen, and Wolpert 2008, for a review of noise in the

721 brain). Sensitivity and robustness are in tension: sensitive processing involves
722 tokening noticeably different vehicles in response to very similar world states;
723 yet, robust processing involves preventing ambient noise from conflating the
724 processing trajectories of the vehicles that are triggered by those world states.
725 As we are about to see, it has been suggested that neural oscillations play
726 an important role in solving this conundrum.

727 Buzsáki and colleagues have claimed that the fundamental “syntactical”
728 units in brain processing (that is to say, the fundamental unit in the construc-
729 tion of vehicles) is not the single neuron but the *cell assembly*: “a collection
730 of neurons that come together . . . to produce a composite downstream effect
731 that cannot be produced by single neurons alone” (Buzsáki 2010, p. 364, recall
732 that von der Malsburg uses a very similar expression). Because the existence
733 of a cell assembly depends on the existence of these “composite downstream
734 effects”, there must be a downstream “reader-classifier” that treats the as-
735 sembly as a functional unit (*ibid.*). According to Buzsáki, the most basic
736 assembly reader-classifier in the brain is the *integration of presynaptic ac-*
737 *tivity*: the process whereby a certain neuron treats presynaptic events (say,
738 action potentials coming from different presynaptic neurons at slightly differ-
739 ent times) as a unit. How far apart from each other these events can be and
740 still be treated as a single whole depends on the so-called *membrane time*
741 *constant* τ (*ibid.*) but, in general, the closer in time those events are, the
742 most likely it will be that they will be treated as a unit. Obviously, a reader-
743 classifier such as this one, that mainly detect coincidences in presynaptic
744 activity, will greatly benefit from synchronized activity upstream. This is the
745 first place where neural oscillations play a role in the generation of vehicles:
746 locking presynaptic firings to concrete phases of an oscillation cycle leads to
747 postsynaptic neurons treating each such phase-locked collection of firings as
748 a functional unit.

749 These cell assemblies should be thought of as the phonemes (or perhaps
750 letters) of the neural syntax. One step up in the Buzsákian hierarchy of
751 vehicles we find *neural words*, made up of “sequences” of these assemblies,
752 quickly following one another through the duration of a (typically gamma)
753 cycle (*ibid.*, p. 365). E.g., we can think of a neural word as assemblies A, B,
754 C, D succeeding one another through a gamma cycle (each, say, occupying 90
755 degrees of the full 360 degrees in a cycle). The sequence consisting of assem-
756 blies A, C, D, B would constitute a different word, possibly discharging an
757 entirely different processing role. Again, neural words will only be real insofar
758 as some entity downstream treats them as a unit: for example, mechanisms

759 with a longer integration window than the membrane time constant, such
760 as NMDA or GABA_A receptors (*ibid.*, p. 366). A more important, and more
761 general, class of reader-classifiers with different integration windows is again
762 provided by neural oscillations (*ibid.*). From the point of view of electronics,
763 neural oscillations are *relaxation oscillators* (Wang 1999): this kind of circuit
764 (which is used, for example, in the blinking turn signals of cars) works by
765 periodically charging and discharging a capacitor (a storage of electrical en-
766 ergy); when the capacitor reaches a certain threshold, the oscillator is “reset”.
767 The concept of neural word relies on two features of relaxation oscillators:
768 first, the phase during which the capacitor is being charged naturally corre-
769 sponds to an integrator window (Buzsáki 2010, p. 366)—recall that this is
770 just a period during which incoming neural activity is treated as an undifer-
771 entiated whole. Second the oscillator “reset” acts as a natural gap between
772 different neural words.

773 There is ample empirical evidence of the existence of neural words, under-
774 stood along those lines. For example, Jones et al. (2007) show how neurons
775 in the gustatory cortex of rats go through four different sequences, each com-
776 prised of four different states, whenever the rat is exposed to sweet, bitter,
777 sour or salty flavors, respectively. The four states that are part of the se-
778 quences are different for different flavors, but always the same within each
779 flavor (see figure 6). Laurent (2002, p. 886) similarly reports population-
780 level representations in the antennal lobe of insects and the olfactory bulb
781 of mammals that are “dynamic, carried by an assembly of neurons . . . that
782 evolves in a stimulus-specific manner over time”. In sections 4.3 and 5.1 we
783 have reviewed in detail theta sweeps in the hippocampus, which provides yet
784 another important example of assembly sequence.

785 Further syntactic structure is provided by nested oscillatory rhythms: for
786 example, the number of assemblies that fit in a theta cycle has consequences
787 for the “memory ‘buffer’ of the gamma-nested theta-cycle” (*ibid.*). More gen-
788 erally, “[theta-gamma] oscillations form a code for representing multiple items
789 in an ordered way.” (Lisman and Jensen 2013, p. 1002)

790 Now, how do neural vehicles constructed out of these syntactic building
791 blocks trade off sensitivity and robustness? First of all, reader-classifiers will
792 help with robustness by *failing* to distinguish between different sequences of
793 events (say, different sets of arrival times of presynaptic activities) as long as
794 they fall within the same activation window—e.g., *neuron 1 firing now and*
795 *neurons 2 and 3 firing in the next 5ms* will be indistinguishable from *neuron*

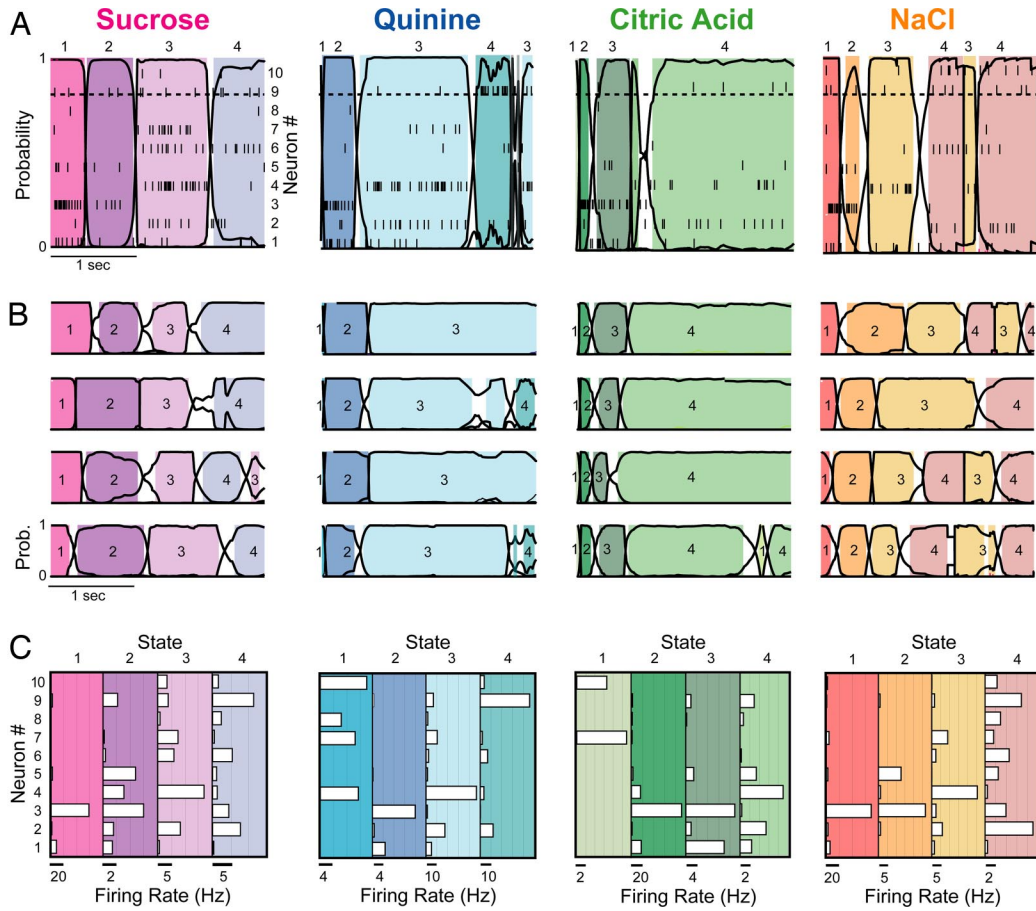


Figure 6: Neural words in the gustatory cortex. From Jones et al. (2007)

796 *3 firing now and neurons 1 and 2 firing in the next 5ms.*¹⁴ As for sensitivity,
797 the production of sequences might be such that initially minute differences in
798 input are taken, as more evidence comes in, into rapidly divergent trajecto-
799 ries corresponding to different sequences that are much easier to distinguish:
800 those initially minute differences, for example, might result in two different
801 sequences with an overlapping initial part, as in the ABCD / ACBD example
802 above (Harvey, Coen, and Tank 2012).

803 The most straightforward way to think of these neural words is as repre-
804 sentational vehicles: they are hypothesized to solve a problem (the sensitivity
805 / robustness tradeoff) that is precisely the kind of problem a representational
806 system in a noisy environment would face. Furthermore, the empirical evi-
807 dence for neural words links them in every case to concrete representational
808 roles (the representation of flavors in Jones et al. (2007), odorants in Laurent
809 (2002), or paths to be taken in space in Jensen and Lisman (1996)).

810 Still, closer examination of the available evidence, and the attitude of
811 researchers toward that evidence, reveals that this representational reading
812 is not without problems. First, note that the mechanisms through which,
813 we suggested, sensitivity and robustness are accommodated by neural words
814 are somewhat at odds with one another: robustness depended on a reader-
815 classifier with a large enough activation window that it may be able to take
816 the full neural word in as a unified whole; while sensitivity depended on
817 neural words being interpreted as diverging *trajectories*—crucially, their di-
818 achronic unfolding, and their responsiveness to incoming evidence that co-
819 heres with the trajectory chosen, is part of what makes them robust. Indeed,
820 many researchers are skeptical that sequences have readers of their own. So,
821 for example, according to Lauren Jones and colleagues, “[c]oherent state se-
822 quences . . . probably do not represent pure ‘sensory codes’ to be interpreted by
823 downstream ‘grandmother neurons’” Jones et al. (2007, p. 18776, emphasis
824 added). According to these researchers, the sequences we see in sensory corti-
825 cal ensembles should be interpreted, not as pure codes, but as computations
826 of motor codes from purely sensory ones.

827 Laurent (2002), on the other hand, claims that sequences of assemblies
828 do play a role in generating a “*large coding space* in which to spread repre-
829 sentation clusters” (*ibid.*, p. 885f, emphasis added). While this is one of the
830 main points of his paper, highlighted in abstract and conclusions, Laurent

14. This is just a straightforward example of what information theorists call *channel coding*, or error correction (MacKay 2003).

831 also warns that, conceivably, “slow temporal patterns, although crucial for
832 the separation of representations, *are never actually decoded as such*. More
833 generally, the creation of spatiotemporal representations by circuit dynam-
834 ics might be a transient phase in signal processing, used simply to spread
835 out those representations in a larger coding space and to facilitate decoding”
836 (*ibid.*, p. 891, emphasis added). That is, it is not clear that the olfaction-
837 related neural sequences in insects and mammals that Laurent is interested
838 in have receivers—i.e., are pure sensory codes. Rather, they would amount
839 to *encoding stages* along which representational vehicles are progressively
840 optimized.

841 This hybrid (part code, part encoding process) nature of spatio-temporal
842 sequences is fleshed out most clearly by Harvey, Coen, and Tank (2012).
843 They show that an ideal observer is able to predict behavioral choices in
844 mice from spatio-temporal neural sequences but not from the synchronic
845 behavior of neuronal populations (see also Yuste 2015, p. 492). The model
846 proposed by Harvey and colleagues is one in which incoming sensory informa-
847 tion initiates a (firstly decision-agnostic) sequence which gets progressively
848 decision-specific as incoming information modifies it. When the sequence
849 overlaps sufficiently with a decision-specific trajectory, this corresponds to
850 the personal-level state of the mouse having decided. The subsequent, en-
851 dogenously generated unfolding of the decision-specific sequence corresponds
852 to the personal-level state of keeping the decision in mind.

853 The upshot of this discussion is that, while very prominent models of brain
854 function accord an important role to neural oscillations in the generation of
855 representational vehicles, there is some vacillation in the literature regard-
856 ing what counts as code (of incoming sensory information); what counts as
857 computation (of decisions from sensory information); and what counts as en-
858 coding processes (whereby sensory codes gets optimized into decision codes).
859 This indeterminacy between merely enabling and properly representational
860 status for neural-sequence-related oscillations will perhaps be remedied as
861 our knowledge of brain processing improves; perhaps it is ineliminable.

862 6 Conclusion

863 The main goal of this paper was to examine whether neural oscillations in
864 the brain actually are representations. As we have seen, whether they do
865 often depends on rather intricate facts about the relevant mechanisms where

866 they participate, and the role they play in these mechanisms. We offer this
867 to philosophers as a cautionary tale: representational status, like the devil,
868 is often in the detail.

869 But we can also glean a few big-picture lessons from the foregoing discus-
870 sion. First, our results shows that the core metaphysical theory of content
871 put forward in Section 2 is a useful tool for understanding and modelling neu-
872 ral representations. It suggests important questions, and provides theoretical
873 instruments with which to answer them.

874 Secondly, the discussion of case studies revealed that neural oscillations
875 can play at least two different roles, enabling and properly representational, in
876 the implementation of representations in the brain. This distinction is a result
877 of the careful consideration of specific cases, rather than a pre-conceived anal-
878 ysis. We hypothesize that this distinction will also apply to the mechanisms
879 subserving other representational phenomena; and that it can potentially be
880 extended by considering other roles that cognitive processes can play that are
881 not representational, but are defined in relation to properly representational
882 states.

883 Thirdly, following a recent call for multi-level analysis (Craver 2007;
884 Boone and Piccinini 2016), our results show that paying attention to imple-
885 mentalational details is relevant for understanding higher-order levels. Even
886 though ‘representation’ is a functional category, considering which specific
887 brain structure actually play a representational role can help us vindicate a
888 particular analysis of the nature of representation and distinguishes different
889 non-representational roles brain states can play, among others.

890 Finally, against recent suggestions to the contrary, we argued that low-
891 level processes can qualify as representational. Furthermore, this result has
892 not been obtained by defining representation so cheaply that just anything
893 can count as such, since we have identified some processes employing os-
894 cillations in which they fail to play a representational role (e.g. attention,
895 retrieval and encoding). The results of this paper support the idea that rep-
896 resentations can be found all the way down without trivializing this notion.
897 This provides some vindication for naturalistic theories of representation.¹⁵

15. For discussion of the objection that naturalistic theories of content are too liberal, see Artiga (2016, 2020).

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