

Chapter 1

The LeabraTI framework: Spatiotemporal prediction with thalamocortical rhythms

1.1 Introduction

This chapter describes the LeabraTI (Temporal Integration) framework, which is a mechanistic description and general model of how prediction and temporal integration works in the brain. It is closely related to the Simple Recurrent Network (SRN) (Elman, 1990; Servan-Schreiber, Cleeremans, & McClelland, 1991) a neural network architecture that explicitly represents temporally lagged information in discrete “context” units whose activity gets integrated with more current information to predict what happens in the next time step (Figure 1.1a). This method of copying a contextual representation from an intermediate representation at discrete intervals was originally shown to be a robust way to leverage error-driven learning to represent latent temporal structure in auditory streams and artificial grammars. More generally, the SRN’s explicit representation of temporally lagged context can capture the latent structure of any stimulus that varies systematically over time, making it a good basis for a generic prediction and temporal integration mechanism.

LeabraTI differs in several key ways from the classical SRN architecture, primarily in the way context is represented and used in predictive processing. These differences are due to biologi-

cal constraints imposed by the microcircuitry of the neocortex, and thus form a number of testable predictions that can be used to evaluate the validity of the LeabraTI framework. The central prediction of LeabraTI is that temporally lagged context is represented by deep (Layer 6) neurons, which is possible in part to the bifurcation of intra-areal and inter-areal processing streams. As neural processing is a continuous operation, LeabraTI requires a regular interval over which to integrate deep context and make predictions, which is approximately every 100 ms. Predictions are made by driving superficial (Layers 2 and 3) neurons with the state of deep neurons through the intra-areal pathway, which is interleaved with standard peripheral sensory inputs over a total period that is also 100 ms. The strong 100 ms dependency in LeabraTI corresponds to the brain's alpha rhythm, which has been studied extensively using scalp EEG (Mathewson, Gratton, Fabiani, Beck, & Ro, 2009; Busch, Dubois, & VanRullen, 2009; Gould, Rushworth, & Nobre, 2011; Rohenkohl & Nobre, 2011; Mathewson et al., 2012; Belyusar et al., 2013; VanRullen & Dubois, 2011).

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1.2 LeabraTI biological details

1.2.1 Laminar structure and microcircuitry of the neocortex

A salient feature of the brain, and potential clue in realizing how an SRN-like computation might be carried out in biological neural circuits, is the laminar structure prevalent across the neocortex (Figure 1.1b). Incoming information from the sensory periphery is transmitted through the thalamus and targets Layer 4 neurons in the primary sensory cortices (e.g., V1). From there, Layer 4 neurons propagate spikes to superficial neurons (Layers 2 and 3) which in turn target Layer 4 neurons of higher-level cortices, forming the prominent corticocortical feedforward pathways that subserve visual and auditory recognition (Felleman & Van Essen, 1991). Corticocortical feedback originates in superficial layers or Layer 6 of the higher-level cortex and generally terminates on superficial neurons of the lower-level cortex (Rockland & Pandya, 1979). In addition to these

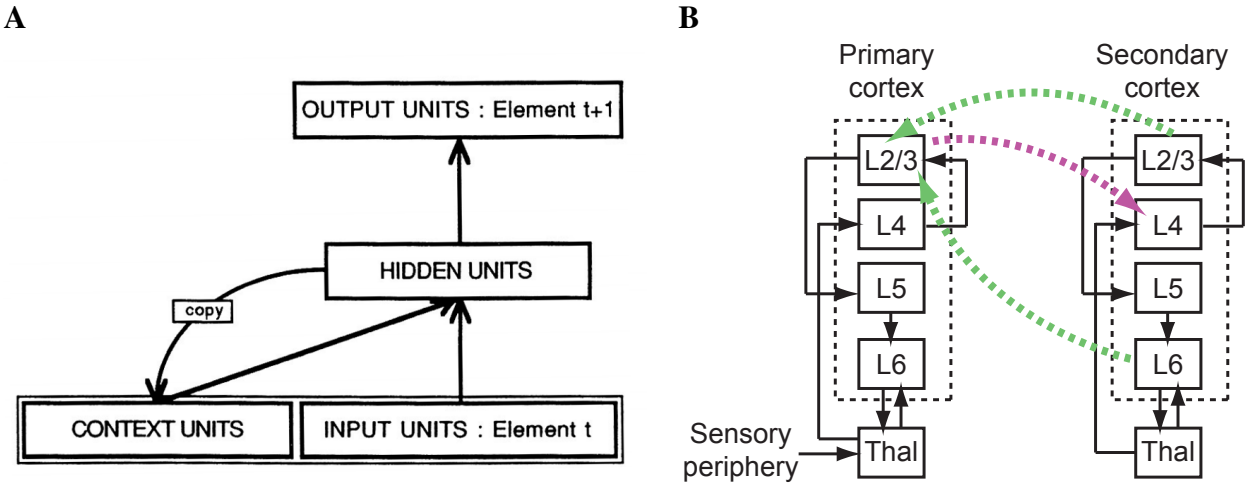


Figure 1.1: The Simple Recurrent Network (SRN) and microcircuitry of the neocortex

A: The SRN represents temporal information explicitly using discrete context units that are updated once per time step. Context is integrated with more current inputs to predict information at the subsequent time step. Reproduced from Servan-Schreiber et al. (1991). **B:** The neocortex is laminated with canonical circuitry between neurons across layers and between areas. Principal intra-areal connections are shown in black with inter-areal feedforward connections in purple and feedback connections in green.

inter-areal pathways, there exists a canonical microcircuit of the form Layer 4 \rightarrow Layer 2/3 \rightarrow Layer 5 \rightarrow Layer 6 that routes spike propagation through the local neuronal structure (Douglas & Martin, 2004; Thomson & Lamy, 2007; da Costa & Martin, 2010). This microcircuit forms the core computational unit of LeabraTI, as will be described in this and the following sections.

The importance of the local microcircuit was first suggested by Vernon Mountcastle in his proposal regarding the gross columnar organization of the neocortex (see Mountcastle, 1997, for a comprehensive review). Mountcastle's proposal states that microcolumns composed of around 80-100 neurons extending vertically through all six lamina with canonical circuitry form the core repeating structure of the neocortex. Neurons within a single microcolumnar circuit possess nearly identical receptive field tunings across lamina while neurons in neighboring microcolumns (radial separation greater than 600 μm) possess very different receptive field tunings but contribute to the higher-order macrocolumn (i.e., hypercolumn) structure (Hubel & Wiesel, 1977; Jones, 2000). Microcolumns have been identified in a variety of neural systems with this electrophysiological

mapping and are also prominently visible under Nissl staining. Despite this evidence for their structural existence, any function of the microcolumn aside from an organizing principle remains debated (Buxhoeveden & Casanova, 2002; Horton & Adams, 2005).

LeabraTI provides a computational role for the microcolumn, by mapping an SRN-like computation onto their Layer 4 \rightarrow Layer 2/3 \rightarrow Layer 5 \rightarrow Layer 6 circuit (Figure 1.1). In this mapping, superficial neurons continuously integrate feedforward and feedback inter-areal synapses to process current information. Layer 2/3 \rightarrow Layer 5 \rightarrow Layer 6 provides an intra-areal pathway for explicitly representing temporal context in Layer 6 neurons, which are relatively isolated from nonlocal inputs. There is also appropriate circuitry for recirculating this context through the local microcolumn via Layer 4 to drive the learning of temporal associations. This basic idea provides a concise explanation for the strong degree of isotuning throughout a single microcolumn, as Layer 6 neurons need to represent the same overall information as superficial neurons except at a delayed interval.

1.2.2 Layer 5 rhythmic bursting and contextual gating

The laminocolumnar organization of the neocortex provides the dual pathways necessary for continuous information processing and the SRN's explicit temporal context representation. The Layer 4 \rightarrow Layer 2/3 \rightarrow Layer 5 \rightarrow Layer 6 microcircuit only contains four synapses plus the transthalamic re-entrant synapses. Intracolumnar monosynaptic latencies for regular spiking neurons are on the order of 5 ms or faster (Armstrong-James, Fox, & Das-Gupta, 1992; Lumer, Edelman, & Tononi, 1997) and thus this relatively small amount of tissue, if driven with constant input, would circulate spikes at a rate too fast to perform enough temporal integration to make useful predictions. Several studies have noted that a subset of Layer 5 neurons exhibit intrinsic bursting at ~ 10 Hz when over threshold (Connors, Gutnick, & Prince, 1982; Silva, Amitai, & Connors, 1991; Franceschetti et al., 1995). This rhythmic bursting might implement a gating mechanism for updating Layer 6 context information at a regular 100 ms interval.

More specifically, Layer 5 neurons can be roughly divided into 5a and 5b subtypes (Thom-

son & Lamy, 2007). Layer 5a neurons have relatively small cell bodies and exhibit regular spiking depolarization responses. They collect input from other Layer 5a neurons both within and across columns (Schubert, Kotter, & Staiger, 2007) and pass it to 5b neurons and thus, likely play a simple information integration role. Layer 5b neurons, in contrast, have larger cell bodies and exhibit the aforementioned 10 Hz intrinsic bursting response profile. In the context of LeabraTI, the interpretation of this data is that the 5a neurons serve to integrate information from multiple Layer 2/3 neurons, with the 5b neurons gating context to Layer 6 neurons with each 10 Hz burst.

Layer 6 corticothalamic neurons receive strong inputs from Layer 5b neurons and send axons toward the thalamus completing the microcircuit within the local column and allowing the temporally lagged Layer 6 responses to integrate with more current Layer 4 inputs. Information is relayed from the thalamus back up to layer 4 in a focal one-to-one manner that maintains microcolumnar separation (Sherman & Guillery, 2006; Thomson, 2010), which could allow temporal associations to be formed by local Hebbian learning mechanisms that track high probability co-occurrences across past and present events (Foldiak, 1991).

1.2.3 Thalamic gating and sensory prediction

Both the SRN computation and the Leabra algorithm (O'Reilly & Munakata, 2000; O'Reilly, Munakata, Frank, Hazy, & Contributors, 2012) that are used to implement the LeabraTI framework are predicated on using powerful error-driven learning mechanisms (in addition to more standard Hebbian learning mechanisms) to represent the mapping between sensory inputs and outputs. In the context of temporal integration, error-driven learning would allow computation of error signals based on the difference between what is predicted to happen at a given moment (given the previous moments context as an input) and what actually happens. However, this computation requires that both the prediction and the actual sensation are represented by the same neural tissue so that an error signal can be computed, which is not possible if the sensory periphery is continuously transmitting incoming inputs.

To resolve this issue, the LeabraTI framework posits that predictions about sensory events

and the sensory events themselves are temporally interleaved through the same population of neurons in an alternating manner. This requires a mechanism to periodically downmodulate or even block the transmission of inputs from the sensory periphery. A subset of cells in the thalamus exhibit ~ 10 Hz intrinsic bursting properties similar to that of Layer 5 neurons (Lopes da Silva, 1991; Hughes et al., 2004; Lorincz, Crunelli, & Hughes, 2008; Lorincz, Kekesi, Juhasz, Crunelli, & Hughes, 2009), and thus perhaps perform a similar gating computation of sensory inputs into cortical circuits. In the context of LeabraTI, these bursting neurons might shift the balance of inputs to Layer 4 and superficial neurons between endogenous inputs local to the microcolumn representing predictions and quick bursts of actual sensory information.

More specifically, during the non-bursting intervals of thalamic intrinsically bursting neurons' response, environmental inputs are downmodulated due to the relative quiescence and Layer 6 neurons provide the dominant driving potential to the microcolumn. Layer 6 corticothalamic neurons exhibit a strong regular spiking depolarization response with facilitating short-term dynamics (Thomson, 2010) unlike all other pyramidal neurons, which exhibit depressing dynamics. This might suggest a specialized function for Layer 6 neurons, which in the context of LeabraTI is to drive a sustained prediction about upcoming sensory information. These layer corticothalamic neurons also sustain their drive through reciprocal projections with the thalamic relay cells that they project to. In addition to the Layer 6 \rightarrow Layer 4 transthalamic pathway, Layer 6 neurons also project directly to Layer 4. While these projections are relatively weak (Hirsch & Martinez, 2006), they do activate a metabotropic glutamate receptor (mGluR) that produces sustained depolarization similar to Layer 6 corticothalamic neurons (Lee & Sherman, 2009) - these direct ascending synapses are another possible route for sustained context information to drive Layer 4 neurons.

The burst response of thalamic intrinsic bursting neurons synchronized with the burst response of Layer 5b neurons destabilizes the Layer 6 sustained prediction through biased competition. This provides a snapshot of the current state of the sensory periphery as well as an opportunity to integrate the state of current sensory event into a prediction about what will happen during the next moment. At this time, standard error-driven learning mechanisms that compute short

timescale firing rate differences (O'Reilly & Munakata, 2000; O'Reilly et al., 2012) compute an error signal between the previous moment's prediction and this current sensory event to minimize overall prediction error.

1.3 Summary of LeabraTI computation

The overall computation of LeabraTI is shown in Figure 1.2 and summarized here. Standard Leabra learning operates across two phases: a *minus* phase that represents the system’s expectation for a given input and a *plus* phase, representing observation of the outcome. Generally, feedforward sensory inputs provide the dominant drive during the minus phase while the plus phase is driven by a combination of feedforward sensory inputs and the target outcome, conveyed via feedback projections. Leabra networks typically only model at the level of superficial (Layers 2 and 3) neurons, since they provide the principal feedforward and feedback projections necessary for error-driven learning.

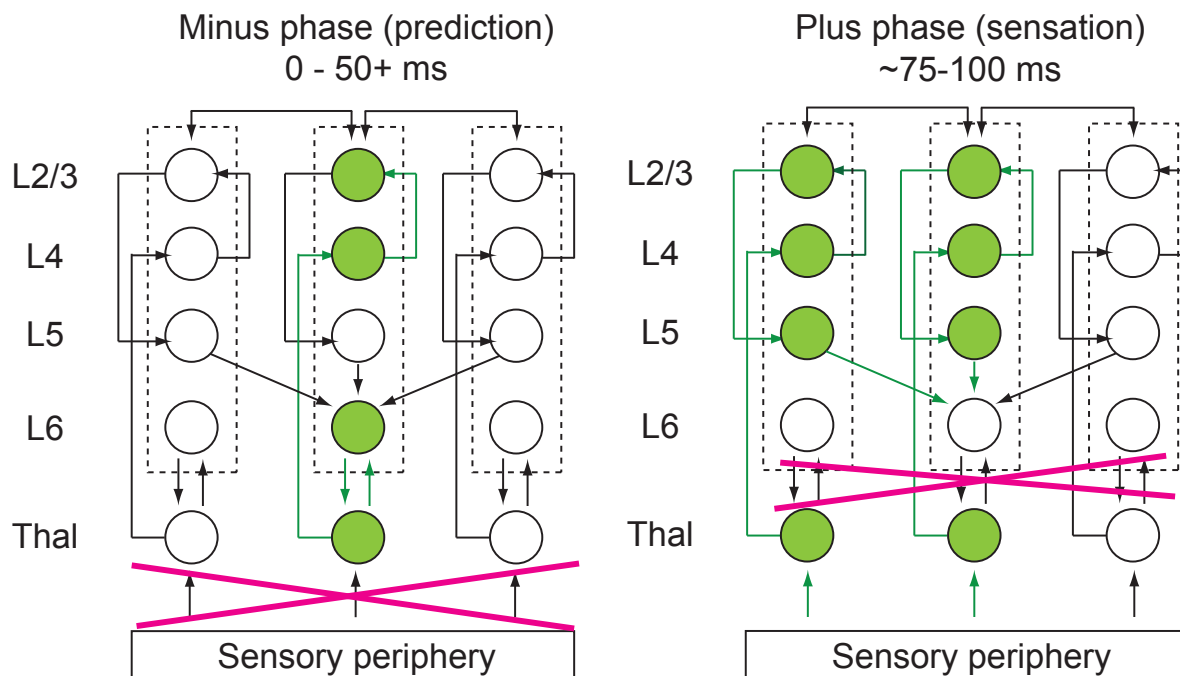


Figure 1.2: The LeabraTI computation

In LeabraTI, deep Layer 6 neurons provide the dominant input to superficial Layer 2 and 3 neurons during the minus phase, relayed via Layer 4 transthalamic and direct ascending projections. This represents a sensory prediction about what is about to happen during the subsequent plus phase, using temporally lagged context from the previous plus phase. To be computationally useful, the prediction needs to last at least 50 ms in order to allow contributions from both the feedforward drive and relatively weaker (and thus, slower acting) feedback from higher-order cortical areas. The short-term facilitating dynamics unique to Layer 6 corticothalamic neurons or mGluR activation from the direct ascending projections provide the sustained spiking response during the minus phase. Reciprocal thalamocortical synapses back to Layer 6 might also assist in maintaining minus phase input drive. During this period, input from the sensory periphery is extremely downmodulated due to the relative quiescence of thalamic intrinsically bursting neurons.

Pick up here...

This information can be used as a prediction as to what will happen next when thalamic bursting resumes and veridical sensory information serves as the input once again.

When thalamic cells burst (roughly every 100 ms), information from the sensory periphery is the primary driving force for Layer 4 neurons in primary cortex. This information is relayed downstream to higher-level cortical areas via the strong feedforward Layer 4 \rightarrow Layer 2/3 \rightarrow Layer 4 pathway (Felleman & Van Essen, 1991). Within the local microcolumn, Layer 5 neurons integrate this information, until thalamic bursting quiets (generally around 50 ms). At this point, Layer 5 cells burst, sending outputs to Layer 6 and shifting and inputs to the microcolumn endogenously.

In the context of Leabra's error-driven learning these two phases correspond to the plus phase (sensation) and minus phase (prediction), which can be used to compute a sensory prediction error signal. This error signal modifies Layer 5 \rightarrow Layer 6 synapses to minimize differences between predictions and sensations over time.

Critically, for the LeabraTI computation to work, thalamic and Layer 5 oscillatory phases need to have an approximately antiphase relationship in order for the error-driven learning scheme described here to work so that Layer 2/3 neurons can represent the current moment's prediction

with Layer 6 context as their primary input and then subsequently represent the veridical sensory input while Layer 5 neurons are queuing up the next contextual event. Such a relationship has not yet been shown yet, but very few studies have recorded simultaneously from thalamic and cortical neurons in *in vivo* in the awake behaving animal. It is also possible that the brain implements error-driven learning in such a way that does not require representing predictions and sensations temporally interleaved on the same neural substrate or even that the brain accomplishes temporal integration completely without supervision, which in case thalamic gating is not required.

1.4 Relation to other frameworks

1.5 LeabraTI testable predictions

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