Learning structured representations

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Abstract

SHRUTI is a connectionist model that demonstrates how a network of neuron-like elements can encode a large body of semantic, episodic, and causal knowledge, and rapidly make decisions and perform explanatory and predictive reasoning. To further ground this model in the functioning of the brain it must be shown that components of the model can be learned in a neurally plausible manner. Previous work has already demonstrated the learning of episodic facts via cortico-hippocampal interactions. Here we discuss how other SHRUTI representations such as causal rules, statistical and semantic knowledge, and categories could be learned in a biologically plausible manner.

Summary (1000 Words)

Although a great deal is known about neural representations in sensory, somatosensory, and motor cortices, the representations underlying higher-order cognitive processes are largely unknown. The SHRUTI model [12, 6, 13] provides a promising set of proposals for what these representations might be, and how they could be employed in a wide range of cognitive processes. An important consideration for high-level neural representations is their learnability. Accordingly, in this paper we discuss how several key representational elements of SHRUTI might be learned in a neurally plausible manner.

SHRUTI is a neurally plausible computational model that demonstrates how a network of neuron-like elements could encode a large body of structured knowledge and rapidly make decisions and perform explanatory and predictive reasoning. Shruti can encode different types of conceptual knowledge including relational schemas/frames for encoding action and event types (e.g., buying); causal rules between relational schemas (e.g., if you buy something you own it); types (categories); individual entities; and different types of facts such as episodic facts that record specific events (I saw John at the library today), taxon facts that record general statistical knowledge (Soccer moms own minivans), and reward and value facts that record associations between situations and reward/punishment.

SHRUTI suggests that the encoding of relational information (e.g., event schemas) as well as that of types and entities is mediated by neural circuits composed of structured ensembles of cells. We refer to these ensembles as *focal-clusters*. The dynamic representation and communication of relational *instances* involves the transient propagation of *rhythmic* activity across these clusters. A binding between a relational role (e.g., buyer) and its filler in a given situation (e.g., John) is represented within this rhythmic activity by the *synchronous* firing of appropriate cells. Causal knowledge (e.g., rules) is encoded by links that enable the propagation of rhythmic activity across focal clusters, and persistent facts in long-term memory are realized as temporal pattern matching circuits.

Learning SHRUTI structures

We use two forms of learning, both of which are related to hebbian learning, in order to learn functional components in SHRUTI. These are: recruitment learning [1, 5] and causal hebbian learning [14]. Recruitment learning can be described informally as follows: Learning occurs within a partially structured network containing a large number of richly interconnected nodes. *Recruited* nodes in the network are nodes that have acquired distinct functionality by virtue of their *strong* interconnections to other recruited and/or sensorimotor nodes. Unrecruited (free) nodes are connected via weak links to a large number of free, recruited, and/or sensorimotor nodes. Free nodes form a pool of nodes from which suitably connected nodes are recruited for representing new functional units. The recruitment process transforms a quasi-structured network into a collection of nodes and circuits with specific functionalities [9]. It has been shown [7, 10] that recruitment learning can be grounded in the biological phenomena of long-term potentiation (LTP) [2].

In causal hebbian learning (CHL) synaptic strength (weight) updates depend on the relative timing of pre- and post-synaptic firing (cf. STDP [4, 3]). Furthermore, different connection types exhibit different dependences; some update their weights only when pre-synaptic firing precedes post-synaptic firing, while others only in the reverse scenario. This enables the learning of bidirectional, but asymmetric links between cells.

Episodic Facts: SMRITI is a detailed computational model of episodic memory formation via cortico-hippocampal interactions [9, 8, 11]. SMRITI demonstrates how the propagation of a rhythmic pattern of activity (corresponding to an activity-based encoding of an event) can lead to the recruitment of a persistent episodic memory trace in the hippocampal system as a result of LTP. SMRITI meshes fully with SHRUTI's representations and provides the encoding of episodic facts. The development of an anatomically and physiologically detailed account of episodic fact learning is important, since it illustrates the efficacy of mapping SHRUTI structures to realistic neural circuitry.

Types: Learning of new types (categories) occurs on the basis of ongoing experience and previously memorized events. A new type structure encompassing a set of entities is recruited incrementally when (i) these entities repeatedly fill the same roles in multiple events, (ii) these events are instances of multiple event types, and (ii) the occurrences of these events are accompanied by strong reinforcement signals.

Both local reinforcement measures (represented by activity within a particular structure) and global indicators (communicated by neuromodulators) can impact the learning of types and other SHRUTI structures.

Taxon facts and value facts: Taxon facts represent statistical knowledge extracted from multiple occurrences of the same type of events [6]. The neural structure of taxon facts is described in [9, 11]. A taxon fact is recruited incrementally when multiple events involving the same relational schemas occur with the same types of entities serving as role-fillers. The neural mass of a taxon-fact is correlated with the observed frequency of relevant events.

Value facts associate situations with utilities. Like taxon facts, they are statistical in nature. Where taxon fact learning depends on the accumulation of episodic facts, value fact learning depends on the accumulation of analogous reward facts, that is, memories of specific instances of reward or punishment.

Causal knowledge (rules): Causal Hebbian Learning (CHL) has been proposed as a partial solution to the learning of cause-effect relationships based on experience. The existence of different connection types with different temporal dependences is key to learning bidirectional, asymmetric links. A modification of CHL allows the learning process to be influenced by the associated flow of reinforcement signals.

Exploration of rule learning, especially the learning complex rule structures involving semantic restrictions and different evidence combination functions is currently in progress.

Conclusion

We will present an overview of how many of the SHRUTI structures are learned. Initial implementations of learning processes described above have been developed. Episodic facts are among the most complex structures of the SHRUTI model, so the success achieved in providing an anatomically and physiologically grounded account of their learning provides strong guidance and well-founded hope that similarly detailed and neurally grounded accounts of learning other SHRUTI structures will emerge.

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