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 rapid 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 might be learned.

1 Introduction

Although a great deal is known about neural representations in sensory, somatosensory, and motor cortices, the neural structures underlying higher-order cognitive processes are largely unknown. The SHRUTI model [11, 7] provides a plausible set of proposals for what these representations might be, and how they could be employed in a wide range of cognitive processes such as semantic memory, reasoning and decision making. An important consideration for any neural representation scheme is its learnability. In this paper we discuss how several key representational elements of SHRUTI might be learned.

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1.1 The SHRUTI model

SHRUTI is a connectionist 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 rewards (or punishment).

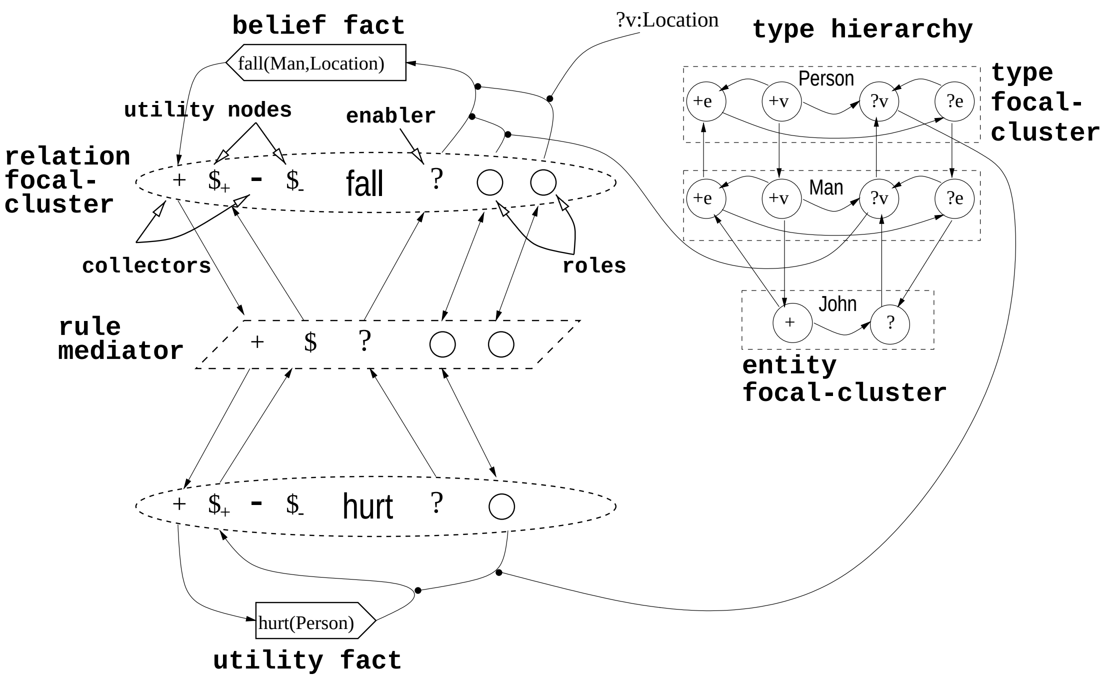

Figure 1: Diagram showing major structures of the SHRUTI architecture.

SHRUTI suggests that the encoding of relational information (e.g., event schemas) is mediated by neural circuits composed of structured cell ensembles, termed *focal-clusters* (see Figure 1). A relation focal-cluster (e.g., for the relation *fall*) consists of (i) role cells (e.g., for the role *fallee*) whose *synchronous* firing with entity cells (e.g., for the entity *John*) encodes role-entity *bindings* (e.g., the binding *fallee=John*) comprising the currently active relational *instance* (e.g., John fell in the hallway), (ii) + and - collector cells whose firing signifies belief and disbelief, respectively, in the currently active relational instance, (iii) enabler cells (?) whose firing signifies a search for support for this relational instance, and (iv) $\$_+$ and $\$_-$ utility cells that encode the desireability of this relational instance and its negation, respectively. Focal-clusters of entities and types are structured in a similar manner. The grouping of cells within a focal-cluster highlights their functional cohesiveness, but does not imply physical proximity.

The processing of relational information involves the transient propagation of *rhythmic* activity across relation and entity focal-clusters. Causal knowledge (e.g., a rule) 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.

1.2 Learning in structured connectionist models

Two forms of learning, both related to hebbian learning, form the basis of learning structured representations in SHRUTI. These are: recruitment learning [2, 6] and causal hebbian learning [13].

Recruitment learning (and also vicinal algorithms [12]) 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 sensorimotor nodes. Unrecruited ($free$) nodes are connected via weak links to a large number of free, recruited, and 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 [8]. It has been shown [9] that recruitment learning can be grounded in long-term potentiation (LTP) [3].

Learning relatively complex structures of the SHRUTI model poses a significant challenge for the recruitment learning approach because learning such structures involves recruiting not just individual cells but also structured ensembles or functional circuits. The probability of extracting a particular structure from a set of random connections quickly approaches zero as the complexity of the structure increases. Consequently, some level of pre-existing organization is required. The sorts of pre-existing organization required for the SHRUTI model to be learnable involve certain recurring pattern of interconnections among nodes. Interestingly, computational modelling has shown that such organization could result from a genetically based developmental process [4]. It is well known that many different regions of the brain are organized differently prior to experience, and these differences are likely to be related to the functional needs of different cognitive processes. An excellent example of this may be found in the idiosyncratic architecture and local circuitry of the hippocampal formation which has been shown to be ideally suited for supporting the rapid encoding of episodic memories [8, 9, 10].

A second learning mechanism, causal hebbian learning (CHL), has been proposed as a partial solution for the learning of cause-effect relationships based on experience. In CHL, synaptic strength (weight) updates depend on the relative timing of pre- and post-synaptic firing (cf. differential hebbian learning [5] and spike-timing dependent plasticity [1]). Furthermore, different connection types may exhibit different dependences; some may update their weights only when pre-synaptic firing precedes post-synaptic firing, while others may do so only in the reverse scenario.

2 Learning SHRUTI structures

In the following we sketch how the learning mechanisms discussed above can be applied to learning various components of the SHRUTI model. While a detailed circuit-level design, analysis and implmentation has been carried out for the learning of episodic facts, only a preliminary account has been developed for the learning of other components focusing mainly on initial structures and network dynamics that would enable learning to occur.

2.1 Episodic Facts

A key step in learning the model of an environment is remembering events as they happen. This is the goal of SMRITI, an anatomically and physiologially grounded and cell-level model of episodic memory formation in cortico-hippocampal circuits [8, 9, 10]. 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 plausible account of episodic fact learning is important, since it illustrates the efficacy of mapping SHRUTI structures to realistic neural circuitry. Moreover, the presence of a storehouse of observations and events provides a strong foundation for other instance-based learning mechanisms.

2.2 Types

Learning of new types (categories) occurs on the basis of ongoing experience and previously memorized events or observations. As a starting point, we assume that the system has the ability to create representations for unique entities or individuals, and also that it has a repertoire of simple relational concepts. Type learning takes place most readily when the system is in a dedicated learning state during which random subsets of memorized events are simultaneously activated. A new type structure encompassing a set of entities is recruited when (i) these entities repeatedly fill the same roles in multiple events, and (ii) these events are instances of multiple event types. For example if the system were to observe $hasFeathers(Sam)$, $hasFeathers(Tweety)$, $hasBeak(Sam)$, and $hasBeak(Tweety)$, it might recruit a new type structure ($FeatheredBeakedThing?$) encompassing Sam and $Tweety$ (see Figure 2.). In general, larger numbers of entities and observations would be required in order to trigger recruitment. The occurrence of reinforcement signals — local reinforcement measures (represented by activity within a particular structure) as well as global indicators (communicated by neuromodulators) — can impact the learning of types and other SHRUTI structures. Type learning in SHRUTI can be characterized informally as follows:

1. Periodically, the system enters "type learning" mode, during which random sets of existing memories (episodic facts) are activated.

2. Existing types and entities receive input from active episodic facts with which they are associated, and become active upon receiving sufficient input from multiple facts.

3. Each type and entity is connected to numerous *free* type focal-clusters in the type recruitment pool. A free type focal-cluster receiving sufficient input during multiple phases gets recruited to serve as the parent type for the types and/or entities that caused it to become active.

4. A new type representation is strengthened with use, particularly when active in conjunction with

reinforcement signals.

5. When not used, connections stengths decay over time and structures become available for re-recruitment.

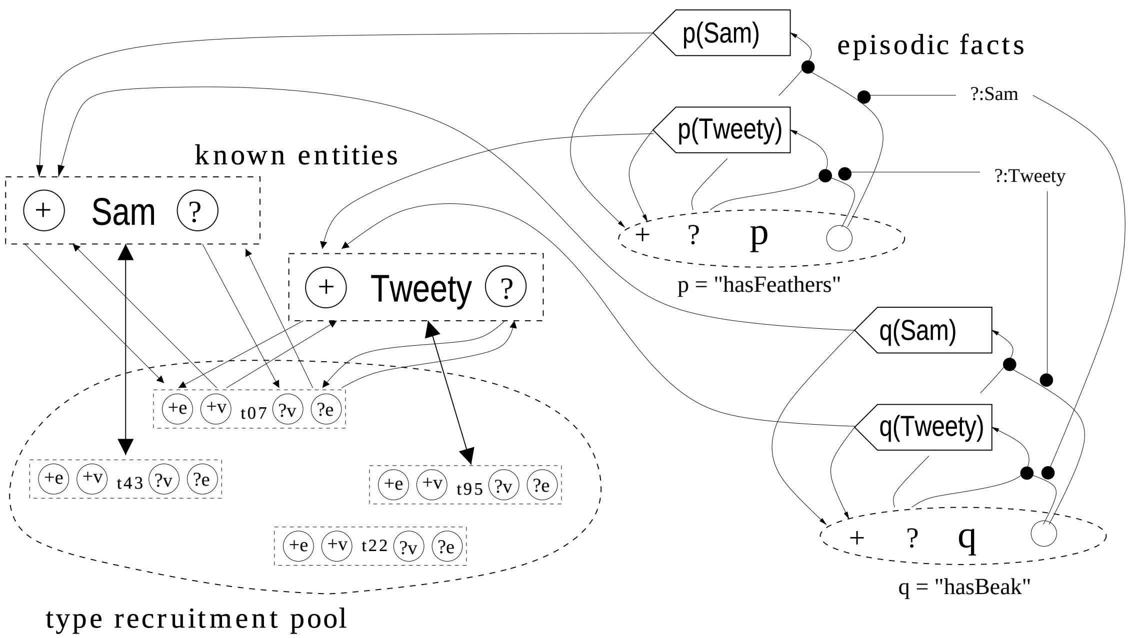

Figure 2: Connectionist structure involved in the learning of a new type/category. Shown are two entity focal-clusters labeled Sam and Tweety, two relations p and q each with a pair of episodic facts, and a pool of free type focal-clusters connected randomly to existing entity representations. The focal-cluster labeled $t07$ is connected to both entities and can therefore be recruited as the representation of their common type. Bidirectional arrows represent multiple connections along both directions.

2.3 Taxon facts and value facts

Taxon facts represent statistical knowledge extracted from multiple occurrences of the same type of events [7]. A possible neural structure of taxon facts is described in [8, 10]. Taxon facts are recruited when multiple episodic facts involving the same relational concepts and the same *types* of entities become active simultaneously. As with the learning of new types, this situation obtains most readily when the system is in a dedicated learning state, and stored instances are randomly activated. Building on the previous example, if the system were to observe $flys(Sam)$ on one occasion and $flys(Tweety)$ on another, where Sam and

$Tweety$ share a common supertype (let's call it "Bird"), then it might create a new taxon fact $flies(Bird)$ in response to these observations (see Figure 3).

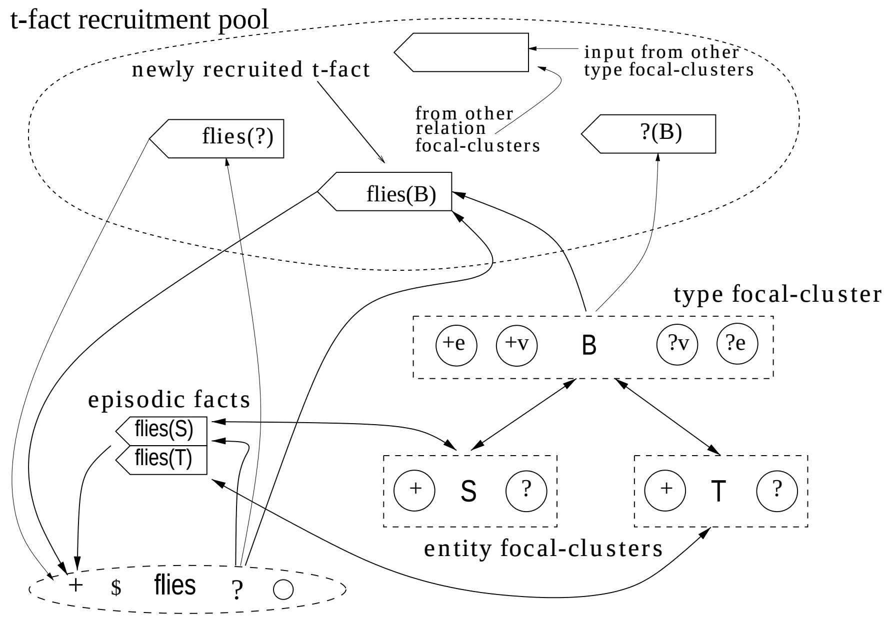

Figure 3: A diagram of the major structures involved in the recruitment of taxon facts (t-facts). Shown are the relation focal-cluster $flies$ with associated episodic facts, entities labeled S and T with learned supertype labeled B, and a pool of free taxon fact structures connected to these.

Value facts associate situations with utilities, and like taxon facts, are statistical in nature [14]. 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.

In addition to their initial recruitment, an important aspect of taxon fact and value fact learning is the updating of their weights as new evidence arrives. Learning is triggered whenever an associated relational instance is active, with fact weight adjusting towards the current level of belief or utility. In this way, taxon (value) fact weight comes to represent prior probability (expected utility) of the relational instance.

2.4 Causal knowledge (rules)

The existence of a CHL mechanism that allows for different connection types with different temporal dependences is key to learning the bidirectional, asymmetric links of SHRUTI's causal rules. Specifically, connections between collector cells are enhanced whenever the source is active before the target (within a certain window of time), whereas connections between enabler cells are enhanced whenever the target is active before the source. Thus, when event A is observed preceding event B, both the forward and backward links for the rule $A \Longrightarrow B$ are strengthened. The initial condition consists of a set of relation focal-clusters, with weak connections linking each cell to others of its type (collector cells linked to other collector cells, role cells linked to other role cells, etc.) The observation of a large number of events as they occur in time (or temporally compressed re-observation of sequences of events from memory) leads to the formation of rules reflecting the apparent causal structure of the environment.

3 Conclusion

A sketch of how major structures of the SHRUTI model may be learned has been presented. This is a preliminary account, and much work remains to be done. In particular, a cell-level implementation of SHRUTI is required in order to explore learning in detail. The recruitment of additional model structures such as relation focal-clusters and rule mediators also needs to be addressed. As a greater understanding of the neural substrate required for learning various structures is obtained, it will be possible to map these structures onto specific brain regions and projections. The success achieved in the development of SMRITI, an anatomically and physiologically grounded and cell-level model of episodic fact learning withinin cortico-hippocampal structures, provides strong guidance and well-founded hope that similarly detailed and neurally grounded accounts of learning various SHRUTI structures will emerge.

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