Neurosymbolic Spike Concept Learner towards Neuromorphic General Intelligence

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Abstract: Current research in the area of concept learning makes use of deep learning and ensembles methods to learn concepts. Concept learning allows us to combine heterogeneous entities in data which could collectively identify as individual concepts. Heterogeneity and compositionality are crucial areas to explore in machine learning as it has the potential to contribute profoundly to artificial general intelligence. We investigate the use of spiking neural networks for concept learning. Spiking neurones inclusively model the temporal properties as observed in biological neurones. A benefit of spike-based neurones allows for localised learning rules that only adapts connections between relevant neurones. In this position paper, we propose a technique allowing dynamic formation of synapse (connections) in spiking neural networks, the basis of structural plasticity. Achieving dynamic formation of synapse allows for a unique approach to concept learning with a malleable neural structure. We call this technique Neurosymbolic Spike-Concept Learner (NS-SCL). The limitations of NS-SCL can be overcome with the neuromorphic computing paradigm. Furthermore, introducing NS-SCL as a technique on neuromorphic platforms should motivate a new direction of research towards Neuromorphic General Intelligence (NGI), a term we define to some extent.

1 INTRODUCTION

Neuromorphic computing (NC) is introducing a new computing paradigm along with a class of processors that differs from conventional computing to simulate neural networks. The neural networks that NC adopts behave as closely as possible to spike-based neurones in biology. Initially the goal of NC was to simulate the brain with large scale integrations of hardware-based neurones. With the prominent advancement of deep learning algorithms, dedicated processors or Neural Processing Units (NPU) are being developed to accelerate machine learning algorithms.

To mention a few NPUs and their use cases, the Tensor Processing Unit (TPU) by Google have been developed to accelerate deep learning algorithms for consumers through Google's cloud AI compute services (Sengupta, Kubendran, Neftci, & Andreou, 2020); Vision Processing Units (VPU) have been developed to serve as co-processors to accelerate vision compute tasks and a few can perform image inference tasks (Barry & Riordan, 2015; Rivas-Gomez, Pena, Moloney, Laure, & Markidis, 2018); Field Programmable Gate Arrays (FPGA) have been used to conduct research on neural networks and their various learning mechanisms (Lammie, Hamilton, Van Schaik, & Azghadi, 2019; Perez-Peña, Cifredo-Chacon, & Quiros-Olozabal, 2020; Rosado-Muñoz, Bataller-Mompeán, & Guerrero-Martínez, 2012), but these applications are demonstrated towards visual pattern recognition (Liu & Yue, 2019).

It is important to note that majority of NPUs are currently being developed to accelerate existing neural network algorithms. Only a few are being developed at the frontier of brain-inspired computing research, that focuses on biologically plausible neural models. Plausible neural models constitute of neurones that neurologically functions much closer to neurones observed in our central nervous system (CNS). These plausible neurones are the spike-based neurones which makes the 3rd generation of neural networks. Intel's Loihi, IBM's TrueNorth, SpiNNaker and Neurogrid (Boahen, 2017; Davies et al., 2018; Debole et al., 2019; Painkras et al., 2013) are few examples that could be considered as NPUs with 3rd generation neural networks but distinctively are being considered as Neuromorphic Processors. The defining aspect of Neuromorphic Processors are

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their scalability and massively parallel compute potential to simulate spiking neurones at grand scales.

With neuromorphic devices on the rise, more specialised devices/hardware is being developed to host and accelerate various neural networks. We acknowledge that these devices increase the performance of such networks but, from a much broader perspective in the domain of neuromorphic computing, there is relatively slow advancements being made on the algorithmic developments for what could potentially be machine learning techniques unique to the neuromorphic platforms.

It is highly probable, perhaps inevitable, that the future of artificial intelligence will have mankind in an age where general intelligence machines are more like human beings contributing to society: reasoning with and learning from its environment causing real world effects. To reach such an age, cognition and behavioural dynamics in general intelligence machines should exhibit the likeness to behaviours of human beings. This may be achieved by somewhat imitating the underlying cognitive processes or neurological processes that is observed in our central nervous systems. Alternatively, purely speculative developments that do not imitate nature may also lead to general AI, this raises the questions as to which is more favourable for the future of general AI. We may perhaps trust more on general AI that work closer to our biology than a more obscure forms of general AI that we cannot relate to in processing rationality.

Artificial general intelligence (AGI) is considered the holy grail of AI for decades and has been the core motivation of machine learning since the birth of the field. AGI is still anticipated to bring about revolutionary advancement to science and technology, with a wave of machine reasoning. Initially, AGI is considered as intelligence expressed by machines in contrast to natural intelligence expressed by humans. Nevertheless, general intelligence can also be considered loosely yet sub-specifically as a form of intelligence that possess cross-domain expertise.

Considering general intelligence in the context of neuromorphic computing, it is reasonable to define a very specific branch of artificial general intelligence that is achieved through Neuromorphic means as a form of Neuromorphic General Intelligence (NGI). General intelligence can be achieved through cognitive models consisting of various machine learning techniques, formal methods and algorithms like *State, Operator, And Result* (SOAR), *Adaptive Control Thought – Rational* (ACT-R) and *Learning Intelligence Decision Agent* (LIDA) (Bruckner, Zeilinger, & Dietrich, 2012). We can differentiate NGI as an approach of general intelligence emerging from Neuromorphics, spike-based neural computing platforms.

In this work we investigate the possibility of delivering general intelligence on the neuromorphic computing paradigm. Specifically, we propose to investigate a method of structural and functional plasticity for learning on a neurosymbolic spike-based network to achieve concept learning on neuromorphic platforms. Concept learning is a crucial element to inaugurate generality in machine intelligence.

Key questions this work will address towards NGI:

- How can spike-based networks achieve concept learning?
- How will such spike-based concept learners be employed in future neuromorphic platforms?
- Will spike-based concept learners inform any design specification for neuromorphic hardware?

The real-world use cases – for concept learning emphasising structural plasticity – can be in situations where intelligent dynamical systems are required that are extensible, flexible and function in real-time. The world of Internet of Things (IoT) are such situations as new sensors are constantly added to extend a system in its wide variety of uses. Applying concept learning in IoT situations allows us to form real-time associations between various sensors regardless of sensor type. The supposed intelligent dynamical systems require algorithms that are unconstrained, we have proposed structural plasticity for our approach to adapt with extensibility as associations can form with new components whilst existing associations remains unaffected yet functional. The intelligence aspect of our approach as a concept learner lies in the neurosymbolic space. Concepts could consist of entities in the symbolic space, representing composites derived by heterogeneous data streamed from different IoT sensors. The universality of neurosymbolic space due to the heterogeneity enables inter-correlation of information across different sensors in an IoT ecosystem. For IoT sensor, data requires spike-encoding for spike-based neural processing. The encoding provides a standard mechanism for processing data further promoting the universality of symbolic space.

The rest of this paper will be presented as follows. In section 2, we cover related works on inter-domain knowledge, representation and concept learning. In section 3, we briefly describe different aspects of our algorithm and their rationale to realise our take on concept learning with spiking neurones. In section 4, we discuss the potential implications of our techniques and the prospect of our approach to further research in NGI.

2 RELATED WORK

Within the domain of computer science, machine learning has given machines the ability to exhibit intelligence and in cases excel humans in certain intelligence tasks. However, modern AI in the current academic standpoint are considered as narrow AI (weak AI), excelling at a very specific intelligence task at which they were purposefully trained for (Fjelland, 2020). Narrow AI are domain specific, requires human intervention to develop with and utilise. Strong AI are not necessarily domain specific because they are, as they should be, domain-neutral (multi-domain). Strong AI should fundamentally learn in an unsupervised general manner, thus, are educated into domains they have been exposed to, as opposed to being trained objectively and specifically.

With cross-domain knowledge in intelligent systems, agents could tackle problems in a more rational way by addressing new information with consideration of patterns acquired from past observations inter-correlated across domains. This feat mirrors the inductive process facilitating reasoning, to make conclusions based on one or several evidence, in all its various forms, from past observations and experiences. Concept learning is a strategy of combining features or attributes (fundamental pieces of information) which collectively identify as one distinct concept. The goal of concept learning, we assume in our context, is the ability to capture complex patterns based on past observations. The complexity of constituents making complex patterns may be derived from the heterogeneity of data. Concept learning is crucial to achieving the domain-unconstrained learning complimentary to general forms of intelligence.

Neural network algorithms are a sophisticated development that has given us the techniques to perform classifications and predictions. However, neural network as a technique alone are obscure in the sense that knowing the basis for which it took to reach its conclusions are near impossible. The reasoning of such is behind a ‘wall of matrices’ with little to no semantic grounds. This has introduced a branch of AI known as explainable AI (XAI) (Barredo Arrieta et al., 2020) in which the goal is to make AI as transparent as possible. Furthermore, a goal to make AI that can explain the reasoning behind its own conclusions and if not be as transparent as possible for humans to interpret and understand. For humans, we understand each other due to the same mental model and social context we innately possess and grew with. XAI aims to endow intelligent systems with the communicative style through that shared model and context for users to understand with minimal comprehension barrier.

Neuro-symbolic AI is one approach that can achieve reasoning with generality and yet with interpretability, this approach couples the opaqueness of old-school rule-based symbolic AI with the obscure internal workings of neural networks. Symbols are established to give fundamental meaning to individual neurones in neural networks. Compositionality through hierarchical attribution is a symbolic method to represent concepts.

The techniques towards concept learning have been explored in machine learning but the approaches often employ ensemble methods – using multiple AI algorithms to accomplish concept learning. Existing literature in concept-learning consists of deep neural networks coupled with natural language processing, taking visual and question-answer pair as inputs in order to learn concepts in a joint visual-linguistic space. This technique is known as grounded learning, using a joint representational space for both visual and linguistic compositions. The shared space further benefits as the semantic interface for users and interactors to understand the reasonings behind AI’s conclusions. Some of the outcomes on this line of research have introduced *Visual Concept-Metaconcept Learner* as VCML (Han, Mao, Gan, Tenenbaum, & Wu, 2019), *Neuro-symbolic Concept Learner* as NS-CL (Mao, Gan, Kohli, Tenenbaum, & Wu, 2019) and *Neuro-symbolic Visual Question Answering* as NS-VQA (Yi et al., 2018).

Further research in the area of concept compositionality and semantic representation that utilise spiking neural networks is the Semantic Pointer Architecture: Unified Network (SPAUN) (Stewart, Choo, & Eliasmith, 2012). SPAUN is among one of the most accurate cognitive models on the spiking neurone framework. The primary component of SPAUN is the Semantic Pointer Architecture (SPA) (Blouw, Solodkin, Thagard, & Eliasmith, 2016) which have demonstrated compositionality and symbolic induction. Compositionality allows items to form associations making composites, in symbolic terms, making up concepts. Symbolic induction in this case is the predictive process based on sequences of temporally presented visual inputs, to be precise, the temporal sequences of activities in the symbolic space in correlation to the visual inputs.

For advanced concept learners; a certain set of inputs patterns could influence and affect other set of patterns regardless of sensory and perception modalities. Associations can be formed from data of disparate sources such as sights, sound and touch – in computing this can extend to sensors beyond common sensory modalities of biology. Symbolically a set of description-patterns can be regarded as individual concepts by compositionality and symbolic induction. Conveniently concepts could consist of description-patterns fragmented across different modalities in a unified symbolic space.

For this position paper, we propose a structurally unconstrained concept learner that can learn dynamically from heterogeneous data streams, Neuro-Symbolic Spiking Concept Learner (NS-SCL).

3 SPIKE CONCEPT LEARNER

In artificial neural networks (ANN) and deep learning (DL) frameworks, neural networks are substantially non-spiking and during the training phases the models undergo global weight changes. Spike-based networks can be feasibly unique in this respect as learning could involve making localised changes only between relevant neurones. These localised changes are mediated and determined by spike activities and is known to play essential roles in learning as observed in biology. Several learning rules have been postulated due to the variety of learning dynamics observed between neurones from various regions of our central nervous system. We will cover the learning rules further on in this section.

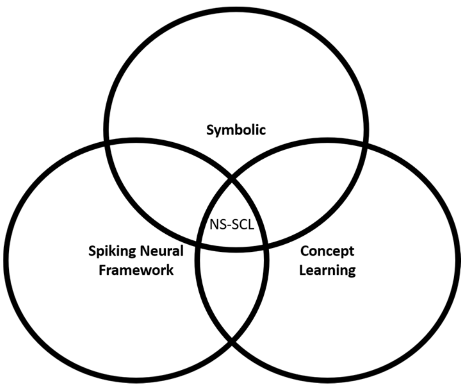

Figure 1: NS-SCL overlapping aspects.

Our proposed concept learner (NS-SCL) is based on the spiking neural framework, but we deterministically and dynamically structure the network in a neuro-symbolic way based on incoming spike-encoded data. In this work, we will exploit the localised learning of spike-based networks and its temporal properties to learn neuro-symbolic constructs in an unsupervised way. We investigate further into synaptic enhancements as derived in neuroscience to mean functional forms of plasticity – how synapse (connections) between neurones adapts during neural processing and learning. We have devised a learning mechanism for NS-SCL to achieve experiential learning. The learning mechanism is inspired by functional plasticity observed in the central nervous system with regards to changes to synapses (connections). The novelty lies in how we incorporate many synaptic enhancements profiles, this is achieved through synapse manifolds briefly covered in ***Section 3.3***.

Furthermore, we investigate the creation and formation of synapse between neurones based on the synaptic enhancement conditions as a form of structural plasticity. New synapse indicates a new association between neurones, in the symbolic space we can form associations between items resulting in the composition of higher symbolic constructs. The conditions for when synaptic association should form depending on spikes (of data). Two neurones spiking may be spuriously correlated yet we form the synapse but treating such synaptic association as a latent connection with no functional effect to the network. Latent synapse will cease to exist after a given period if not subjected to further stimulation. However, if further stimulation occurs the latent connections will persist to exists and it should have a functional effect in the network. Persistent stimulation indicates a deterministically coordinated activity, it is then reasonable to treat the synapse as overt since the frequency of firings would satisfy some synaptic enhancement conditions as it could be part of a genuine association. We will cover briefly the mechanism of structural plasticity within a neuro-symbolic space in ***Section 3.4***.

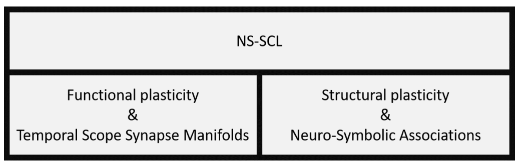

Figure 2: Essential algorithms of NS-SCL.

The essential algorithms in Figure 2 are required to realise spike-based concept learning. The functional plasticity aspect of the network is very much like ANNs and DL with connections between neurones strengthening or weakening based on the training data given. The difference is our adoption of

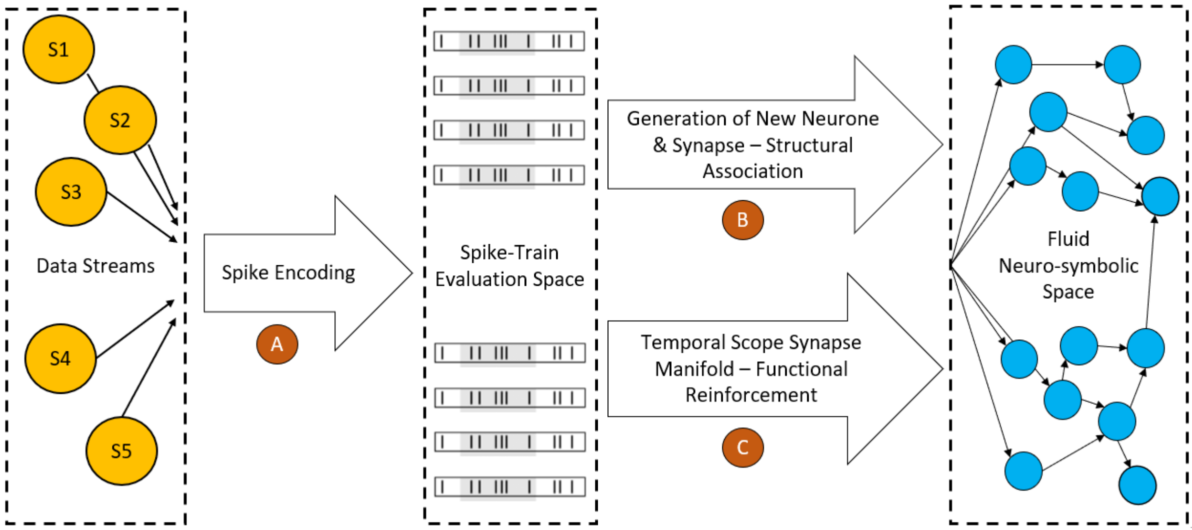

Figure 3: NS-SCL framework.

the spiking neurone paradigm and so our approach to functional plasticity would differ, an approach being unique to the spike-based paradigm. Structural plasticity is our approach to introduce a symbolic space with spiking neural networks, this symbolic space allows us to examine and make sense of the network – this represents an unconstrained ontology-like space that holds relationships and concepts. Introducing a neural-symbolic space with live learning mechanisms as concept leaners opens the possibility of a self-learning NGI agent that can learn through experience (with structural and functional plasticity).

We will employ NS-SCL for concept learning in an IoT space, as such space is rich with data of various forms, with varying breadth and lengths. Here, NS-SCL will generate concepts constituting patterns present in data across several sensor streams. Figure 3 illustrates the framework of NS-SCL. At process A, data from sensor streams are encoded into spike-trains. At process B, we form new neurones and synapse in symbolic space, where associations are non-existent – will be based on spike timings in spike-train evaluation space. At process C, we apply our manifold algorithm to process spikes in evaluation space – reinforcing associations where relevant in symbolic space. In summary, the framework is a real-time learning model with characteristics of functional and structural neuroplasticity.

3.1 Learning with Neuroplasticity

In ANNs and DL, the core algorithm for learning is founded on functional plasticity. Functional plasticity refers to the changes made to weightings of connections between neurones as training takes place. We will not go into further details about functional plasticity regarding ANNs and DL since the direction of this paper is towards spike-based functional plasticity.

Functional plasticity is derived from synaptic enhancements in neuroscience. Synaptic enhancements are the changes made to the neurotransmitter release probability as observed at the synapse between neurones. Effectively, higher probability indicates more influence a neurone has through such synapse in causing another neurone to fire. Furthermore, short-lived synaptic enhancements have been classified as paired-pulse ***facilitation***, synaptic ***augmentation*** and post-tetanic ***potentiation*** (Regehr, 2012). The variation between these classifications are the magnitude and duration for which the synapse can influence subsequent neurones, these duration ranges from milliseconds to minutes. For our concept learner, NS-SCL, we propose a novel mechanism for learning to cater all scopes of synaptic influence (***facilitation***, ***augmentation*** and ***potentiation***) into one unified neuro-symbolic spiking model. The method in which we achieve all this is through a technique we call Temporal Scope Synapse Manifolds (TSSM), further covered in ***Section 3.3***.

In biology, spiking activities and synaptic enhancements functions on the 100th millisecond timescales. With the compute performance of current general-purpose computers, simulating spiking activities at natural speeds is unachievable. Hence, it is the core motivation of Neuromorphic Computing. Nevertheless, we can exploit the mechanisms by simulation altering the duration of spikes and simulation speed to a larger scale in order to demonstrate the feasibility and potential of our algorithm.

Structural plasticity is another form of neuroplasticity regarding the changes to the structure of the network. It has been observed that neural structures are continuously growing and rearranging. Dendrites are parts of neurones that allows connections from/to other neurones. Dendritic spines have been observed to appear and disappear depending on their relevance. Spines can last for months to few days and less (Trachtenberg et al., 2002). It has been revealed that dendritic spines allow for the formation of new synapse and is considered to play a role in learning. The dendritic spine evidently implies neural networks not only adapts by changes to connections but by establishing new connections.

In ANNs and DL, the structure of the network is often defined at the beginning during initialisation – number of layers, neurones and connection configurations. The structure of networks in ANNs and DL do not change once initialised and remains constant, but the weightings are subjected to alteration during training. In spiked-based networks, it is plausible to allow structural change since in biology this phenomenon happens continuously and frequently. The structural plasticity method for NS-SCL will be briefly covered in ***Section 3.4***.

3.2 Functional Plasticity Fundamentals

There is well-known postulate by Donald Hebb in 1949 regarding the activities of neurones during learning (Hebb, 1949). Hebbian learning, as it is well-known as, have led to significant advancement in machine learning for the past decades - specifically the area of neural networks across its generations. The very most recent technological advancement in the past decade that had emerged from the long-credited postulate have led to the sophisticated deep learning algorithms.

Hebb's rule is a learning rule regarding the activities neurones exhibit during learning, specifically, by persistent stimulation of a neurone results in the rise in synaptic efficacy (influence on subsequent neurones). With higher synaptic efficacy, the more influence the pre-synaptic neurone has on the post-synaptic neurones. Following the date of Hebb's postulate, the field of neuroscience have made further progress through new observations in the biological process of neurones and spike activities. Later observations have found that the timing of neurones firing is a critical component in the process of learning.

Synaptic plasticity is the observed process that demonstrates that synaptic efficacy only rises when connected neurones fires within a very short time-window. Spike-Time-Dependant-Plasticity (STDP) is the biological process by which neurones changes the synaptic efficacy exclusively depending on the timings of spikes between neurones, the inter-spike interval (Shrestha, Ahmed, Wang, & Qiu, 2017). Spike-Rate-Dependant-Plasticity (SRDP) is another extension by which the persistent number of spikes leads to more pronounced adjustments to synaptic efficacy (He et al., 2014). SRDP uses spike averages to temporally sum the potentials for synaptic enhancements.

For NS-SCL, we will investigate how STDP can be used with our discrete-time spiking neural model for synapse formation. Spiking neural networks in Neuromorphics embraces the learning rules adapting with local changes to achieve synaptic plasticity (Liu & Yue, 2019; Moraitis et al., 2017; Shrestha et al., 2017). The localised nature of the adaptation conveniently allows us to extend the structure of the network without affecting the entire network functionally. This kind of dynamic structural characteristics is perhaps not so different to our own central nervous systems.

3.3 Functional Plasticity with Temporal Scope Synapse Manifolds

In order to cater for all scope of synaptic influence we can assume having one connection between neurones but functionally we can compute the connection with many different synaptic enhancement profiles – facilitation, augmentation and potentiation.

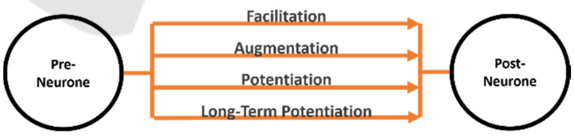

Figure 4: Temporal Scope Synapse Manifold (TSSM).

Figure 4 illustrates four synaptic enhancements (SE) each would have different profiles – varying in duration and magnitude of influence. All enhancement profile shares the same vector-direction component between neurones. Since each SE functions at different durations, we have imposed temporal boundaries – for spikes satisfying within, only the corresponding synapse would be made the subject to adaptation.

Increasing the base speed at which the network operate could yield abnormally different result with the same SE profile. For temporal manifolds, we can introduce and establish our own parameters that do not necessarily correspond to natural synaptic enhancement properties as observed in neuroscience. We can change to find ideal parameters optimal for certain base network speeds. We consider defining SE parameters as the optimisation aspect of our algorithm.

Table 1: A crude temporal upscaling of SE profiles.

SE Profile	Mag.	Dur.	Condition
Facilitation	0.8	1 s	0 < s < 1s
Augmentation	0.2	10 s	1s < s < 10s
Potentiation	0.05	5 mins	10s < s < 5mins
Long-Term **P**.	0.05	1 hr	5 min < s < 1hr

Table 1 is an example of such SE profiles for synapse manifolds. The magnitude represents the weight of influence synapse have on post-neurone at each spike simulation tick. The duration is how long the influence will last on post-neurone. The condition is what must be satisfied for the influence to take place. Our algorithm will not treat the SE profile parameters as definitive constants but as modifiable parameters to fine-tune the behaviour of our spike-symbolic network. We assume that different applications for our algorithm will benefit from different set of SE profiles.

3.4 Structural Plasticity for Neurosymbolic

This aspect of NS-SCL is to allow the generation of new neurones and synapses. We will form new synapse between neurones when they fire satisfying the manifold rules, and if there are no existing synaptic connections between them. In the neuro-symbolic space, new neurones and synapse effectively forms new symbolic representation of an item. Manifold rules and unconstrained structure results in a deterministic yet dynamic behaviour as unsupervised learning.

Initially the generated synapse will be treated as latent synapse, causing no real functional effects in neuro-symbolic network but subjected to functional plasticity. Latent properties are applied to individual SE profile. Latent synapse is our mechanism to structurally regulate the neuro-symbolic space. We will give generated synapses a probationary period. If no subsequent changes are made to the synapse within a set period, we will discard the SE profile associated as we can conclude that the spike activities leading to their generations were spuriously grounded.

Latent synapse could become more progressively enhanced through our plasticity learning mechanics; they can be promoted to an overt state. In an overt state, synapses are effectively active in the network. Progressive synaptic enhancement can only occur with well-coordinated spikes across spike-trains; therefore, we can conclude that the synapse is well-grounded yet not necessarily known for what cause. However, the cause can be traced to by observing neurones that fire depending on the input spike-trains (data) and would fire somewhat deterministically. NS-SCL requires each neurone to atomically represent a concept/constructs in the neuro-symbolic space. When a neurone fires it would indicate that a learned-pattern or concept is relevant in present moment which can be considered as short-term recall.

Two unrelated neurones – having no direct connections – can form synapse by the temporal manifold conditions. Thus, NS-SCL can form complex hierarchical structures of which is determined by temporal activity.

4 DISCUSSION

Concept learners such as VSCL, NS-CL and NS-VQA are examples on some of the work aiming to couple different types of learning spaces. These approaches have demonstrated learning can be done on joint visual-semantic space. NS-SCL is our approach where the joint space is universal. We use spike-based neural framework which allows us to temporally encode any information into a shared universal symbolic space – allowing for information such as those originating from visual sources, semantic sources, auditory sources, etc. Hence, NS-SCL should be able to relate information from one sensory mode to other sensory modes. This approach is inspired by how our central nervous system handles information from various sources.

Major constraints of our approach of concept learning relates to compute and memory resources. Since new synapse and neurones can be formed dynamically, it would require a machine with considerable processing capabilities and storage volumes to handle large NS-SCL networks. On general-purpose computers with the Von Neumann architecture, the processor would need to process the number of dynamically formed neurones in under milliseconds along with synapse which could be much greater in number. This is impracticable, there is a point at which exceeding a certain number of neurones in the NS-SCL neuro-symbolic space will render the whole algorithm incomputable. We

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proposed upscaling the algorithm's timing-related mechanisms and slowing the spiking simulation speed to avoid such scenarios allowing the processor time to compute. Though, reducing the spiking simulation speed allows for the system to function with heavy loads, the feasibility depends on the use case of the algorithm. For IoT use case, we can adapt sensors to function slower to better accommodate the sensor data in numbers considering the limitations of NS-SCL algorithm on the Von Neumann computing paradigm.

Neuromorphic Computing is a broad field and requires contribution from many different disciplines. The motivation of Neuromorphic Computing is to allow for extreme parallel processing of neurones at grand scales. Developing algorithms for NC can also inform the design requirements for neuromorphic processors. Adapting NS-SCL for Neuromorphic platforms is the ideal solution as it would eliminate the Von Neumann compute and memory constraints that impedes neural processing. NS-SCL requires dynamical creation of neurones and synapse. In neuromorphic hardware we require a reserved pool of unused neurones that can be utilised spontaneously at runtime in addition forming latent synapse.

Further algorithmic developments should be made in neuromorphic computing as it has the potential to influence future developments of neuromorphic hardware. Future improvements, regarding concept learning on such platform, could further reach a level of sophistication where spike-based concept learners exhibit a degree of general intelligence functioning in real-time. There have also been emerging concerns as to the level of sophistication AI could reach on the intelligence spectrum. A valid proposition of maintaining AI is to contain the general forms of AI within isolated computing mediums like Neuromorphics. Thus, it is plausible to define a specific branch of artificial general intelligence that emphasises the neuromorphic approaches – where intelligence is coupled to hardware. We identify this specific branch as Neuromorphic General Intelligence, NGI.

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