# Adapter-Enabled Multimodal Spiking Encoder/Decoder Neural Subnetwork Ensembles for Large-Scale Logical Neuromorphic Accelerators

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Throughout synthetic biology among other domains, artificial neural networks (ANNs), through the replication of biological neural networks, have aided and automated several applications. With the emergence of spiking neural networks (SNNs), the increased biological plausibility through replicating membrane potentials has significantly outperformed state-of-the-art (SOTA) methods in single-domain tasks. However, as SNNs contain a spatiotemporal dimension within their spiking neurons as denoted by the Leaky Integrate-and-Fire equation, they are detrimentally limited in the number of possible parameters. In addition, they cannot effectively generalize to multiple domains. As such, for neuromorphic computing to become a SOTA field, the scale and task-processing abilities of SNNs and neuromorphic accelerators must be addressed. Hence, if a novel SNN-based machine learning framework with an encoder/decoder network utilizing the multi-head self-attention mechanism is combined with an adapter-enabled subnetwork ensemble capable of processing neural and symbolic primitives in a multimodal fashion, then a neuromorphic accelerator can be created which outperforms SOTA methods of SNNs and ANNs in multi-domain tasks and has a higher synaptic density than SOTA accelerators. Accordingly, the framework generalizes to domains such as codon optimization, tumor forecasting, and de novo biomaterial creation. It significantly outperforms SOTA ANNs and SNNs with general and specialized frameworks. Through ablation studies, it is shown that the novel integration of adapters and first-order recurrent synaptic neurons enables large-scale SNNs, and neuro-symbolic programming enables logical reasoning in all domains, increasing the biological plausibility and scale of SNNs by over 16-fold.

**Awards Won:**