# Building Neural Maps of Motor Primitives via Self-Organization and Reinforcement Learning

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## ABSTRACT

Complex animals are thought to construct complex movements by combining fundamental *motor primitives*. Learning the primitives and a control hierarchy is a complex task in a high degree-of-freedom (DOF) system. Motor control using a hierarchy of primitives is a promising strategy for use in high-DOF robots. This project presents a simple, biologically-inspired neural network model of how an agent capable of very simple drawing movements can learn to generate good motor primitives through a combination of unsupervised and reinforcement learning. The model produces an ordered self-organized *control map* that could mediate the triggering of specific learned primitives through simple control signals.


## BACKGROUND

The model is inspired by a few fundamental biological ideas:

1. Georgopolous et al. [1] found that an organism's direction of movement is comprised of a *population code* of directionally-tuned motor neurons [2].
2. Averbeck et al. [3,4] found that each segment of a sequential activity was encoded with decreasing strength in serial order before activity began.
3. Mussa-Ivaldi et al. [5,6] found that complex movements are represented as linear combinations of motor primitive encoded in the cortex.
4. Graziano et al. [7] found that common movements in the monkey correspond to the stimulation of specific cortical regions.
5. Graziano et al. [8,9] also explored how a behavioral repertoire can be algorithmically mapped onto the motor cortex, finding similar results to real life observations.

## MODEL

The model has four layers:

**1. The Effector Layer (E):**
a motor system of directionally-tuned spiking neurons. Further described in the next section.

**2. The Code Layer (C):**
an encoder of the serial order of effector activity.

**3. The Duration Layer (D):**
an encoder of the duration of firing of each effector.

**4. The Map layer (M):**
a Self-Organizing Map (SOM) which organizes "useful" patterns and produces variations of patterns as input into the code layer.

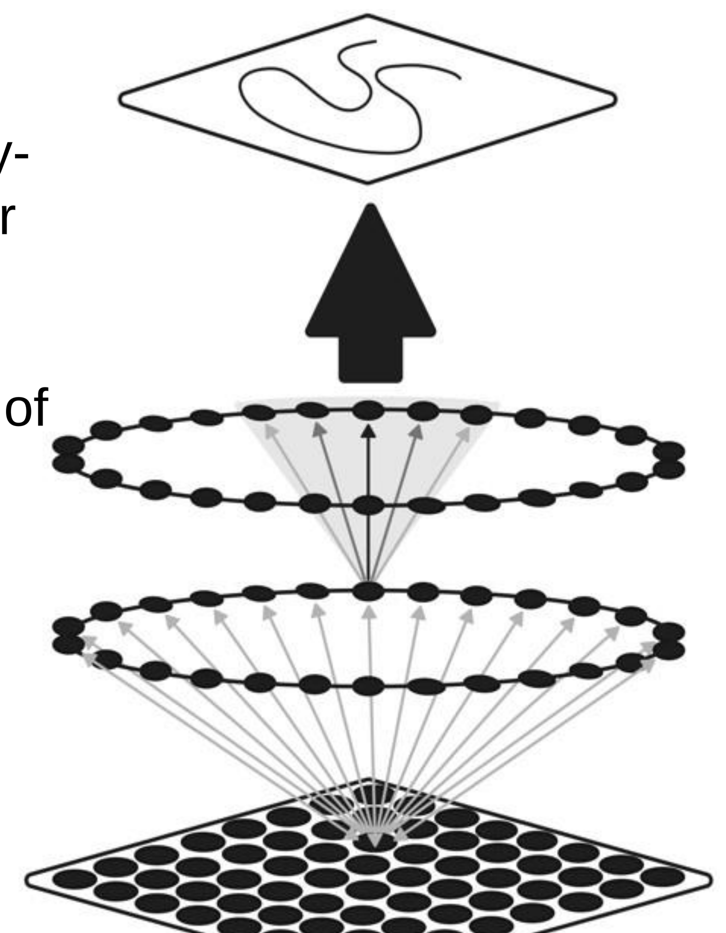

*Figure 1: The model architecture. Top to bottom: Canvas containing doodle, E, C, M. Duration Layer not depicted as it was not implemented in this project.*

## THE EFFECTOR SYSTEM

The Effector layer has 36 effectors, where each effector drives the pen in its preferred direction. Effector $i$ activates based on the activity dynamics of four quantities:

1. **The Membrane Potential ($v_i$):** represents the stimulation level of $i$.
2. **The Depressant Signal ($u_i$):** deactivates $i$ by lowering $v_i$.
3. **The Energy Resource ($r_i$):** the energy resource of effector $i$, which depletes while $i$ is active.
4. **The Effector Activity ($z_i$):** the activity of $i$, which is a sigmoidal transform of $v_i$.

The activity dynamics of the Effector layer are as follows:

$$\frac{dv_i}{dt} = \frac{1}{\tau}\left(-\lambda u_i v_i + r_i'\left(1 - \psi \sum_{j \in E: j \neq i} z_j\right)\right);\ v_i(t=0) = 0$$

$$\frac{dr_i'}{dt} = -\varphi r_i z_i;\ r_i'(t=0) = r_i$$

$$\frac{du_i}{dt} = -\rho u_i + \frac{\gamma r_i' z_i}{d_i + \epsilon};\ u_i(t=0) = 0$$

$$z_i = f(v_i) = \frac{1}{1 + \exp\left(-\beta_z (v_i - \mu_z)\right)}$$

The parameters of the Effector layer equations are:
$\tau = 1, \lambda = 20, \psi = 1.2, \varphi = 1.2, \rho = 0.1, \gamma = 0.1, \beta_z = 200, \mu_z = 0.1.$

The Effector layer demonstrates two salient qualities:

1. **Robustness** – input variations that preserve the activity sequence preserve the general shape of the output. Thus, the system is robust to meaningless noise.

**2. Sensitivity** – changes in sequence cause changes in resultant shape. Thus, the sensitive to meaningful noise.

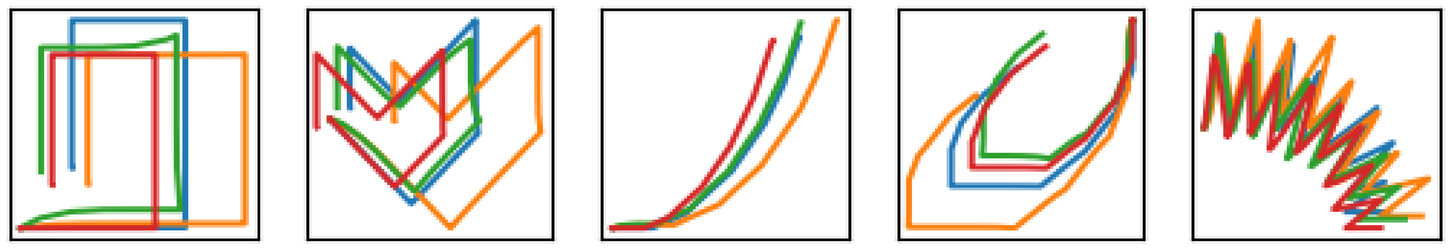

*Figure 2: Doodles produced from 5 different activity sequences. Each plot has 4 widely-varying activity patterns that preserve the activity sequence and therefore the general doodle shape.*

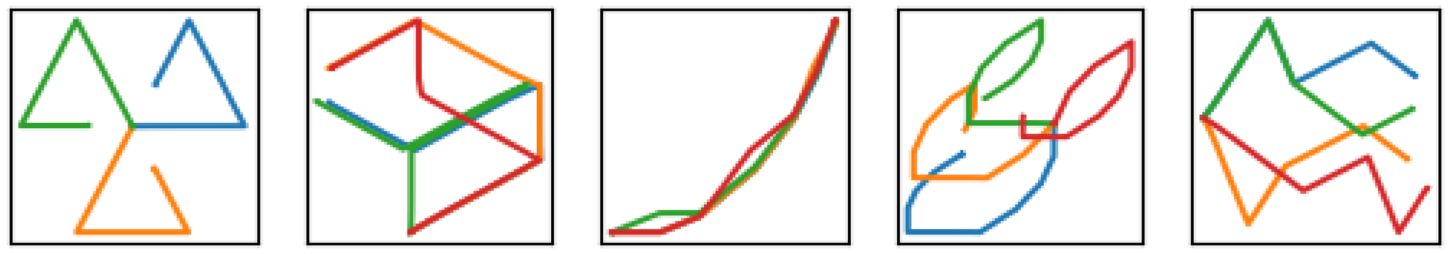

*Figure 3: Doodles produced from 5 different activity sequences, with 4 examples of changes in activity sequence in each plot.*

## LEARNING ALGORITHM

- The model is trained over 1000 epochs.
- During each epoch, the Map layer iteratively propagates forward a signal from which the Effector layer generates a doodle.
- The signals have a decreasing amount of noise throughout training, so early signals are nearly entirely noise.
- As the map encodes higher quality doodles, the map has greater influence on the signals.
- Each doodle is evaluated based on sufficient length and smoothness of curve.
- High-quality curves are encoded in the Map using an SOM learning algorithm.

## RESULTS

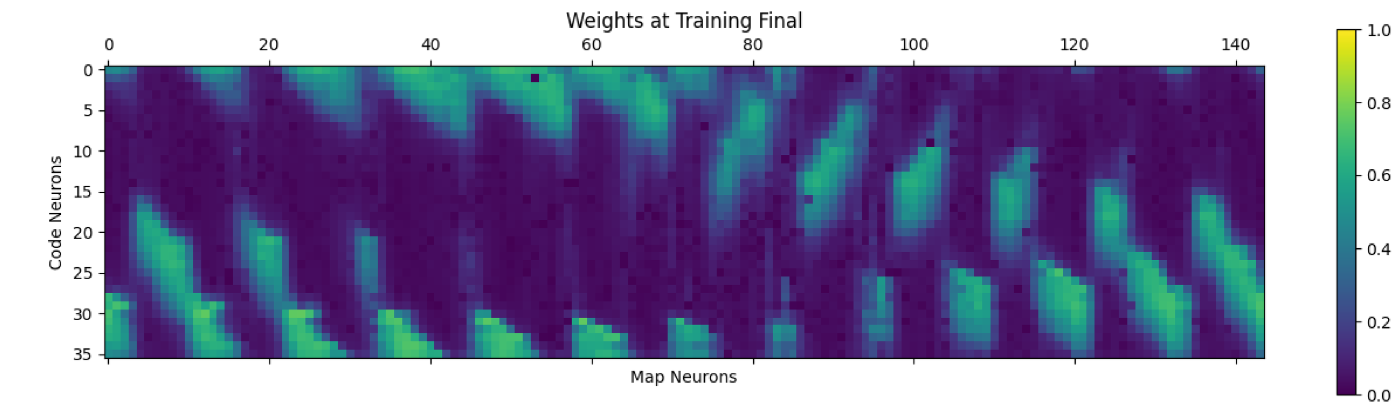


*Figure 4: The final model weights between Code and Map layers.*

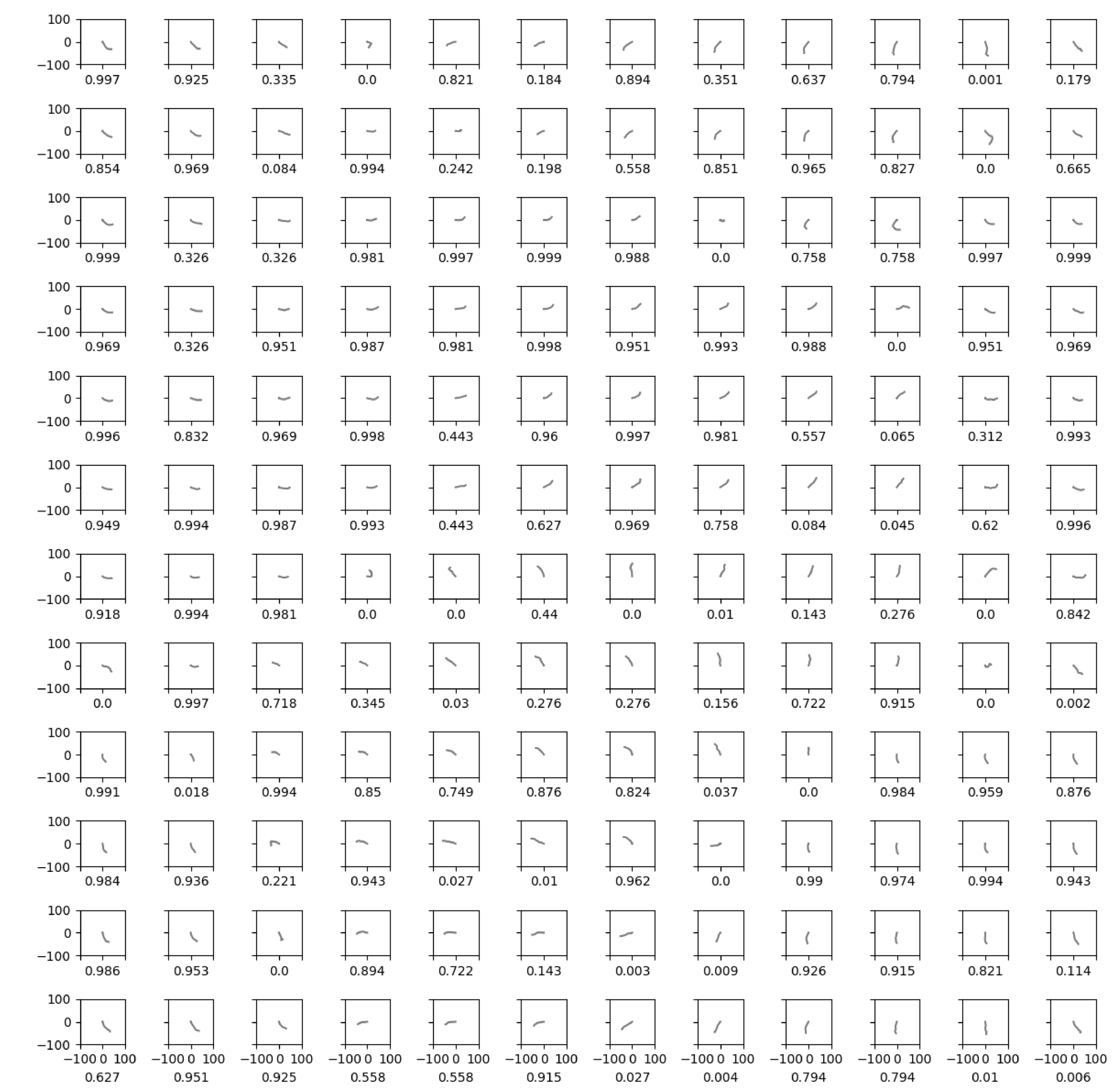

*Figure 5: The final doodles generated by each neuron in the Map layer.*

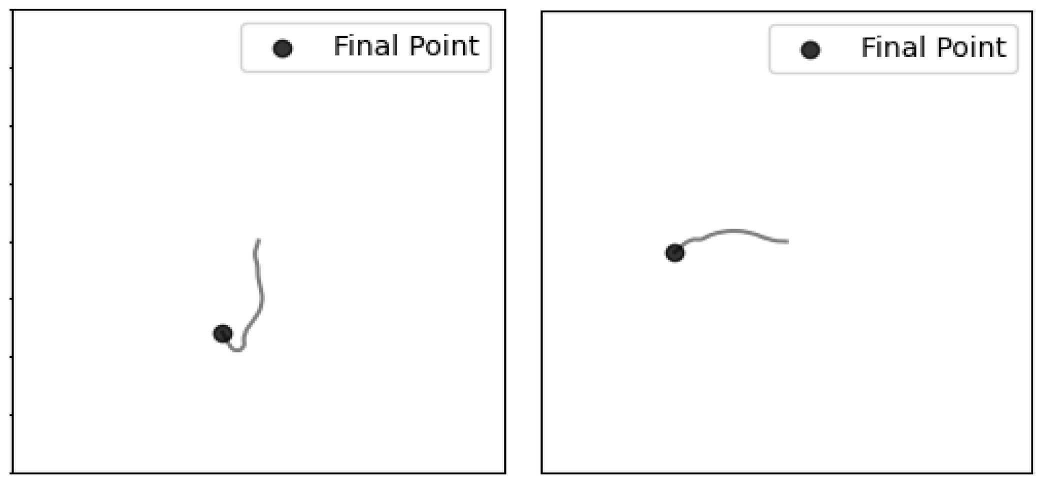


*Figure 6: The initial doodle (left) and the final doodle generated by one map neuron (right).*

## REFERENCES


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