Manifesting Multiple Personalities in a Single LSM
Via Controlled, Instantaneous Synaptic Weight Changes

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Introduction:
We are attempting to figure out the physiological changes in the brain when someone with multiple personality disorder switches between personalities. To do this, we take a single LSM and try to implement both personalities on the same LSM, with a switch between personalities occurring with the least possible number of controlled changes to the synaptic weights. The “personality” is defined by the consistent response of the LSM to a given set of inputs. For example, we may take two personalities on the same LSM called Personality A and Personality B. Personality A and B respond to the same set of inputs to give two different but consistent outputs each.

Aim:
For our study, we are using the LSM proposed by Zhang et al (2015) and improved by Saraswat et al (2021) on the TI-46 Spoken Digit Recognition dataset. Our aim is to obtain two distinct “personalities” on the same LSM model. Personality ‘A’ will respond to the inputs with the correct outputs, i.e a spoken 0 will be classified as 0 and so on. Personality ‘B’ will respond to the inputs with predetermined incorrect outputs, (eg. a spoken 5 will be classified as 4, and so on) but these outputs will remain consistent throughout the input data. We intend to achieve this through minimum change to the synaptic weights of the LSM.

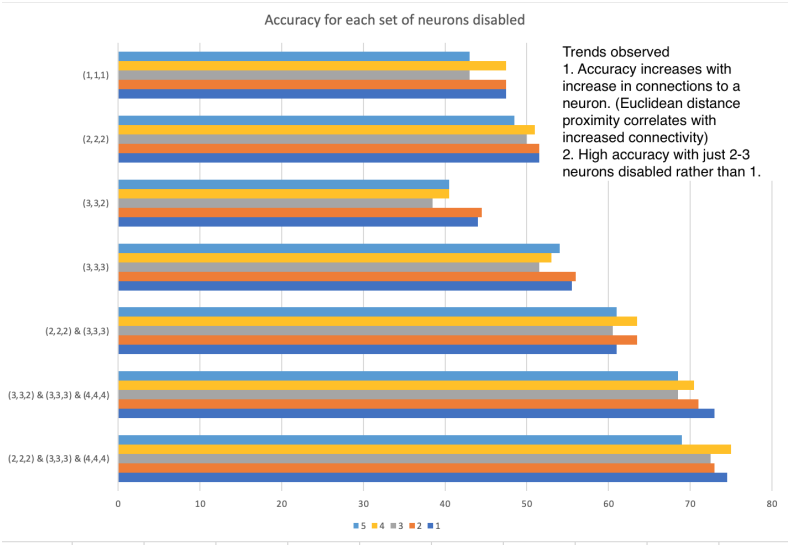
Theory:
Based on [DOI: 10.1177/155005940603700314] and [DOI: 10.1016/S0193-953X(18)30285-5], we make the hypothesis that different personalities can be said to manifest in the brain physiologically when different neural pathways are followed for the same input. Since there can be only a discrete number of personalities manifested (as opposed to a spectrum or a mix), the physiological switching mechanism between them must be ‘*digital*’. By digital, we mean that a physiological examination of the brain must unambiguously tell us which personality is currently active. Hence we rule out analog mechanisms like synapse strength, chemical concentration, etc. Since each personality remains consistent, and the person can go from A to B and back multiple times, we can say the mechanism must be ‘*repeatable*’. The mechanism must not change the structure of the brain since the difference between two personalities is less than the difference between two different people. Hence the mechanism must be ‘*simple*’. We also note that a simple mechanism has better repeatability. Due to these 3 characteristics, we choose the switching mechanism to be based on disabling and enabling a small set of neurons in the reservoir.

Method:
In order to maintain one LSM structure across the two personalities, the preprocessing of data to input neurons and the creation of connections between reservoir neurons is run only once. Subsequently, a controlled number of neurons are disabled via setting their fan in and fan out weights to zero in the given LSM structure and this configuration is saved separately.
The inputs are then processed separately for these two configurations (call them personalities ‘A’ and ‘B’) and the processed neuronal spikes are stored separately as well.

Given the TI-46 dataset, our aim is to measure the prediction probability such that personality A labels a ‘0’ sound as 0, a ‘1’ sound as 1 and so on, and personality B labels a ‘0’ sound as 9, a ‘1’ sound as 8 etc. This is so that the two personalities give different but consistent outputs to the same set of inputs.
To achieve this, the DATA consisting of the raw sound input, its label and the processed neuronal spikes for personality A is concatenated with the DATA of personality B with the labels reversed and having it’s own processed neuronal spikes. This concatenated DATA is then trained and tested in order to measure the prediction power of the entire singular LSM (consisting of two configurations A and B) to give a consistent output between its two personalities. The single classifier attempts to run both configurations and hence, its accuracy increases with an increase in the difference between the personalities.

Results:

We can clearly see that there is a correlation between the difference in personality and the difference in the two structures. We also see that the same LSM classifier can have two completely different outputs when simple changes are made in the reservoir.



The center neuron has more chances to be connected to multiple neurons compared to the (2,2,2) neuron (and so on). Hence switching it off makes a larger difference as compared to the neuron located slightly off the center. Since the synapses are probabilistically present based on euclidean distances, we hypothesize that the topology of the reservoir affects this phenomenon in a large manner. The current cube topology is very sparsely packed. A more dense reservoir topology would mean that a single neuron being turned off or on can have an even larger impact on the personality.

Further Considerations:

Some stretch goals for this project are: analysing the output and running classification based on the temporal response of the neuron rather than a time-average of the output spikes, and visualising this temporal activity as the Liquid State Machine progresses in time to see the step-by step changes in neuronal firing taking place inside the LSM.
Through this project, we have aimed to discover in a unique fashion the inner workings of an LSM which so far has proved itself to be a black box to modern science. By making fine structural changes to an LSM, we have attempted to make a correlation between physiological changes and their effects such as multiple personality disorder. We hope that our humble attempt at manipulating the reservoir to produce desirable results will go a long way towards completely working out the functioning of the reservoir in the future and help train it.