Cellular Automaton

And

Spiking Cellular Automaton

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# Introduction

TODO: references

Biological neurons form the brain and its network of sensory inputs and motor control outputs in animals, including humans. Individual neurons communicate with each other by sending spikes of voltage along axons and receiving them on dendrites. Understanding how this system works is one of the keys to diagnosing and treating neurological disorders. Imitating the system has been successful in achieving limited artificial intelligence in fields such as image recognition and behaviour prediction.

# Biological Neurons

## Neurons

A neuron is a living cell that has many points of input (called dendrites) and a single output (called an axon) [1]. The neuron is affected by a number of ion channels that allow the concentrations of Sodium (NA), Potassium (K), Calcium (Ca) and Chloride (Cl) ions to change over time, at rates which depend not only on their current concentrations, but also influenced by input voltages applied through the dendrites and the presence of chemicals such as neurotransmitters. A neuron responds to changes in the concentrations (often but not always a potential threshold being crossed) by generating spikes of voltage on their axon. The axons connect to the dendrites of other neurons via synapses. Cells in the brain typically have around 10,000 synaptic connections, up to as many as 100,000 in some cases.

A picture containing text, vector graphics

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Figure Structure of a Typical Neuron

dhp1080 - Creative Commons License - <https://commons.wikimedia.org/wiki/File:Neuron.svg> – accessed 2021-01

In the 1950s a model of the behaviour of a giant squid neuron was developed through experiment [2] [7]. Known as the Hodgkin Huxley Model it is a 4-dimensional family of exponential differential equations, describing the changes in state of the neuron and its potentials over time. These equations have been used to describe other neurons in other species and a wide variety of configurations exists [2, pp. 46-48] leading to different behaviours, both in how a neuron becomes excited enough to trigger a spike, and the shape and pattern of the spikes generated.

The giant squid neuron is also not representative of all the possibilities. “At least a dozen types of ion channel can be involved in the spike generation of human neocortical neurons.” [1, p. 33].

Examples of distinctly different spiking behaviours are neurons which produce a single spike, or a sequence of repeating spikes, or a rapid burst of spikes followed by a quiet period. While many neurons fire in response to a potential threshold being crossed in response to input spikes it is by no means all [2, pp. 238-239], some respond to incoming spikes only at the correct resonant frequency [2, pp. 232-235] and there are others which emit spikes in response to a *decrease* in their inputs [2, pp. 244-246].

Information flows from one neuron to another in the number of spikes transmitted, the time between the spikes [1] [2], and the time taken for them to travel down the axon [3] [4]. To what extent each of these is significant is still open to debate, but all of them have been shown to increase the theoretical computational power of a neuron.

## Spikes

The response of a neuron to an excitatory input is often modelled as a sigmoid curve, which is useful when doing mathematical analysis, but not representative of what is seen, since it doesn’t inherently show the output rapidly falling back to zero. The spikes generated by neurons tend to show a rapid rise in voltage followed by a slower exponential decay [8] but there is quite a bit of variety possible even within a single neuron, depending on the input it receives.

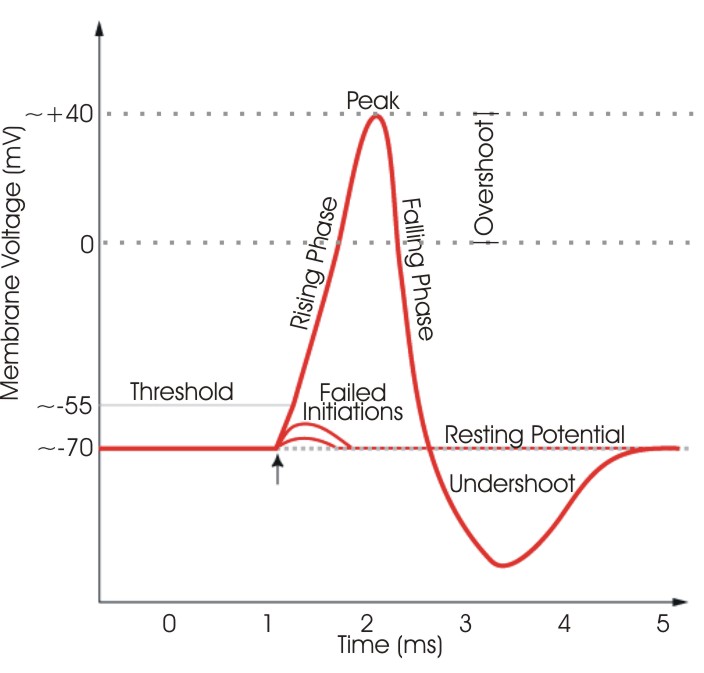


Figure Action Potential

Original author Synaptidude at English Wikipedia. GFDL 1.2, <https://commons.wikimedia.org/w/index.php?curid=6030880>. Accessed 2021-01-31

Typical spikes have a peak voltage of the order of a few millivolts and last for up to a few tens of milliseconds. The neuron producing the spike will generally have a refractory period following it during which it will be unable, or at least very reluctant, to produce another spike.

## Inhibition

## Noise

## Brain Structure

## Consciousness and Wakefulness

# Artificial Neural Nets

The first artificial neuron was designed in 1943 [7], and since then there has been a great deal of progress, with neural networks now in use in a wide range of fields, from image recognition to self-driving cars.

## Feed-Forward Networks

A common use case of computational neural networks has been data classification (such as image recognition), and this is typically achieved with a feed-forward network in which neurons are arranged in layers with each layer sending data to the next (Figure 3).

Diagram

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Figure A feed-forward neural net with one hidden layer

The operation of such a system is a single processing event. Inputs are received in the input layer, information flows through the network, and the result is seen in the output layer.

## Recurrent Networks

The human brain clearly does not only act in response to external stimulus. An input triggers processes involving memories of previous inputs that were similar in nature (associative memory [1, p. 147]). This can be mimicked by adding state to the network. Figure 4 shows the network from Figure 3 expanded to include feedback nodes in the hidden layer.

Diagram

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Figure A variation on an Elman Recurrent Neural Network

This arrangement would form an IIR LRNN (Infinite Impulse Response Locally Recurrent Neural Network) of a type known as an ENN (Elman Recurrent Network). FIR (Finite Impulse Response) network designs also exist, as do nonlocal recurrent arrangements. IIR RNNs have been shown to be effective at making predictions from time series of discrete inputs [7] and predicting failure of engineered components and systems [8].

## Wakefulness

The neural net described above can be augmented with a new input, one which is always on and feeds into the memory nodes. It would not be appropriate to refer to such a network as conscious (even defining what it means to be conscious in this context is troublesome [9]), but it will have an output even when deprived of all other inputs. With more locally recurrent hidden layers it could even have an output which changed over time, which brings it one very small step in the right direction. An artificial neural network which is considered conscious is referred to as a strong AI, and to the authors knowledge no strong AIs exist at this time.

## Generations

The first artificial neurons had a binary state; they were either on or off. A network of such neurons is often referred to as a 1st generation neural net [11]. 2nd generation networks allow for real valued outputs and inputs, which can be thought of as representing the rate of fire of spikes from a biological neuron. Neural networks which use spikes, and thus attempt to mimic the behaviour of biological neurons more closely, are considered 3rd generation. A key difference between 2nd and 3rd generation networks is that timing of spikes becomes important, whether in the form of propagation delays [4] [5] (comparable to axon transmission speeds), delays between spikes [1] [2] (a burst of spikes followed by silence may trigger a response that a regular series of spikes would not, or vice versa) or coincidence (spikes received simultaneously from multiple sources may trigger a response where staggered arrival times would not). This increases the potential for information flow between neurons, and 3rd generation networks have been shown to have more processing power per neuron than 2nd generation, but at the price of greater complexity [1] [2] [4] [5].

## Spiking Neural Net Models

The Hodgkin Huxley model is complicated and correspondingly slow to simulate (Izhikevich approximates it to 1200 FLOPS per neuron per iteration [12]). Faster approaches to it have been proposed [9] and it is interesting from a biological point of view, but for a large and/or fast neural network in software we need to look for alternatives.

There have been many SNN models developed for this purpose, with different goals and advantages [11] [13] [14].

### Leaky Integrate and Fire

Integration is a repeating theme in many spiking network models and refers to summing up incoming spikes over time. This is comparable to the biological process of spikes encouraging the movement of ions across the cell membrane, with the integral mapping to the membrane potential. A leaky integrator is one in which the potential decays over time. A LIF (Leaky Integrate and Fire) neuron [1] [15] is one which integrates incoming spikes into its potential, leaks over time, and fires a spike of its own if its potential exceeds a predetermined threshold.

A LIF neuron with a very slow leak acts mostly as an integrator, which makes it indifferent to the timing of incoming spikes, and as such is difficult to distinguish from a 2nd generation neuron.

A LIF neuron with a very fast leak acts as a coincidence detector. Incoming spikes separated by quiet periods will leak away and the potential only reach the threshold if many spikes are received at the same time.

An equation for a simple LIF neuron, excluding tests for the threshold being exceeded, is shown in Equation 1.

Equation LIF Neuron

When a spike is fired the potential is reset. Some models may also apply a refractory period [1], or attempt to mimic one by resetting to a potential below zero.

Variations of the LIF theme have been proposed, including quadratic formulas [12]. The Mihales-Neibur [16] neurons are essentially multiple LIF systems combined into one, and can give rise to bursting, rebound spiking, bistability and a number of other behaviours seen in biology but absent from the basic LIF behaviour described above.

### Izhikevich

In 2003 a neuron model designed to give the spiking patterns seen in biology at a low computational cost was developed [17] and uses two internal variables instead of a single potential. This can be thought of as roughly corresponding to two different ion concentrations in the cell membrane (specifically Sodium and Potassium).

An Izhikevich neuron is able to exhibit 20 different spiking behaviours using two simultaneous differential equations, one quadratic and one linear, and can be an integrator, coincidence detector or resonator, and does so using only 13 FLOPS per neuron per iteration.

The dynamic state of an Izhikevich neuron is given by Equation 2.

Equation Izhikevich Differential Equations

And this is coupled with a firing threshold (V > 30) and a reset behaviour when a spike is fired (Equation 3).

Equation Izhikevich Reset Behaviour

V, u, a, b, c, & d are all stated to be dimensionless, although the spiking threshold of 30 is given in millivolts. The mismatch does not cause any problems.

### Kumar et al

Kumar et al [12, pp. 24-30] present an alternative model to Izhikevich, again with only two equations. They refer to Izhikevich as inspiration and provide a similar set of possible output forms. It is not clear why this model might be preferred over Izhikevich, but it demonstrates biologically similar behaviours in response to short pulses of DC current, where Izhikevich seems inclined to use a unit step function as input. This is encouraging in a system that will be using spikes as inputs. The dynamic state is given in Equation 4, and the reset behaviour is identical to that of Izhikevich.

Equation Kumar Differential Equations

Unfortunately, the paper in which this method is described does not provide example values of the parameters used to obtain different output types, which makes it difficult and time consuming to use.

### True North

IBM have developed a True North architecture [14] with the goal of creating a neuron model that can be effectively implemented in custom hardware "sufficient to support useful and interesting cognitive algorithms, while the cost should be no more than necessary in terms of power, area, and speed".

They state "we were able to qualitatively replicate the 20 behaviors of the Izhikevich dynamical neuron model using a small number of elementary neurons" which is interesting, since it implies a simpler model that has the Izhikevich model emergent from it, and emergent behaviour is relevant to this project.

There are some oddities of True North, however, with regards to its response to input spikes. Many of the repeating or bursting behaviours it can exhibit are triggered by a single spike, of any weight at all. A spike with a weight of 0.001 can cause a series of output bursts. This means that it is not acting as an integrator or coincidence detector in these configurations, and problems arising from this are referenced in section 4.2.

### Spinnaker

The SpiNNaker system [18] approaches the performance problems of large spiking neural nets by simulating them on 1 million arm cores, and by doing so is able to run many spiking models, including Izhikevich, for 1 billion neurons at biological real time. For the Izhikevich model real time means 1 iteration per millisecond [17]. SpiNNaker is not a model in its own right, but a hardware system on which they can be run. Its existence and scale, however, is a strong indicator of the important role efficiency and speed will play in any implementations of SNNs.

## Stochastic Behaviour

## Available Software

Software already exists for simulating neural nets, of all three generations, some commercial and some open source and freely available. IBM make software simulation of the True North architecture an option [12]. Nest provides a python module which can simulate many neuron types (including Izhikevich) [13]. OpenSourceBrain provides an enormous suite of neural net related simulation software [14]. Annarchy makes an impressive attempt at overcoming the difficulties of efficiently simulating spiking neural networks by exposing a scripting interface that automatically generates C++ networks on the users behalf [15]. This is far from an exhaustive list.

What all these solutions have in common, however, is that they cater to the traditional use of neural nets as a device which learns (or at least has the capacity to learn) and then applies what it has been taught. The goals of this project are sufficiently unique that a custom software solution has been chosen instead (see section 6).

# Automatons

## Life

A cellular automaton is a regular arrangement of discrete cells in which the state of each cell depends on the state of its neighbours, such that the cells change state over time.

A popular cellular automaton is Conway’s Game of Life [5] in which each cell is either ‘alive’ or ‘dead’ and changes between those states depending on the number of live immediate neighbours it has. Complex behaviour emerges from the simple rules.

## Goals

The goal of this project is to make a cellular automaton in a similar style to Conway’s Game of Life but using a biologically inspired spiking neuron model for the cells. This provides an opportunity to experiment with and investigate the behaviour of the chosen SNN models, but also extends an unusual requirement to them. A feed forward neural net is generally given an input and provides an output. A recurrent network may receive a series of inputs over time and have memory like nodes modifying its behaviour based on its past. An automaton does not necessarily have an obvious input, nor output, but is instead expected to act on its own state and to continue changing over time, possibly indefinitely. It is for this reason that a short introduction to wakefulness was presented in section 2.6. It would be very unreasonable to suggest that a simple automaton is awake, but achieving continuous activity without an external input is a challenge in its own right, and gives rise to a number of questions that need to be answered.

The automaton needs to avoid quickly collapsing into a quiescent state. For this to be true the number of neurons which fire as a result of N other neurons firing must average at least N. However, if the average is greater than N then we can expect the automaton to quickly saturate instead, with everything firing as fast as it is able, which is not our intent. Life avoids this by killing any cell that has 4 or more neighbours, but it does not seem appropriate to directly prevent a neuron from firing when it is overstimulated. Instead we expect to need inhibitory behaviours to maintain balance. These can be simple negatively weighted inputs (subtractive), “shunting” in which a connection decreases the effectiveness of excitatory inputs (divisive) [1, p. 22], or fatigue [1, p. 35].

The potential of a neuron in most of the described models can grow without limit and is only prevented from doing so by the reset that follows a spike being fired. However, although the Izhikevich model can act as an inhibitory neuron and even mimic the output of the biological ones in the brain, there does not appear to be anything limiting the negative potential a neuron can have. This will not be a problem with shunting inhibitions, but otherwise seems to part of a common theme through all the literature reviewed here - the existence of inhibitors, whether neurons or otherwise, is acknowledged but mostly ignored. We suspect this is because most work on neural nets has been geared towards forward connected nets that respond to an input event, rather than a continuously updating system such as our automaton that needs to self-regulate.

IBM make many arguments for combining multiple kinds of neuron [14] and our design will account for this from the start, and should be able to incorporate the need for inhibitory neurons.

There are many references to stochastic integration (a random chance of synapses being integrated) and noise, with noise being given as an explanation for the speed of the brains response to visual stimuli [1] [2][14]. Unfortunately, any random influence will break repeatability in our automaton. The same pattern of inputs to an automaton would usually result in the same behaviour, regardless of where or when it occurs, and we would rather respect that than take the biologically more realistic stochastic approach.

A similar argument can be made about learning. Individual neurons should not begin changing their associated synapse weights if we want our automaton to have consistent and repeatable behaviour. There is also the problem that the automaton has no output, other than its own state, which makes the usual Hebbian teaching mechanism difficult to imagine. There is no clear “correct” result to propagate through the network and learn from.

# Objectives

Conway’s objectives for the Game of Life [5] serve as a starting point for the objectives for this project:

1. “There should be no initial pattern for which there is a simple proof that the population can grow without limit.”
2. “There should be initial patterns that apparently do grow without limit.”
3. “There should be simple initial patterns that grow and change for a considerable period of time before coming to end in three possible ways: fading away completely (from overcrowding or becoming too sparse), settling into a stable configuration that remains unchanged thereafter, or entering an oscillating phase in which they repeat an endless cycle of two or more periods.”

Additional objectives have been added, relating to the use of SNNs:

1. Information flow between cells must be in the form of spikes similar in nature to those conveyed by axons in biological nervous systems.
2. The behaviour of the automaton should be distinguishable from behaviours which are possible with a 1st or 2nd generation neural net.
3. There will be a deliverable from the project in the form of a piece of software that can be used to experiment with different neuron models and configurations in an automaton.
4. It will be possible to easily configure the software to run an automaton which meets objectives 1 to 5.

Objective 1 is rather vague (especially since the game of life itself has some simple examples that do grow without limit [5]) but its intention serves as a guideline.

We have no proof that objective 5 is possible, but provide a tentative argument that it has been achieved in section 7.

# Software Design

This project is entirely software based. Where possible platform independence has been aimed for, but the Microsoft Windows OS on an x64 architecture is the primary target, and Visual C++ the project format and language.

The MVC (Model View Controller [23]) pattern has been used, with a particular focus on keeping the view separate from the rest of the program. This has allowed multiple views to be created, as an automated test framework (NeuronTest), a GUI for editing and executing networks (Neuron), and a simple genetic algorithm (Genetics). All of these link to and use a simulation library (NeuronSim) which does most of the work. NeuronSim is written in pure C++ and has no external dependencies beyond the runtime libraries. NeuronGui uses the Qt library for a cross platform GUI interface. All of this software is available from <https://github.com/adn510/Neuron> but will require Qt and Visual C++ (both available for free) to build.

## Layers and Synapses

## NeuronSim

A simplified UML diagram of the NeuronSim library is shown in Figure 5. The Automaton class is the primary interface, but the layers and synapses it contains can also be created and used in isolation, which is useful when testing and in one or two other places. The expected use case is that an Automaton is created with a desired width and height, and is then used to create layers and synapses. These are configured independently. Running the automaton simply requires the tick() function of the Automaton class to be called repeatedly, once per iteration.

Diagram

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Figure NeuronSim Class Diagram

## Object Orientation, Data Orientation and Threads

Object-oriented design has been used for most of the software, in the manner common to C++ for most of the code base and augmented with signals and slots for the GUI in keeping with the Qt architecture. However, there is a requirement for speed when dealing with neural net simulations, and the regular grid layout of the automaton provides an opportunity to take a more data-oriented approach to the inner loop.

First, each neuron within a given layer has the same configuration as all the rest, and so that data can be moved out of the neuron and into a specialization of the layer. By doing this we save a lot of memory, but we also hope to reduce the number of cache misses that occur while iterating through the grid. The neurons themselves are simple structs rather than classes, and are treated as POD throughout.

Layers interact with each other only via spikes. By separating this interaction into two phases within the tick() function it is possible to process each layer in isolation, the first phase pushing spikes onto layers and the second phase processing the layer and outputting spikes. This means a separate thread can be used for each layer (see Figure 6) without any overhead in mutex locks, which is a significant performance improvement for multi-layer networks. The program is still basically single threaded and only divides temporarily while iterating through layers, which prevents a lot of the complexity associated with threading from permeating the rest of the code base.

Diagram

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Figure Multithreading Pathways

# Automaton Design

## LIF inhibited feedback loop

# Ethics

We do not anticipate any ethical issues arising in this project, beyond those typical of any other software project. This specific research will make only sporadic use of one computer.

From an environmental point of view it may be worth noting that neural nets are very processor intensive and that if projects of this nature became common place we would expect them to drive a similar energy consumption pattern to that seen in bit coin mining (which is more energy intensive than actual mining [6]). Purpose built hardware should mitigate this effect to some extent.

# Further Research

# Biological Neurons

## Neurons

## Spikes

## Phase Diagrams and Bifurcations

If the state of a neuron, or indeed anything, can be represented with N variables, then it can be considered as a point in an N dimensional space of possible states. If the behaviour can be represented as a rate of change over time of the N variables then the behaviour can be considered as a set of N dimensional vectors within that space, each indicating the direction and magnitude of the differentials at a point [2, pp. 8-20]. A diagram of these arrows is called a Phase Space plot.

If all the arrows on the plot near a point tend towards it then that is a stable point of equilibrium. Small perturbations to the state will not result in lasting changes. If the arrows all tend away from a point it is an unstable equilibrium. If the arrows tend towards a point along one arbitrary axis but away from it along another it is called a saddle. A set of arrows forming a loop is called a limit cycle attractor.

We will consider two-dimensional phase spaces here, for simplicities sake, but remain aware that biological neurons have more (Hodgkin Huxley has 4 for example). A diagram a 2D phase space is shown in Figure 3, showing a saddle-node bifurcation. The system will rest at the stable equilibrium, and small inputs will have no lasting effect, but any change to the state moving it to the right of the saddle node will cause a significant change in the behaviour, possibly resulting in the limit cycle being reached.

If this diagram were to represent a neuron with the potential on the horizontal axis then we can see we have a coincidence detector that ignores small increases in potential but, on receiving one large enough to cross an internal threshold, begins firing spikes repeatedly until inhibited by an external influence.

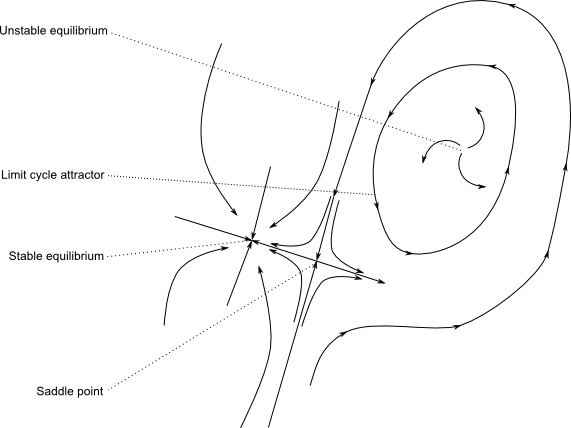


Figure Features of a 2D Dynamical System (recreated in the style of Izhikevich [2, pp 17])

There are four possible kinds of bifurcation in such a system [2, p. 11], depending on whether there exists a saddle node, and whether there exists a limit cycle. For a single model of neuron behaviour to be able to exhibit a good range of different types of behaviour it needs to be configurable to act as any of the four. Those without limit cycles fire only one spike in response to excitation, and those with no saddle node act as resonators instead of integrators.

## Computational SNNs

The Hodgkin Huxley model is complicated and correspondingly slow to simulate. Faster approaches to it have been proposed [9] and it is interesting from a biological point of view, but for a large and/or fast neural network in software we need to look for alternatives.

There have been many SNN models developed for this purpose, with different goals and advantages [10] [11] [12].

A simple and well-known model is Leaky Integrate and Fire (LIF) of which there are several variants. Each neuron has a potential that decays (leaks) over time, incoming spikes increase it, and a spike is generated if the potential passes a predefined threshold. An LIF neuron with no leakage is an integrator – it has a potential which is the sum of all incoming spikes over time. An LIF neuron which leaks extremely fast is a coincidence detector – it has a potential which will only cross the threshold if multiple spikes are received simultaneously [1] [2]. An integrator is essentially the same principle as a 2nd generation neuron (it cares only about the number of spikes emitted, not the timing of them) and as such probably cannot be used to meet our 5th objective (behaviour distinct from that of a 2nd generation network). LIF neurons also cannot reproduce many other behaviours of their biological counterparts, such as resonance and bursting – they cannot form the four bifurcation types.

An equation for a simple LIF neuron, excluding tests for the threshold being exceeded, is:

An often referenced alternative is a 2D model named after its creator Izhikevich [13] which is able to exhibit 20 different spiking behaviours using two simultaneous differential equations, one quadratic and one linear, and can be an integrator, coincidence detector or resonator, which makes it far more interesting for our automaton. Izhikevich can behave as any of the four bifurcation types. Furthermore, we can see no way to create such a system using less than 2 variables, and we doubt it is possible with two variables without at least one quadratic (because a bifurcating system needs two nodes and we don't get that without two solutions to our equation) which means the Izhikevich model may be the simplest possible to meet our requirements.

The dynamic state of an Izhikevich neuron (again excluding threshold responses) is:

Kumar etal [12, pp. 24-30] present an alternative model to Izhikevich, again with only two equations. They refer to Izhikevich as inspiration and provide a similar set of possible output forms. It is not clear why this model might be preferred over Izhikevich, but it demonstrates biologically similar behaviours in response to short pulses of DC current, where Izhikevich seems inclined to use a unit step function as his input. This is encouraging, since we will be using spikes as our inputs and a DC pulse is more representative. The equations used include an exponential, which makes them a little more complicated, but if they also give better results it will be worth it.

## Hardware SNNs

IBM have developed a True North architecture [14] with the goal of creating a neuron model that can be effectively implemented in custom hardware "sufficient to support useful and interesting cognitive algorithms, while the cost should be no more than necessary in terms of power, area, and speed".

They state "we were able to qualitatively replicate the 20 behaviors of the Izhikevich dynamical neuron model using a small number of elementary neurons" which is interesting. It implies a simpler model that has the Izhikevich model emergent from it, and emergent behaviour is a good thing in cellular automatons.

The algorithm works entirely in integer (fixed point) arithmetic, which is great for hardware implementations but means we may need a different kind of synapse matrix and spike to implement it in our own code, which could prove awkward. Fixed point maths is possible in software but not generally built into the available languages. We might assume that using floats instead will be close enough.

## Challenges Presented by Cellular Automata

Our automata will not learn, which excludes a large amount of the complexity of neural nets from the project. However, other issues do need to be addressed.

## Performance

An effective automaton needs to be fairly large, in order to provide enough space for interesting behaviours to emerge. This means it also needs to be fairly fast, so as not to take an unacceptable amount of time to execute. No precise definition of “fairly large” or “fairly fast” is available.

Izhikevich claims a 1ms simulation time for 10,000 neurons with 1,000,000 synapses on a 1GHz PC [13]. That is only a 100x100 grid of neurons, which is rather small for an automaton and would limit the size of feature we could hope to detect. It is also only 100 synapses per neuron, rather than the 10,000 typical of the brain [1]. There is a balance to be made between designing for speed and premature optimization and we will try to be reasonable, but it is obvious even without profiling that efficiency will be an important factor here [10] [11].

Note that an automaton of this nature is extremely parallelizable and any attempt to fully optimize it should almost certainly be targeting a GPGPU. This project needs to be flexible and will therefore target the CPU, and consequently the investigative phase will only aim to be fast enough to be usable, rather than as fast as possible.

# Requirements Specification

Because we begin this project with no idea what kind of SNN will allow us to meet the objectives, or how it will need to be configured or connected, the software we produce will need the flexibility to run many different configurations to allow us to search for one.

1. The software implementation will be organized according to the Model/View/Controller pattern
2. The software will allow different sizes of automaton to be modelled
3. The software will allow the simulation to be run at different speeds, stopped, or stepped one frame at a time
4. The software will allow selection of different neuron models
   1. There will be a LIF (Leaky Integrate and Fire) model
   2. There will be an Izhikevich model [13]
   3. There may be other models
5. The software will allow easy configuration of the selected model
   1. Any appropriate parameters will be made available for change via the GUI
   2. It will be possible to persist interesting combinations of parameters for reuse
6. The software will allow different spike shapes to be configured
7. The software will allow different connection patterns of neurons via synapses to be configured
   1. There will either be a synapse matrix editor built into the software or it will have the ability to load synapse matrices from image files
8. The software will display an animation of the automaton as it progresses
   1. The software may provide alternative display styles such as spikes vs neuron potentials
9. The software will allow different starting states to be configured.
   1. There will either be a state editor built into the software or it will have the ability to load states from image files
10. The software will allow a given starting state to be reused
    1. A given starting state, used multiple times with the same model and configuration, will give the same progression and end state each time

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