Predicting seizures with artificial neural networks

Matthew Wootten

Jeremy Angel

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Artificial neural networks (referred to here as ANNs or just "neural networks"), are a loose mathematical model of how the brain functions. They can be used to form remarkably good algorithms for problems that hand-designed algorithms cannot practically solve, such as recognizing complex features in images and signals. An ANN is a network of artificial neurons, which each perform a simple computation, which varies based on the type of neural network. Some of these are input neurons, which take input from the outside world. All other neurons take their state from other neurons in the network. Some neurons serve as outputs, which take on values that encode the solution. These networks become useful when they are trained, a procedure that gives example inputs so that the network "learns" to correctly classify outputs (Schmidhuber, 2015).

ANNs are a large class of very different models. While all ANNs are composed of connected neurons, they differ by the connections between those neurons (*topology*), and in the behavior of the neurons themselves. These differences enable a specific *architecture* to be tailored to a specific application (Schmidhuber, 2015).

Feed-forward and *recurrent* neural networks are two of the simplest ANN topologies. A feed-forward neural network consists of a number of "layers" of neurons. Each layer is connected only to the previous layer as input and the next layer as output. Recurrent neural networks, on the other hand, are less strictly defined. Neurons still have

inputs from the previous layer, but also loop back on themselves. This makes them strictly more powerful than the simpler feed-forward neural networks (Schmidhuber, 2015).

Another topology is the convolutional neural network, even more complex than feedforward and recurrent neural networks. In contrast to the mostly homogeneous layers of feed-forward and recurrent neural networks, a convolutional neural network is made up of two distinct stages: a set of layers that perform a convolution and a feed-forward or recurrent network. A convolution, conceptually, takes a large number of small sub-samples of the data. Applying a convolution reduces the volume of data, and also allows the network to better ignore small differences in the position of inputs that have no relevance to the outcome. This is especially useful for multidimensional inputs, like images (Schmidhuber, 2015). Multiple time-varying signals (such as EEGs) can also be used as inputs, as each signal can be treated as a separate dimension (Ren and Wu, 2014). This transformed data is then passed along to the second stage, where it goes through the network as described above.

The previous sections discuss the layout of the neural networks, but make no reference to how the neurons themselves function. There are two broad categories into which neurons fall: traditional and spiking. Traditional neurons take in a single value from each input; all of the inputs together form the input vector. This is then combined with a vector of weights (values that determine how important inputs from certain neurons are), usually by using the dot product, to get a single value. The *activation function* is applied to this value. Common choices are sigmoid functions, hyperbolic cotangent, and a simple $f(x) = max(x,0)$, known as ReLU (Schmidhuber, 2015). Each of the output neurons then receives this value. This process continues, cascading throughout the network, until the values are read out from the last layer, the output neurons.

Spiking neural networks are another class of neurons that more closely model how the brain works, and have recently outperformed traditional neural networks in some situations, because they require less power to compute (Lee, Delbruck, and Pfeiffer, 2016). Spiking neurons use a different model. Instead of taking a single value as input, it takes a time-varying value with rapid increases, called a *spike train*. The most common model for a spiking neuron is an *integrate-and-fire neuron*. Integrate-and-fire neurons are modeled as an exponentially decaying signal, with weighted inputs from other neurons added on (Lee et al., 2016).

Most spiking neural networks are single-spiking. Single-spiking means that for every input transmission a neuron in the network receives, the neuron outputs one spike at most. However, Ghosh-Dastidar and Adeli (2009) have described a multi-spiking neural network where each neuron can output more than one spike for every input transmission it receives. In a single-spiking neural network, a single connection (called a synapse) links each neuron to the layers next to it. In a multi-spiking neural network, each connection between neurons is made up of multiple synapses, and when a neuron outputs, it outputs along each of the synapses. Each of the synapses in a multi-spiking neural network have different weights and delays determining when the output is received and how much of an effect the output has on internal state of the receiving neuron. The internal state is what determines when a neuron fires. Ghosh-Dastidar and Adeli (2009) found that the multi-spiking neural network outperformed the single-spiking neural network with an accuracy of 92.3% while the single-spiking neural network achieved only 82% correctly detected siezures.

The network architecture alone does not account for any results it can achieve. A neural network must be *trained* in some way to become useful. Aside from the architecture of the network, which the network designer preselects, the only parameters the network

has are the weights. These weights are present in slightly different forms in both spiking and traditional neural networks. This can be treated as a multi-dimensional optimization problem, with each weight being a dimension, and the quantity to minimize is a function measuring how far the predictions are from correct (also known as a *loss function*). What "correct" means is often solved by first running through *training data*, data which has been pre-classified (Schmidhuber, 2015).

One highly useful technique for solving this optimization problem is known as *backpropagation*, which uses techniques from calculus to attempt to find an area where the slopes downward on the cost function (measures of how much of an improvement a nudge in that direction could make) are low. Gradient descent consists of taking large steps in the decreasing direction on the graph where there are large improvements to be made, and small ones where there are not (Schmidhuber, 2015).

Many older models of spiking neural networks, such as Cao et al. (2015), use looser variants of this basic backpropagation algorithm, because the derivative is not strictly defined where the spikes occur, as there is an instantaneous jump down in membrane potential. These models resort to training the network on traditional-neuron ANNs, or training with another algorithm entirely. Cao et al. (2015) used a traditional convolutional neural network, trained with backpropagation, and then transformed the weights for use on a spiking neural network.

Lee et al. (2016) more recently described a spiking neural network with single spikes, which therefore can support training directly on the spiking neural network, without the need for any transformation. They accomplished this by ignoring the discontinuities, which they found did not unduly reduce the network's accuracy. Also, while Cao et al. (2015) found that the spiking network was about 2% less accurate than the traditional network at detecting cars, Lee et al. (2016) found that the spiking network

performed about 0.4% better at the related task of classifying handwritten digits (they are both image classification problems, so they should have similar solutions).

Neural networks have been used to predict epileptic seizures. Ramgopal et al. (2014) compared a number of previous attempts at predicting and detecting seizures. These techniques ranged from simple linear regression to multiple chained machine learning techniques, with varying accuracy, sensitivity, and false positive rates. Most studies in the field focus on detecting siezures, though there has been success at predicting them ahead of time, as discussed below. Many approaches use EEGs (electroencephalograms). EEGs are recordings of electrical activity in the brain; specifically, the differences in voltage between pairs of electrodes on the head.

The amount of time we will be able to predict seizures in advance remains unknown. Le Van Quyen et al. (2001) claimed to anticipate seizures on average seven minutes in advance based on scalp EEG recordings, by using a statistical analysis on the wave to determine (loosely) how chaotic the waves were. However, De Clercq (2003) tried and failed to replicate those results, so they should be examined skeptically. Entirely disregarding EEGs, Mula and Monaco (2011) state that one third of epilepsy patients have premonitions hours or even days in advance. Therefore, the theoretical upper bound on prediction length is very long.

Seizure detection is important because it allows medical intervention to minimize harm. For example, Ramgopal et al. (2014) discuss one system which alerts caregivers when a siezure is detected, and another that could automatically administer drugs or an apparatus to stimulate the brain in case to halt the seizure. Siezure prediction opens up more opportunities for intervention, because there is a longer period where the patient or a caregiver can take corrective action; the person affected could be taken to a hospital during the several minutes of pre-predicted time if the epilepsy was particularly severe.

To use EEG data as inputs to a convolutional neural network, the data must first be transformed. Ren and Wu (2014) describe one method to preprocess EEG data so that it can be fed into a neural network, albeit non-spiking (though the methods could be adapted to spiking neural networks). A Fourier transform (which converts a signal to a representation of the frequencies of the sine waves which form it) is applied to the data, in order to pull out the more-relevant frequency components. Specifically, Ren and Wu (2014) chose the frequency band 8-30 Hz, which Darcey and Williamson (1985) found was a highly predictive band. The resulting signal still has a large number of dimensions, while a convolutional neural network can only handle a few. Principal component analysis is used to reduce the number of dimensions to a more manageable number. At this point, one of the methods described below can be used to convert the waveform into a series of spikes, which make up the input to the network.

There are many other methods which can be used to transform the raw EEG data to use as an input for a convolutional neural network. Kasabov and Capecci (2015) used an AER (Active event representation) encoding method to transform the EEG data into discrete spikes. In the AER method, the spikes are determined by the times when the derivative of the EEG signal goes above or below a threshold. Nuntalid, Dhoble, and Kasabov (2011) used filters to strip the EEG signals down into spikes. Filters remove unwanted features from a signal, usually certain frequencies. These methods would probably also have to be used along with principal component analysis to reduce the number of dimensions to a number a convolutional neural network can handle.

We plan to test whether single-spiking or multi-spiking neural networks, trained using backpropagation, form a better model for predicting epileptic seizures based on EEG data. We plan to use a similar training method to Lee et al. (2016), and a similar method of

inputting the EEG to the network as in Ren and Wu (2014). None of the papers described in Ramgopal et al. (2014) utilize spiking neural networks, and we found only one in the literature. Ghosh-Dastidar and Adeli (2009) used a multi-spiking neural network to detect siezures, showing that spiking neural networks can be used effectively on EEG data. Our research differs because we plan to predict the seizures ahead of time, rather than detect them when they have already begun. We plan to compare the single-spiking neural network described in Lee et al. (2016) with the multi-spiking neural network described in Ghosh-Dastidar and Adeli (2009). We have multiple potential sources of the EEG data. The most promising is University of Pennsylvania and Mayo Clinic (2014), which has a number of studies with annotated EEG recordings of epileptic and healthy patients. We have already gained access to the data, which consists of months of EEG data, when combined.

References

Cao, Y., Chen, Y., & Khosla, D. (2015). Spiking deep convolutional neural networks for energy-efficient object recognition. *International Journal of Computer Vision*, *113*, 54–66. doi:10.1007/s11263-014-0788-3

Darcey, T., & Williamson, P. (1985). Spatio-temporal EEG measures and their application to human intracranially recorded epileptic seizures. *Electroencephalography and Clinical Neurophysiology, 61(6)*, 573–587. doi:10.1016/0013-4694(85)90977-0

De Clercq, W., Lemmerling, P., Van Huffel, S., & Van Paesschen, W. (2003). Anticipation of epileptic seizures from standard EEG recordings. *The Lancet, 361(9361),* 971. doi:10.1016/s0140-6736(03)12780-8

Ghosh-Dastidar, S. & Adeli, H. (2009, December). A new supervised learning algorithm for multiple spiking neural networks with application in epilepsy and seizure detection. *Neural Networks*, *22*, 1419–1431. doi:10.1016/j.neunet.2009.04.003

Kasabov, N., & Capecci, E. (2015). Spiking neural network methodology for modelling, classification and understanding of EEG spatio-temporal data measuring cognitive processes. *Information Sciences*, 294, 565–575. https://doi.org/10.1016/j.ins.2014.06.028

Lee, J. H., Delbruck, T., & Pfeiffer, M. (2016, November). Training deep spiking neural networks using backpropagation. *Frontiers in Neuroscience*, *10*. doi:10.3389/fnins. 2016.00508

Le Van Quyen, M., Martinerie, J., Navarro, V., Boon, P., D'Havé, M., Adam, C., … Baulac, M. (2001). Anticipation of epileptic seizures from standard EEG recordings. The Lancet, 357(9251), 183–188. doi:10.1016/s0140-6736(00)03591-1

Mula, M. and Monaco, F. (2011). Ictal and Peri-Ictal Psychopathology. Behavioural Neurology, 24(1), 21-25. doi:10.3233/BEN-2011-0314

Nuntalid, N., Dhoble, K., & Kasabov, N. (2011). EEG classification with BSA spike encoding algorithm and evolving probabilistic spiking neural network. In *Neural information processing* (pp. 451-460). Springer Berlin/Heidelberg.

Ramgopal, S., Thome-Souza, S., Jackson, M., Kadish, N. E., Fern´andez, I. S., Klehm, J., … Loddenkemper, T. (2014). Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy. *Epilepsy & Behavior*, *37*, 291–307. doi:10.1016/j.yebeh. 2014.06.023

Ren, Y. & Wu, Y. (2014). Convolutional deep belief networks for feature extraction of EEG signal. In *2014 International Joint Conference on Neural Networks (IJCNN)*. IEEE. doi:10.1109/ijcnn.2014.6889383

Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, *61*, 85–117. doi:10.1016/j.neunet.2014.09.003

University of Pennsylvania and Mayo Clinic. (2014, April 15). IEEG-Portal documentation: Collaborative research in the cloud. Retrieved from https://main.ieeg.org/sites/ default/files/IEEGDocumentation.pdf