

Abstract

Seizure prediction is a well-studied problem within medicine as most of the danger of a seizure can be mitigated with successful predictions. While several other algorithms exist, they have limitations, such as short prediction timeframes, low sensitivities, or high false positive rates. We propose a model based on a combination of traditional convolutional and spiking neural networks. These spiking neural networks are newer and more closely model how the brain learns than traditional networks. By using a combination of traditional and spiking networks, we will be able to determine how effective spiking neural networks are at complicated tasks such as seizure prediction. We have so far tested our convolutional neural network model on a prediction timeframe of 10 minutes. Initial, incomplete results are promising, showing a very high sensitivity and accuracy, validating our data processing plan. Improving our confidence in this assertion will require more testing and a more complete model with the multi-spiking side included and controls for comparison.

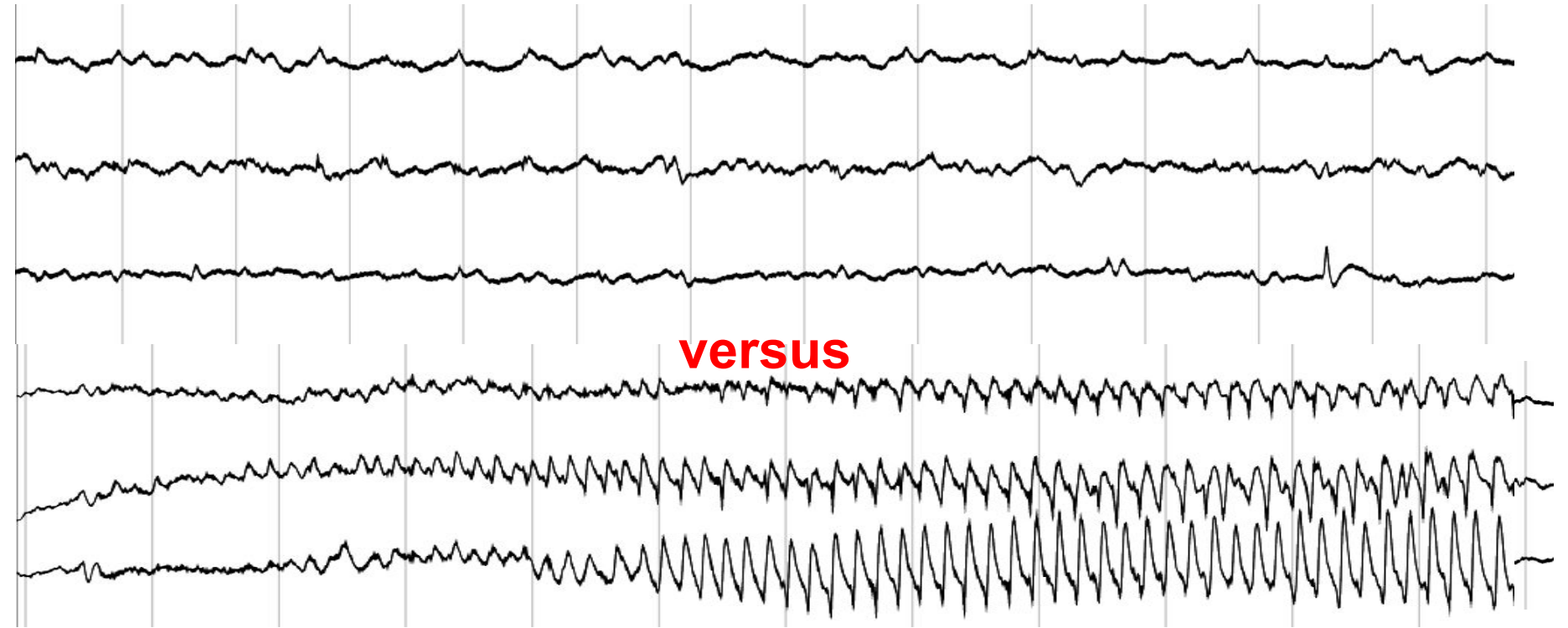
Predicting seizures with artificial spiking neural networks

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Chae

Motivation

- The unpredictability of seizures can be problematic
 - People with severe epilepsy are unable to drive, in case they have a seizure on the road
 - People with epilepsy report a significantly lower quality of life, due in part to the unpredictability of the condition (Camfield, 2010)

The effects of seizures are clearly visible on EEGs



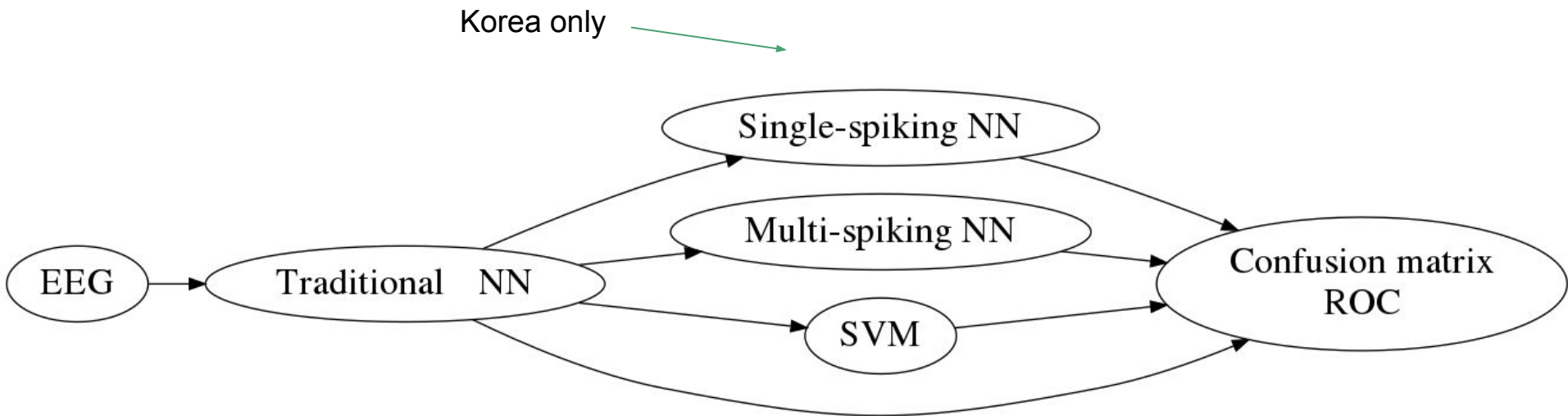
Some Existing EEG-based Solutions (not exhaustive)

D'Alessandro et al. (2005)

- 10 minutes
- 100% sensitivity
- 1.1 false positives per hour

Netoff et al. (2009)

- 5 minutes
- 79% sensitivity
- 0.0 false positives per hour



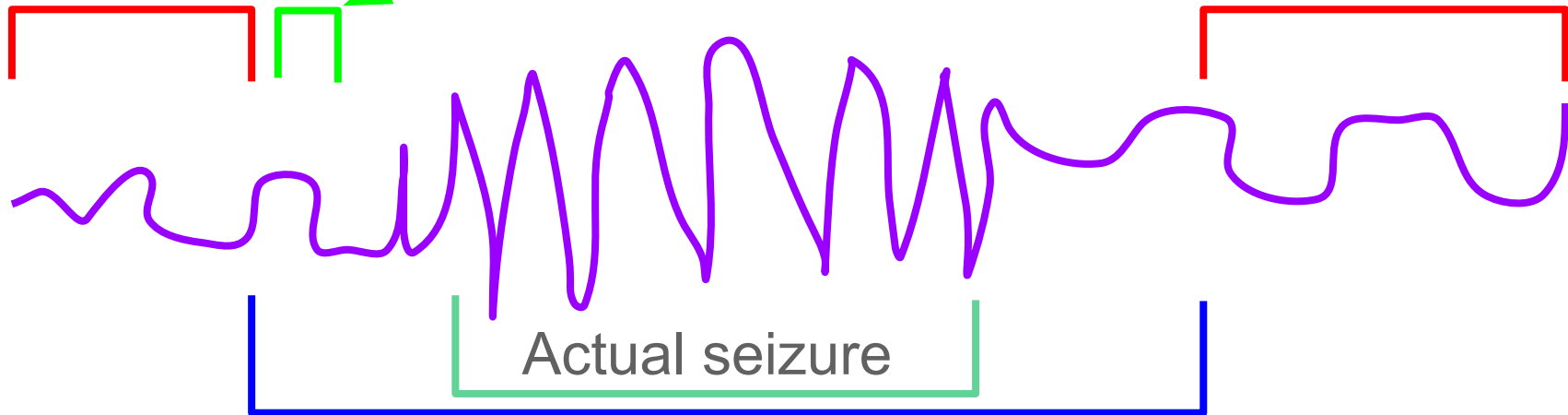
Hypothesis: The Spiking NN will have the highest prediction accuracy followed by the Traditional NN and SVM

Our data processing pipeline

How we pick samples

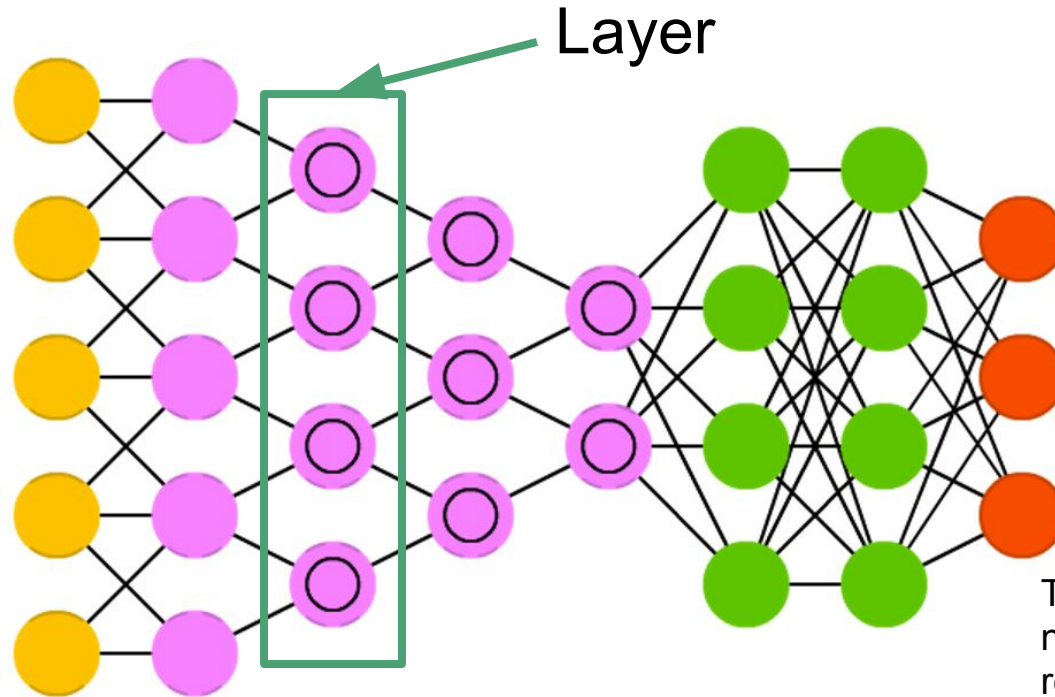
Negative samples
No seizures within 10 minutes

Positive sample



Seizure, plus 10 mins on each end

Traditional NN



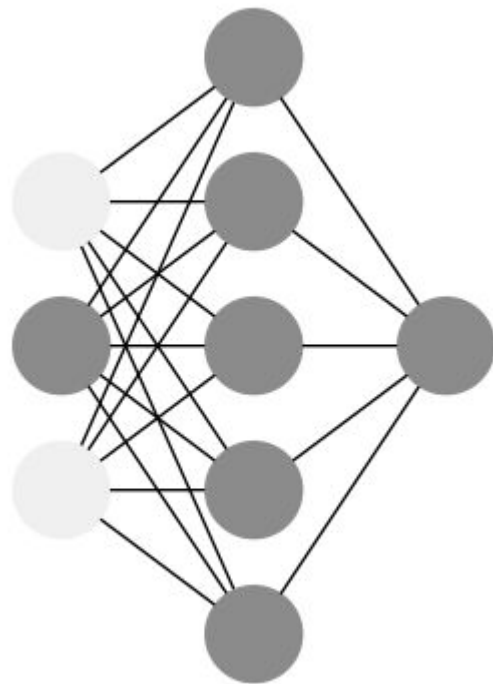
This use of traditional networks was recommended by Dr. Turaga at HHMI

Direction of data

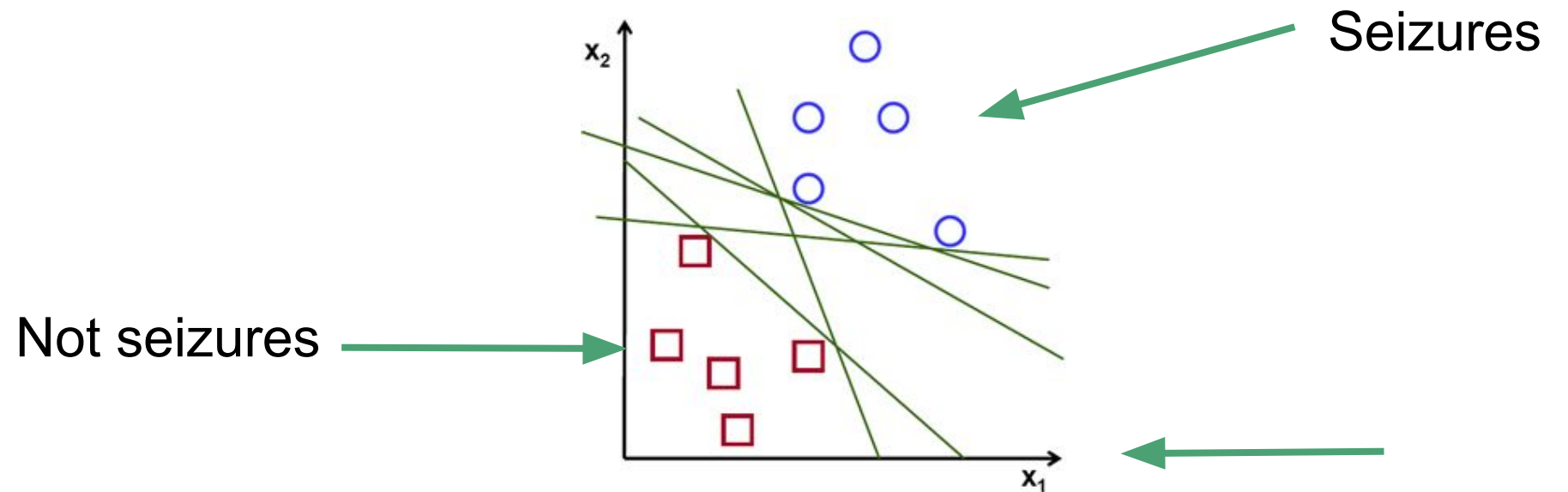
Multi-spiking NN

- More closely models the brain
- Requires fewer neurons
- “Remembers” values

Currently, we have a Multi-Spiking NN in python coded without the use of libraries.



Support Vector Machines (SVMs)



https://docs.opencv.org/2.4/_images/separating-lines.png

Axes: Traditional
NN outputs

This control was recommended
by Dr. Scheffer at HHMI.

EXAMPLE DATA

Analysis

Collect the data into something that looks like this:

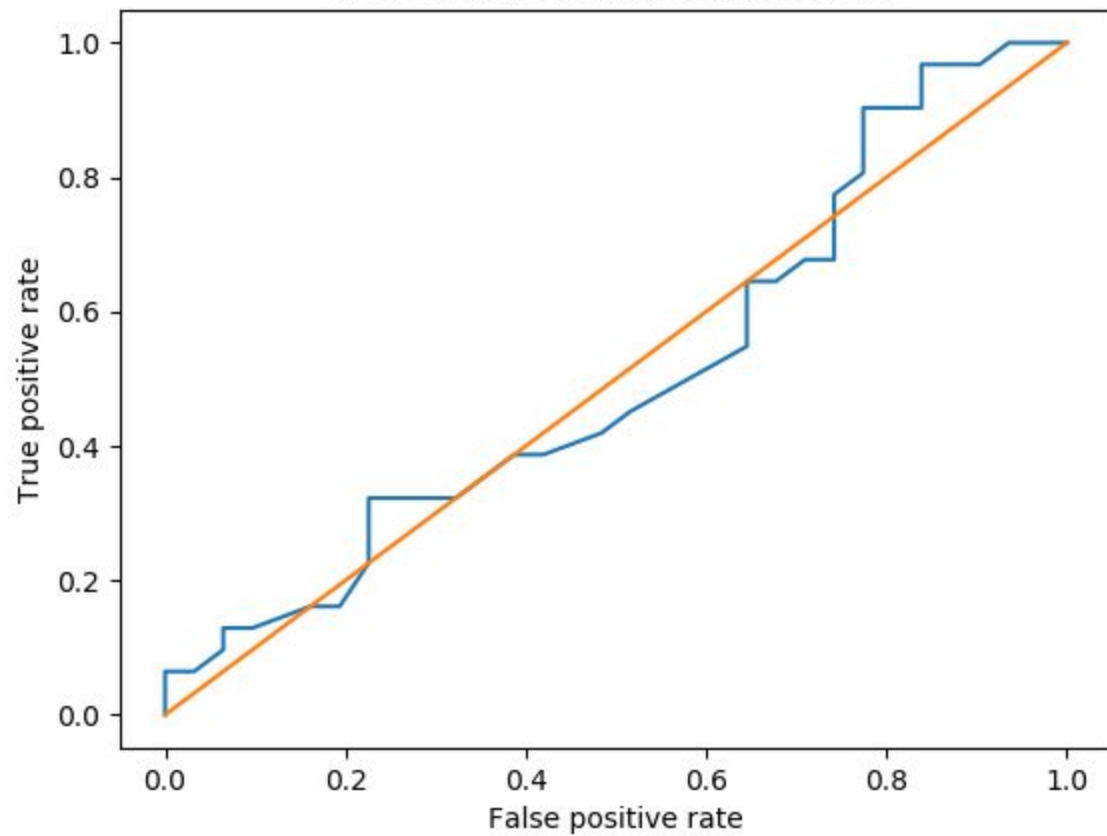
Confusion Matrix		Actual	
		Seizure	Not seizure
Predicted	Seizure	True pos.	False pos.
	Not seizure	False neg.	True neg.

Final metrics

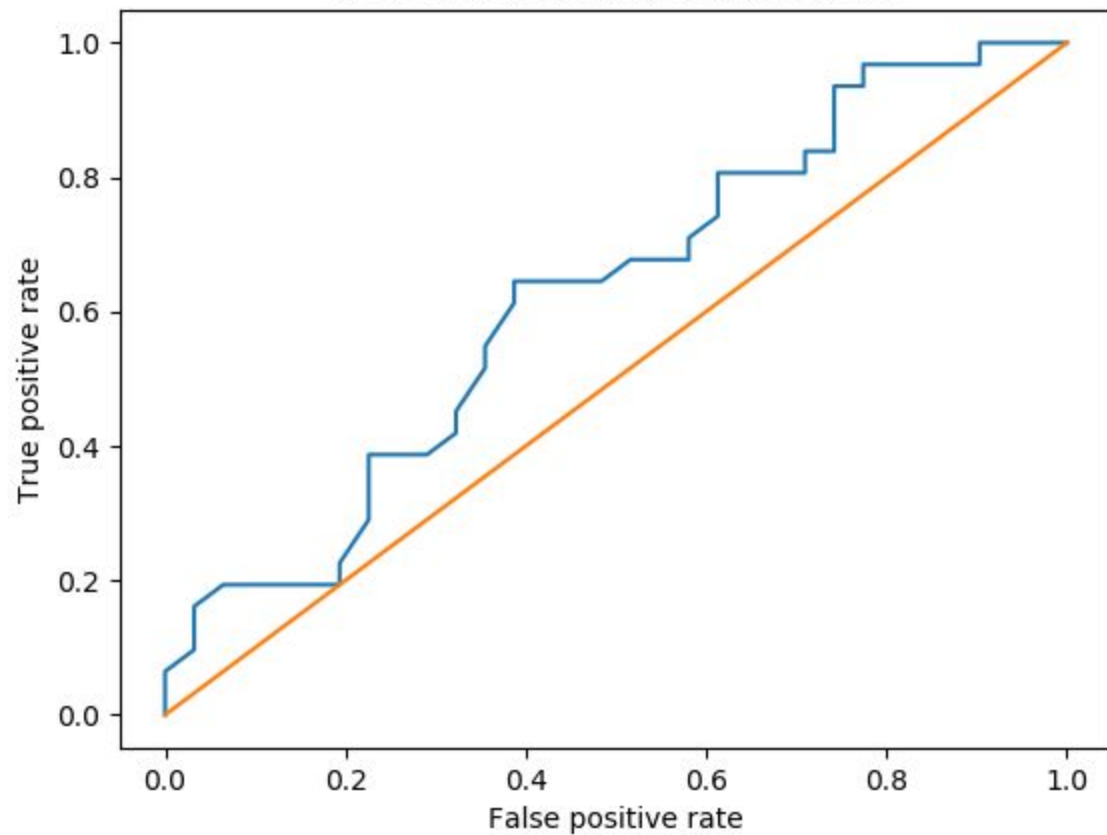
- True positive rate (sensitivity): how often a seizure was **predicted** and **actually occurred**
- False positive rate: how often a seizure was **predicted** but **never occurred**
- There's a tradeoff between the two, so we need to pick a threshold
- What if we try all the thresholds at once? What does that look like?

These statistical metrics
were recommended by Dr.
Oguz at NIH

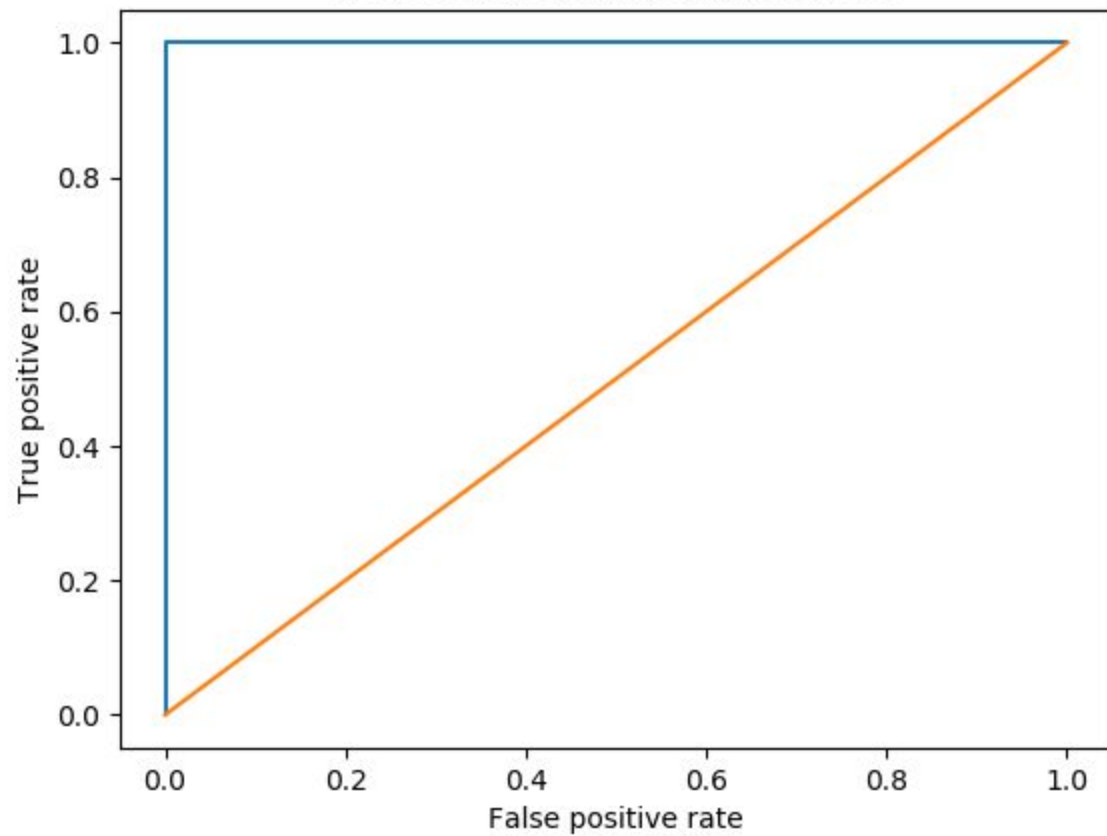
Receiver operating characteristic (ROC)



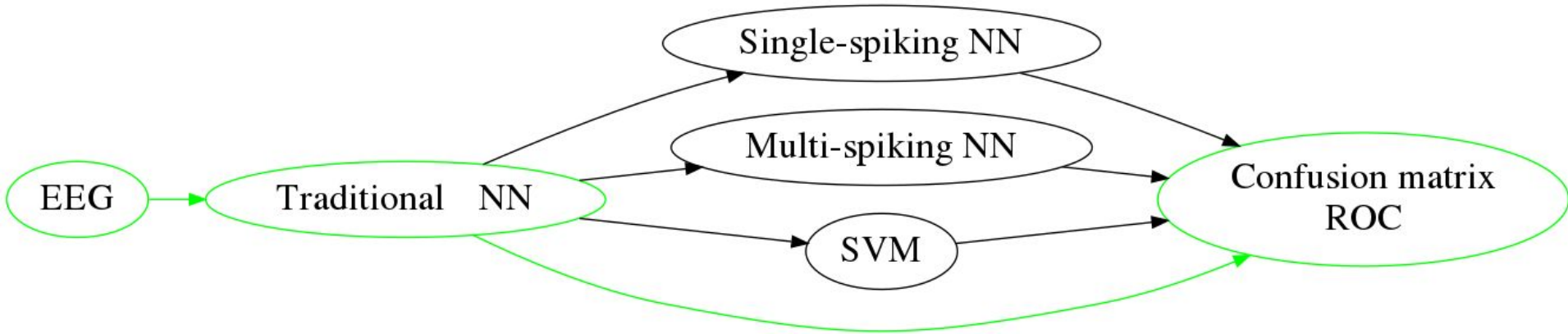
Reciever operating characteristic



Reciever operating characteristic



Progress



Immediate Future

- Find new, more effective step to go before the conventional neural network
- Work on an efficient implementation of the multi-spiking network
- Add an SVM

References

- Camfield, P. & Camfield, C. Idiopathic generalized epilepsy with generalized tonic-clonic seizures (IGE-GTC): A population-based cohort with >20 year follow up for medical and social outcome *Epilepsy & Behavior*, Elsevier BV, 2010, 18, 61-63
- D'Alessandro, M.; Vachtsevanos, G.; Esteller, R.; Echauz, J.; Cranstoun, S.; Worrell, G.; Parish, L. & Litt, B. A multi-feature and multi-channel univariate selection process for seizure prediction *Clinical Neurophysiology*, Elsevier BV, 2005, 116, 506-516
- Netoff, T.; Park, Y. & Parhi, K. Seizure prediction using cost-sensitive support vector machine 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2009

Important Works

Ghosh-Dastidar, S. & Adeli, H. A new supervised learning algorithm for multiple spiking neural networks with application in epilepsy and seizure detection Neural Networks, Elsevier BV, 2009, 22, 1419-1431

University of Pennsylvania and Mayo Clinic IEEG-Portal documentation:
Collaborative research in the cloud 2014

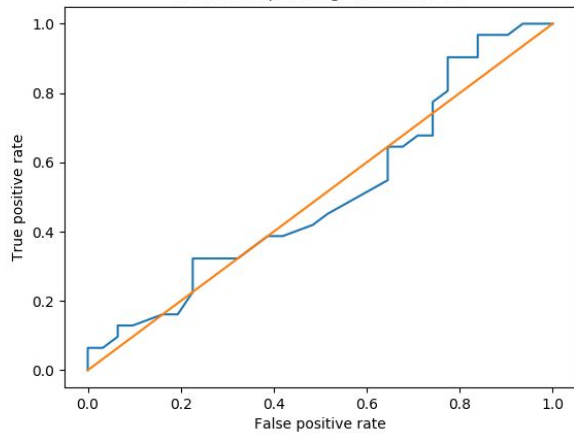
Lee, J. H.; Delbruck, T. & Pfeiffer, M. Training Deep Spiking Neural Networks Using Backpropagation Frontiers in Neuroscience, Frontiers Media SA, 2016, 10, 508

THE END

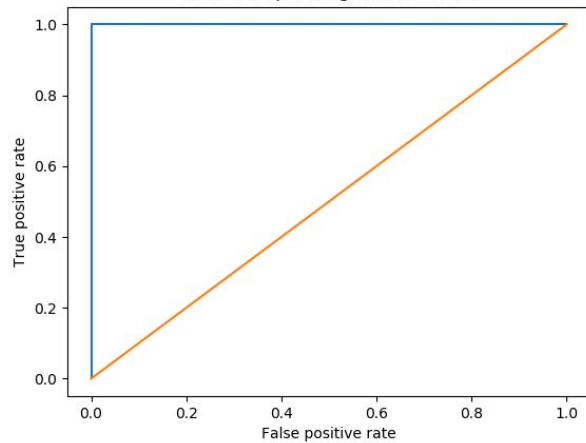
Go back; there are a bunch of discarded slides

Data

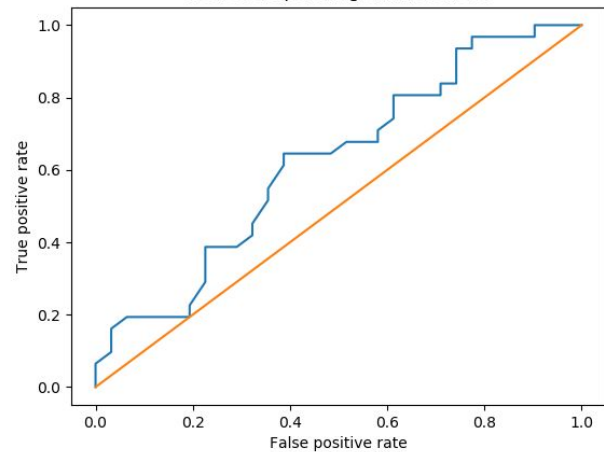
Receiver operating characteristic



Receiver operating characteristic

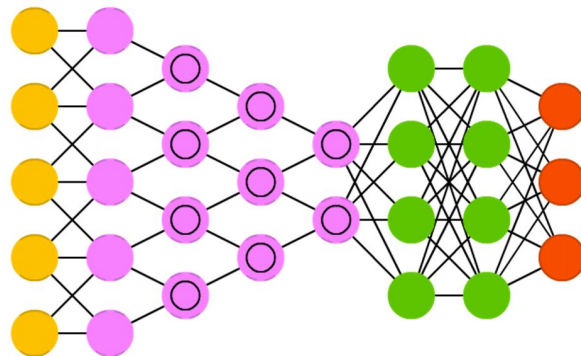


Receiver operating characteristic



Traditional NN

- Data flows through the network
- Its inputs, on the left, each have a series of numbers
- Each layer, the data get a bit more organized
- The network makes a prediction and self-corrects
- Does more preprocessing
- Trains more quickly, so we can iterate faster
- Provides input for the subsequent steps



<http://www.asimovinstitute.org/neural-net-work-zoo/>

Progress up to Progress Report 1

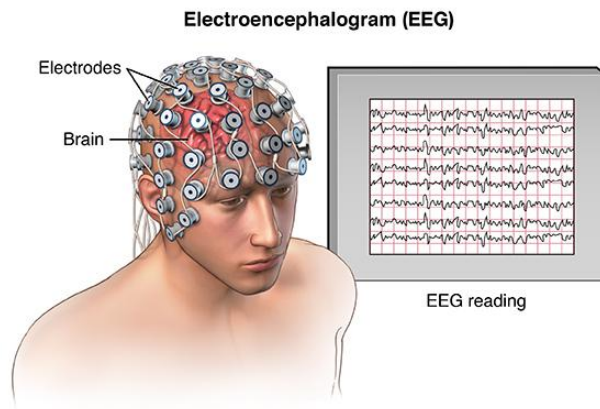
- We have a single multi-spiking neuron that can take inputs and receive outputs in isolation.
- We have an initial more advanced preprocessing step based on EEG signal steepness instead of signal height
- Discussion with Dr. Scheffer

Progress After Progress Report 1

- Multi-spiking neural network in python without the use of neural networking libraries
- Preliminary work on a slightly different mathematical formulation that *may* run faster (if it works)
- Convolutional neural network in python using PyTorch
- Some lightly preprocessed data for the convolutional network
- Discussions with Dr. Turuga and Dr. Oguz

EEG Preprocessing

- Reading the raw EEGs
- Picking positive and negative samples
- Picking out features we know will be important
- Combining channels into a single list of numbers



<http://i.imgur.com/ZrmxJRu.jpg>

More Preprocessing

COMING SOON...

(our current experiments with preprocessing have been unsuccessful --- making the prediction worse)