Real Time Seizure Recognition via EEG

I would like to thank Eleanor Thomas, my Springboard Data Camp mentor, for all her help as I learned Data Science and for her ability to crystallize the ideas I had in applying machine learning and nonlinear dynamics to this final Capstone project. Thank you!

Background

My wife is an epileptic, and, like many others, her seizures are life-threatening. Her childhood was characterized by misdiagnosis and accusations that she was "faking' it for attention even though her mother was a diagnosed epileptic. The hospital system in question was so incompetent, they even had her admitted to a mental hospital. In 2013, admitted for uncontrollable seizures to the same hospital system (there aren't many to choose from when one can't afford to travel to the best of the best), the doctors made a mistake and overdosed my wife on Dilantin, the first of two times this would happen. They were forced to admit her, and even though they almost killed her, still sent us the bill. There is a distrust for 'experts' that runs deep in this family. In the present day, my wife recently had brain surgery to correct her seizures. Given a Medtronic Deep Brain Stimulator, we are waiting to see if this will be successful.

My career took me to Charleston, SC. Soon after, my wife wanted a child. We knew there were risks. We sought out someone who could make having a child as safe as possible, and after being treated for a period of time, Jonathan C. Edwards MD. Chair, Department of Neurology, MUSC informed us of the risks and said it was as safe as it was going to get with my wife's current medical regiment. At the 20-week anatomy scan, they found a mass in the baby's brain that was initially diagnosed as brain cancer. The baby began having seizures in the womb at 7 months, and was born with Ohtahara Syndrome and Cortical Dysplasia, the prognosis of which is generally death by age 2, and for those survivors, a much shorter life as Ohtahara usually results in Dravet Syndrome or Lennox-Gastaut syndrome.

Most people become absorbed in the details about the hundreds and thousands of seizures Nicolette had daily until they removed half her brain at age 6 months, or the experimental things done to save her, and the miracle that is Nicolette today, but this is not about that. It's about how two people were driven to find better solutions and answers as a cascade of disasters fell on our heads with insurance companies and hospitals cementing our beliefs that people must take personal responsibility when it comes to the decisions made while in a hospital setting or when talking to insurance companies. MUSC in Charleston, SC taught is this lesson and they live what the preach.

It didn't start out like that though. While Dr. Edwards certainly listened to the patients before giving careful advise, the pediatric neurologist first assigned to Nicolette after birth suffered from what many of these highly trained specialists suffer from: a narcissistic, god complex where comments like, "You are a parent of a patient and I'm the expert! Nicolette doesn't have Infantile Spasms and YouTube isn't a doctor! I am!" The misguided narcissist not only shut us down when we even attempted to help her with a difficult case, but the solution she ever offered was "just add more meds." At one point, and at only age 5 months, Nicolette was on about 10 medicines, one of which made her mostly blind in her right eye: a side effect of this medication. Believe me when

I say choosing between blindness and death is not a stress free decision, especially when your daughter could die at any moment and the decision had to be made fast! Unfortunately, it is not common knowledge that being on many meds isn't a good idea. Which one is the one that's working? Is the interactions between them all causing the one that would work to not work? Are all of them causing other medical conditions that make the solution worse than the cause? MUSC's Dr. Samir Karia taught us this.

That first narcissists, fortunately, went to an out-of-state conference at one point when the baby was admitted and the aforementioned Dr. Samir Karia came into the room and said, "Those are Infantile Spasms. Babies having seizures and these spasms are likely Ohtahara patients" and just like that, she was soon correctly diagnosed and soon had the live-saving surgery performed by MUSC's Dr. Ramin Eskandari. To demonstrate MUSC's competence, they soon terminated the first doctor's contract and Dr. Karia quickly reduced the meds the baby was on so we could track what was actually happening.

Dr. Ramin Eskandari, Dr. Samir Karia, Dr. Edwards, Julie Desmarteau, Laura Doherty, and many wonderful people in MUSC's PICU and NICU saved our daughter's life. They taught us to be advocates for our daughter's care. Advice that my wife and I heeded. Thank you, and I'm still going to keep my promise to Dr. Eskandari, Nicolette will walk up to him and hug him. And if we can get to Louisville, KY, where Dr. Karia currently is, she will hug him.

The insurance side had many challenges when it came to advocating for Nicolette, one of which became my catalyst to find solutions so the parents of other children with these conditions could be spared what happened to us. Dravet and Lennox-Gastaut syndromes are only diagnosed by EEG, but half my daughter's brain had been removed and donated to science; therefore, when doctors wrote prescriptions for drugs designed to combat these, insurance denied it because Nicolette's EEG patterns didn't match the EEG patterns from Dravet and Lennox-Gastaut syndromes. And why would they match? Nicolette only half the brain most kids have. That, one would think, alter an EEG reading. This was a very stressful time for my wife and I as we waited daily for the appeal process to play out, watch our daughter have seizures and hospital expenditures accumulate. It was finally approved after MUSC went to war for us and this marked the first time I asked myself the question: "why can't an EEG see these patterns even if the brain's anatomy is different?"

MUSC didn't just talk the talk, they walked the walk. They made it a priority to ensure we knew we could carry out personal research, as my wife had finding Infantile Spasms on YouTube. My wife's personal research was just as critical as the best doctors that we had. After my daughter's gene mutation was identified, it was my wife's research that found the chemotherapy drug, Everolimus, that eventually was used to successfully treat Nicolette's condition. Yes! It's irony that she was initially diagnosed with brain cancer, then told it wasn't cancer, then have a cancer drug be successful for an Epilepsy condition.

Like many hospitals, even MUSC made mistakes, although they were always quick to correct it and take responsibility. It's not that these errors were made because of incompetence, rather the natural human ability to handle real time stress. Understaffed hospitals with overworked staffs getting yelled at by patient families do cause mistakes. There is a reason the nurse per patient and doctor per patient are tracked statistics. The most common error my wife and I saw was administering the wrong dose of the required medication. Had we not been there verifying what the medication label said to what we knew the baby needed, Nicolette may have overdosed, or had a deadly seizure

from getting a wrong dose. The next most common mistake was some sort of input error when a doctor or nurse typed into the medical file. In other words, what the doctor told us was going to happen wasn't what the nurse was about to do the next morning because the doctor hit the 3 instead of the 2 and my wife had been very attentive when the doctor said what he was going to do. My wife even went to the extent of posting the correct medication doses outside the hospital room so nurses could compare that note to what she was about to bring in and catch it before adding more stress to us. My wife being treated unfairly, and quite frankly as a woman, during her own personal medical issues hardened her so much, she is the person that really saved Nicolette's life. She refused to believe what any doctor said and after a doctor said it, she would exhaustively research it to make sure what she found matched what even Eskandari and Karia said, both of whom often credited her thoroughness.

Before moving on, I'd like to address the relationship between hospitals and the families of patients. Doctor's aren't miracles in white coats. They work hard to find solutions, and yes, they are only people, and yes, some are flawed narcissists who lose their way for other motivations... just like some of your coworkers or family members do, so be a part of the solution rather than the problem, have some self-reliance, and take some personal responsibility in the decisions made by hospitals. When my wife and I go see a doctor, it's very clear to that doctor that my wife and I know what we are talking about, and they are very careful to make any suggestions without being able to justify it to us from a medical or mathematical perspective. And if they get sassy, we go straight to the business side of the hospital with facts, and just like any business, they have usually fixed it. Bad PR in a place that advertises care and concern for what the patient has to say is not what the business side wants to get out into the public.

My own personal research went in a different direction. During one of the many nights in the hospital I read that seizures were in a class of mathematical problems related to something called the Navier-Stokes equations. I received a math award in high school, so intrigue lead me to Wikipedia, which led to the Clay Mathematics Institute, where I saw there was a million dollar prize to prove something-or-other with this differential equation about turbulence, which led to a search on dynamics, which led to nonlinear dynamics, which led to Nonlinear Dynamics and Chaos: With Applications to Physics, Biology, Chemistry, and Engineering, Second Edition by Steven Strogatz, which I bought and then proceeded to read the first paragraph and be utterly lost. So much for high school math awards translating to systems of nonlinear differential equations with infinite variables on the continuum. So began over 5 years of complete and painstaking dedication to understand that book so I could understand my wife's and daughter's condition and solve that equation and collect that prize from Clay Mathematics Institute. No big deal.

That of course isn't what happened...yet, at least with the prize money, but what did happen was I learned what I needed to understand that book. I began tutoring high school and college students in higher mathematics. In short order, I realized I needed to be able to program so I could model my own seizure differential equations. So I learned python. Then I found out that pesky phrase "...so I could model..." was a lot more complicated than it innocently sounds, so I enrolled in Springboard Data Camp where a background in Calculus, Linear Algebra, and Probability might finally pay off. And it has.

The brain is nonlinear, and a seizure is chaotic turbulence, hence Nonlinear Dynamics

My initial goal for my final Springboard Capstone was to get the EEG data for my daughter before and after surgery and via Bayesian Inference find the numerical patterns for Lennox-Gastaut and Dravet after brain surgery, and I'm still working on that. Getting my daughter's data in the proper format from MUSC has been a challenge, but they are working on that, and then I need to get the EEG data for other patients with these syndromes for analysis. That, I'm sure, will be more difficult. I'm hoping MUSC can help with that by asking the families of these patients for special permission for me to access only the anonymous raw data. MUSC asked my wife and I on several occasions for permission so other parents could speak to us about something that another child was going through.

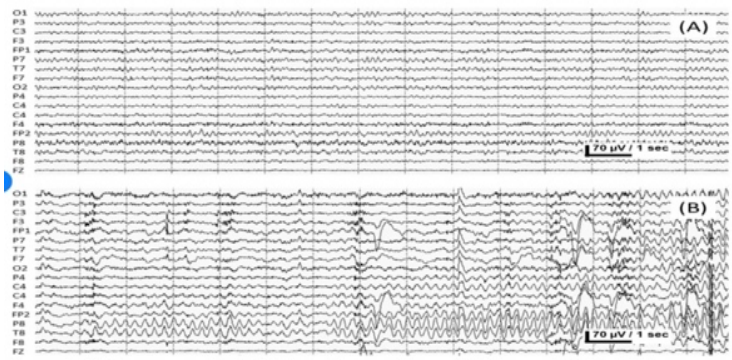
My intermediate goal for the second capstone project was predicting a seizure before it happens, and I thought prediction via Bayesian Inference was the best shot. What library would I use? PyMC3 came up in many searches, but there seemed to be some confusion about PyMC4 being built on top of TensorFlow Probability, and more confusion about Theano being maintained, all of which led to PyTorch and Tensorflow as the only viable candidates, but TensorFlow apparently had a steep learning curve, which wasn't dealt with extensively at Springboard, and PyTorch didn't have much in the way of Bayesian Inference capabilities, so I veered of Springboard on my own and learned Tensorflow on top of Keras, which required learning Keras, and the Springboard program is only 6 months, and my daughter and wife were still have seizures every night, and they could still pass away unexpectedly! Lots of pressure is all I can say. Nerve-racking pressure. But it didn't appear I could avoid learning Tensorflow. And I'm glad I did.

The brain is considered nonlinear, which is why Steven Strogatz listed Epilepsy in the same class of problems as the Navier-Stokes Equation. These problems are defined as having Spatio-temporal complexity with the number of variables considered to be on 'the continuum.' This means the problems can exhibit behavior that varies in space and time as well as over different scales. Other similar problems exist in climate systems, biological systems, and geological systems.

Seizure Prediction with Tensorflow, statsmodels, and scikit learn.

Figure 1: Fürbass, Franz. (2017). EEG monitoring based on automatic detection of seizures and repetitive discharges.

The brain has a baseline electrical output measured in microvolts. A seizure is 'abnormal' brain activity. On the right, the baseline is on top, and a seizure is on the bottom.



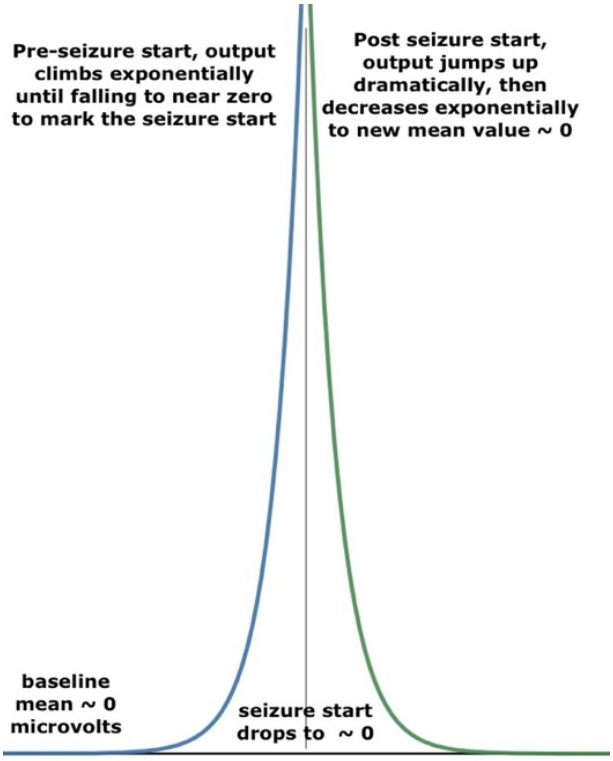
Normal EEG compared to EEG including a seizure: (A) Normal EEG of 15 seconds; (B) EEG of the same patient having an epileptic seizure visible as rhythmic activity starting on electrodes P8 and T8.

However, I was more interested in the raw data, i.e. the actual microvolt measurements, and more specifically, those values in a NumPy array for manipulation. The array on the right shows the hundredths of a second before the seizure, the seizure start is labeled “START,” and then the hundredths of a second after the seizure. Note: the data frame on the right was normalized. The mean was zero and the standard deviation was one. This shows that electrical output was an incredible 35 standard deviations away from the mean leading into the seizure before falling to zero to mark the seizure start before climbing back to almost 23 standard deviations from the mean and falling away exponentially to a new mean near zero for what could be considered the “baseline” seizure. And all that happened in less than a second.

10233	22.308598	23.530069	23.654020	23.742293	20.757780	22.651415	22.717404	23.341978	19.386261	22.011902	...
10234	25.432541	26.149967	25.778174	26.309404	25.122121	25.790256	25.487630	25.902212	24.334235	25.619769	...
10235	28.669189	29.043821	27.848500	28.696904	29.484150	28.836210	28.192146	28.315532	29.314687	29.167735	...
10236	31.629114	31.579793	29.479894	30.680710	33.510780	31.466153	30.692076	30.485880	33.939171	32.337422	...
10237	33.708997	33.243740	30.444402	32.016235	36.751413	33.460409	32.397207	31.909040	37.774925	34.898700	...
10238	34.843117	34.151906	30.768939	32.676646	39.038424	34.758680	33.302897	32.622349	40.607076	36.749754	...
10239	35.425091	34.491160	30.692781	32.991932	40.473440	35.438399	33.964128	33.199653	42.413717	37.865077	...
START	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...
10241	22.706046	22.153794	23.834506	22.805012	24.098736	23.708124	22.906869	22.447269	29.141551	22.312318	...
10242	19.825963	21.361974	23.018960	22.080666	20.661425	22.868135	22.297515	21.666525	20.954133	21.461971	...
10243	17.334067	20.445016	21.933233	21.310456	17.637132	21.826972	21.524288	20.883771	14.255200	20.472858	...
10244	16.459263	19.537962	20.751027	20.250707	16.651512	20.815971	20.542393	19.875212	12.532384	19.626378	...
10245	17.238271	18.710014	19.568394	19.215535	17.658062	19.893522	19.393759	18.883833	15.736248	18.956105	...
10246	18.427276	17.872006	18.362029	18.187454	19.072326	18.930983	18.188856	17.801931	20.263371	18.246395	...
10247	18.462324	16.820853	17.033125	16.880916	19.159613	17.772454	16.898438	16.621152	21.605465	17.234100	...
10248	17.018945	15.595952	15.580265	15.495259	17.537438	16.345050	15.514086	15.333625	18.936342	15.851368	...
10249	14.925187	14.374228	14.092303	14.240846	15.094085	14.751012	14.175211	14.198160	14.776036	14.238801	...

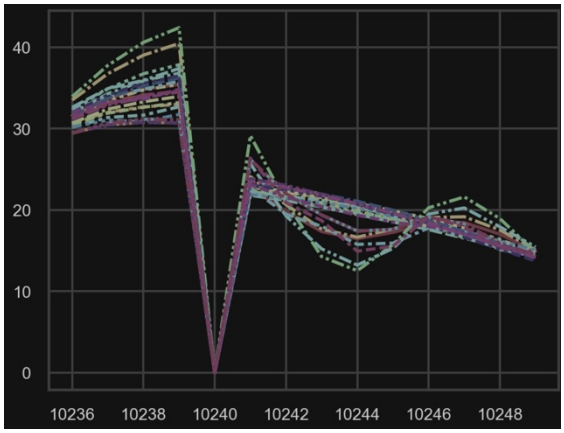
“START” is where the seizure officially begins.

Note the dive in electrical output, like a surge protector failing



All EEG data I accessed had this same pattern. A steady, normal baseline brain output before an exponential climb, an instantaneous fall, an instantaneous climb, and an exponential fall to a “baseline” seizure. This pattern is seen on the right. Below on the left is the actual data for one of the patients. The lines are EEG lead measurements climbing until the seizure starts, where it falls, then climbs back out, all in 1/256th of a second.

In my 2nd capstone, I showed how this “volcano” property made modeling via traditional means impossible, and all models failed in predicting a seizure. I concluded that predicting a seizure, like predicting the weather, would be impossible due to Chaos. Chaos demonstrates that 2 systems can vary wildly in their long term behaviors depending on the initial conditions when the system begins. I could take it to its logical beginning and say it’s impossible to know those initial conditions when an epileptic is born, and of course, no two epileptics will be born with the same initial conditions. I was able, however, to use clustering to identify a “baseline” from a “seizure” with respect to electrical output. With this information, I was able to write a simple program that, while not predicting a seizure, could provide warning that something was wrong if the electrical output climbed dangerously. But first, it’s important to know what happens during EEGs.



The Current EEG Process and it's problems

1. My daughter is hooked up to the EEG
2. My wife and I are instructed to watch my daughter 24/7.
3. If we suspect there is a seizure, we press a button to mark the event on the EEG.
4. When pressed, the room lights up, in rush nurses and doctors to administer emergency medications if needed.

Each step of this is fraught with stress:

- Families looking for something odd in their kids behavior results in the button being pressed more than necessary. This in turn takes up valuable hospital resources, which could adversely affect other patients.
- 24/7 monitoring of the patient is dangerous for those not sleeping. I wrecked 2 cars from lack of sleep. My wife's seizures increased from lack of rest. At one point, doctors were working on my daughter, to save, her and the ER staff came up to the NICU to transport her down to the ER. I believed I was about to watch my wife and my daughter die in the same night from the same condition.
- The wait for a doctor to read EEGs causes stress and is costly for both families and hospital budgets.
- The child may not have a seizure. This is common in the EMU actually. We were warned that Nicolette may not have a seizure when hooked up.

Capstone 2 solution

So predicting a seizure may be impossible, but this process could be simplified to ease the burden for families.
The only pitfall to this system is that a previous EEG for the patient's baseline would have to be on file in order to run the clustering algorithm that determines where the threshold is that marks a point where, if the electricity climbs above that point, the alarm will warn the family in the room, which in turn allows them to look at the child, determine if they believe it's a seizure and press the button to call upon hospital resources. Given this baseline EEG, I demonstrate
ed in my second capstone how a simple python for loop could alert the family in the room that something was wrong. This eliminated silent seizures as a risk through the night. To eliminate noise in the data, the EEG readings were run through a Fast Fourier Transform. With patient specific threshold established via unsupervised clustering and the noise filtered out via a Fast Fourier Transform, a simple program attached to EEG software would look like:

```
for (index, row) in p1_1.iterrows():
    if 0.1 < row.mean() < 1:
        print(f'WARNING SEIZURE POTENTIAL NOTICED AT TIME = {index}')
    if 1 <= row.mean() < 17:
        print('-------------------------------------------------------')
        print(f'WARNING SEIZURE LIKELY = {index}')
    if row.mean() > 17:
        print('-------------------------------------------------------')
        print(f'SEIZURE! SEIZURE! = {index}:\n\nvalue: {row.mean()}')
```

with output while an alarm sounds.

```
SEIZURE! SEIZURE! = 10231:

value: 17.641233734478295
-------------------------
SEIZURE! SEIZURE! = 10232:

value: 20.04229124050437
```

Of course this is helpful for established epileptics admitted to the EMU for further analysis, but not so much for those experiencing what they believe is a seizure for the first time after being rushed to the ER. That became the focus for my final Springboard Capstone project as I continued to work with MUSC for my daughter's EEG data properly formatted.

Capstone 3: Real time seizure recognition for even unknown patients

In addition to generalizing my second capstone to give real time feedback that would allow doctors and families to know if a person was in a seizure, I wanted to demonstrate Object Oriented Programing in Python, all of which would culminate in a career change that not only allow me to solve complicated problems in any field, but also have a more stable schedule so that I could spend more time with my wife and two daughters. My wife is the strength to my weaknesses. Such an incredible person who has suffered through her own daily seizures, depressions, 2022 brain surgery, researched for Nicolette, organized Nicolette's therapies, Nicolette's 2021 Make-A-Wish, and raising my 16 year old daughter, Madison, and all while I worked a full time career to barely support the four of us, and when not out working in that field, I spent 5 years learning higher mathematics, and now another 7 months in Springboard's Data Science Program, all of which was basically a second career. Thank you to my wife, Brandi, and my teenage daughter, Madison for supporting me to accomplish what seemed like an impossible task. I will keep my promise to you both.
And a special thank you to Nicolette, who continued to smile and laugh even between deadly seizures. If she can survive, so can I!

That promise is why I cannot reveal the entire python program and how exactly I generated the results. I consider this proprietary. I can only refer you to my second capstone, parts of this capstone, and my Springboard mentor, Eleanor Thomas, as a reference. She was there guiding the unknown parts as I chose very uncommon and difficult capstones to learn data science. When this began last July, during my initial conversations with Eleanor, I remember her getting excited at my goals after learning about the background above. She said, "You got me excited for this and I know you can do it!" In the rabbit hole I was many a time, and those words, along with my wife's, kept me going when I wanted to give up. Thank you Eleanor, who agreed to be a reference for this project. One can reach out to me for her contact information.

The original goal was to use Bayesian Inference to update a posterior distribution that would give a probability that any EEG reading in any moment in time was a seizure or not. In Bayesian terms, I wanted the conditional probability that given the data, it was a seizure. In LaTeX:

$$P(S|D) = \frac{P(S) * P(D|S)}{P(D)} : \text{where}$$

$$S = \text{Seizure EEG data}, D = \text{ any random EEG data},$$

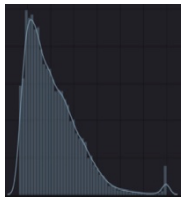
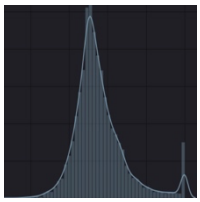
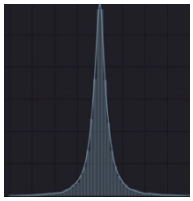
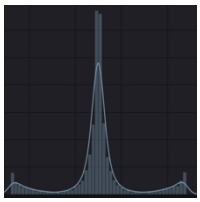
$$P(S|D) \text{ is the posterior}, P(S) \text{ is the prior},$$

$$P(D|S) \text{is the liklihood}, P(D) \text{ is a normalizing constant, if needed.}$$

In words, I'm saying: the probability that this is a seizure given new data is equal to the probability of a seizure times the probability that this data is a seizure given the seizure data divided by the sum of probabilities of all the possible hypothesis. No one said Bayes Theorem was easy. The prior was simple enough, statistics on the number of new epileptics in any given year is about 150,000 and divide that by an estimate of the number of people given EEGs for suspected seizures. I chose a Poisson Distribution for this. Choosing the likelihood function was much more difficult. After many sleepless nights, I decided I needed it to be a normal distribution since it's the most common distribution in nature and seizures are nature? That was my thinking anyway. The early models had a nasty flaw though, the posterior always went to zero, which meant the numerator was going to zero in the limit, and that makes perfect sense now: numbers less than one multiplied together will go to zero. And so much for pressing the easy button.

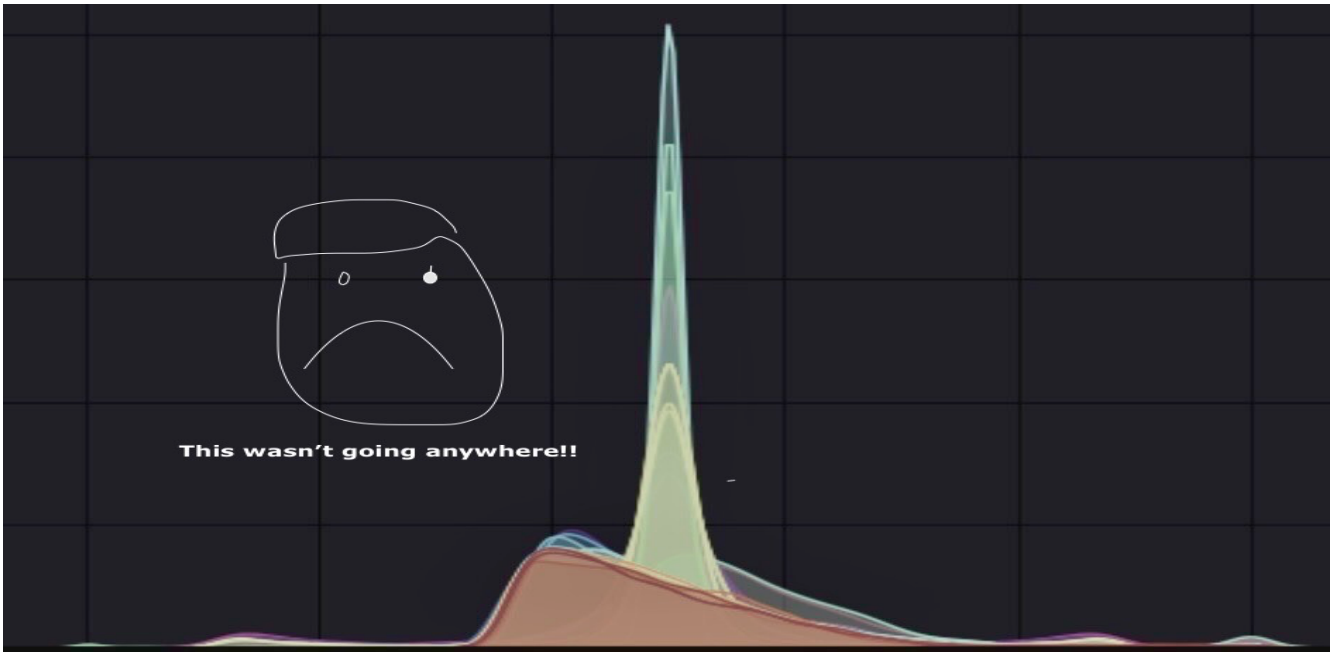
I turned to Tensorflow Probability and the DenseVariational layers, among others. These types of layers need to clearly identify the prior and posterior distributions via returning them as instances of a TensorFlow Distribution. So I was back to the trickiest part of Bayes, choosing distributions. This time, I went to the data, commanding the universe to make them normal distributions. Let's look at the non-seizure distributions. I got:

a little of this… and a little of this… some of this… and a little of this

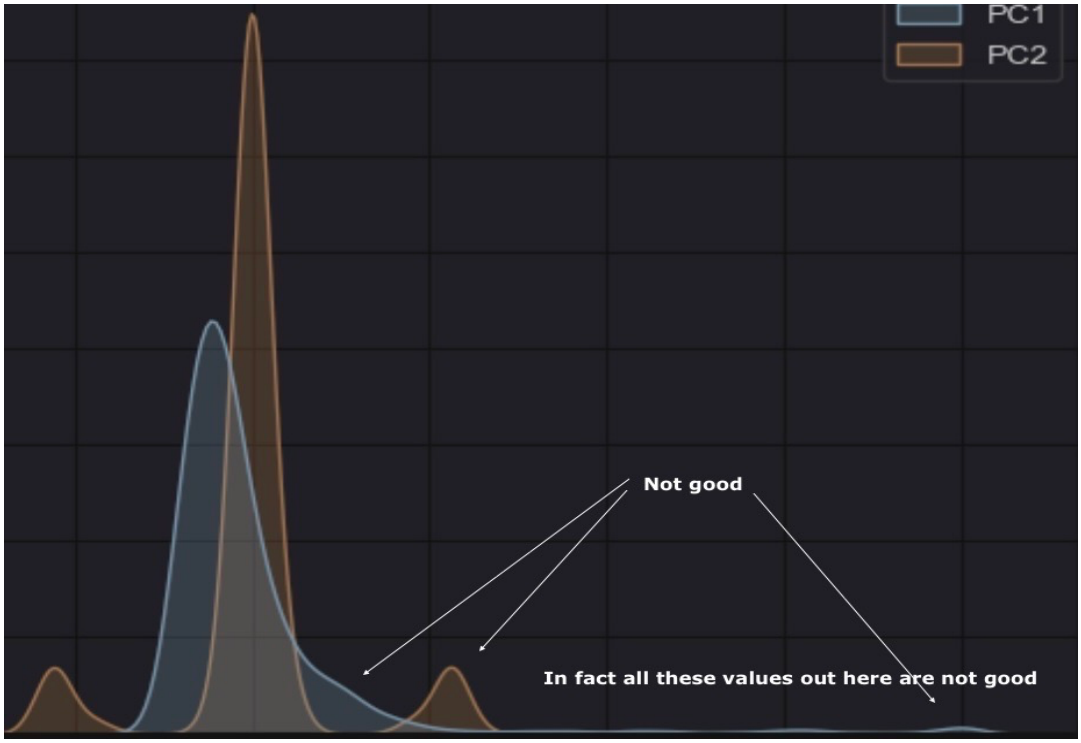





bimodal beta bimodal normal a normal trimodal normal

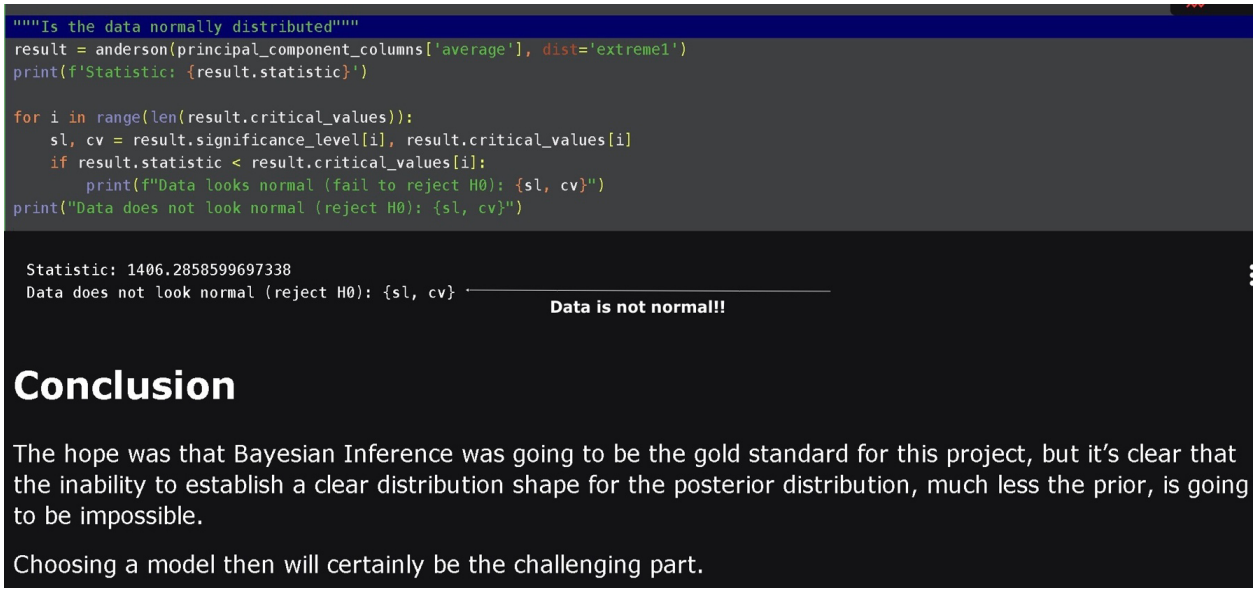
None of this was good news: merging different distributions into one. How about the seizure distributions? Seems like this graph is sending me a couple of messages about what it thinks about my efforts to solve this riddle.



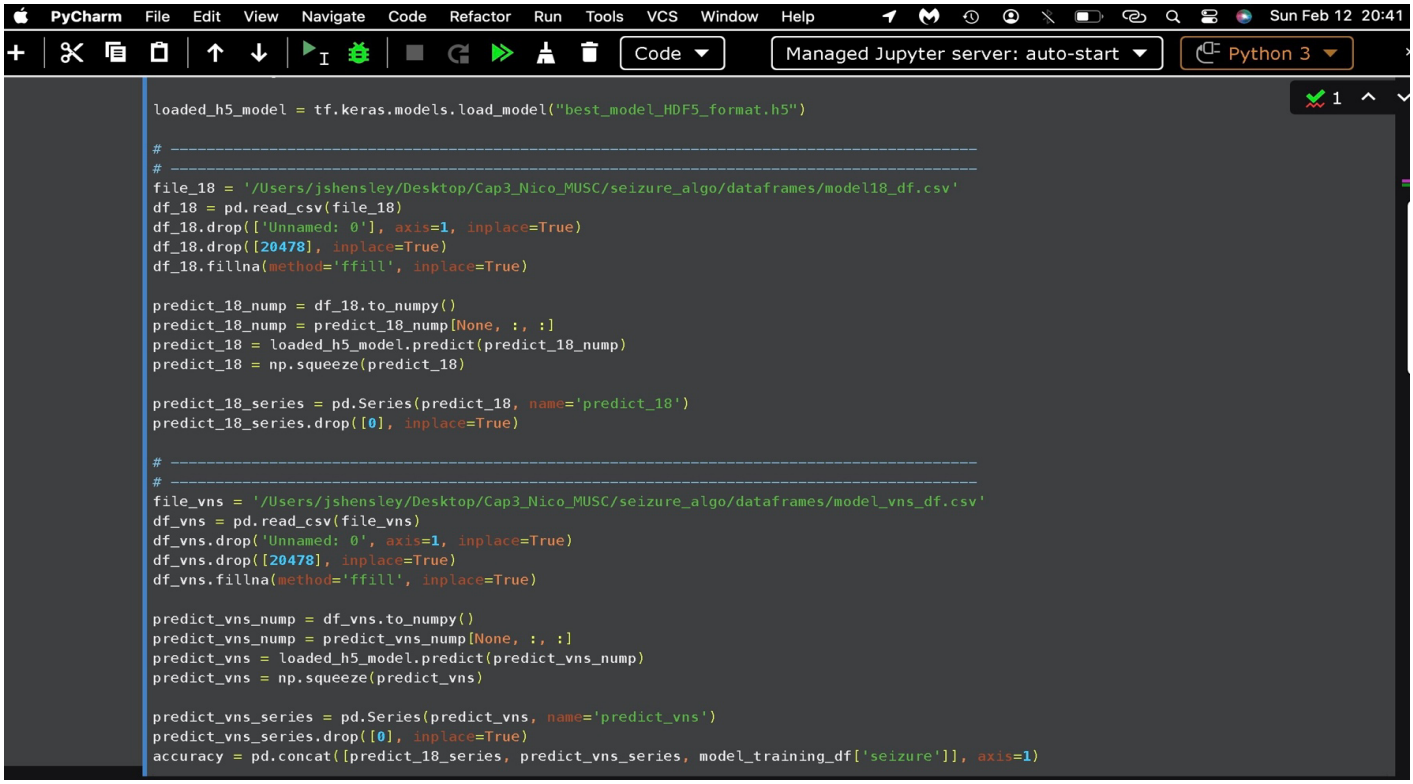
How about PCA using covariance matrices to reduce the dimensions to 2? Maybe something there?



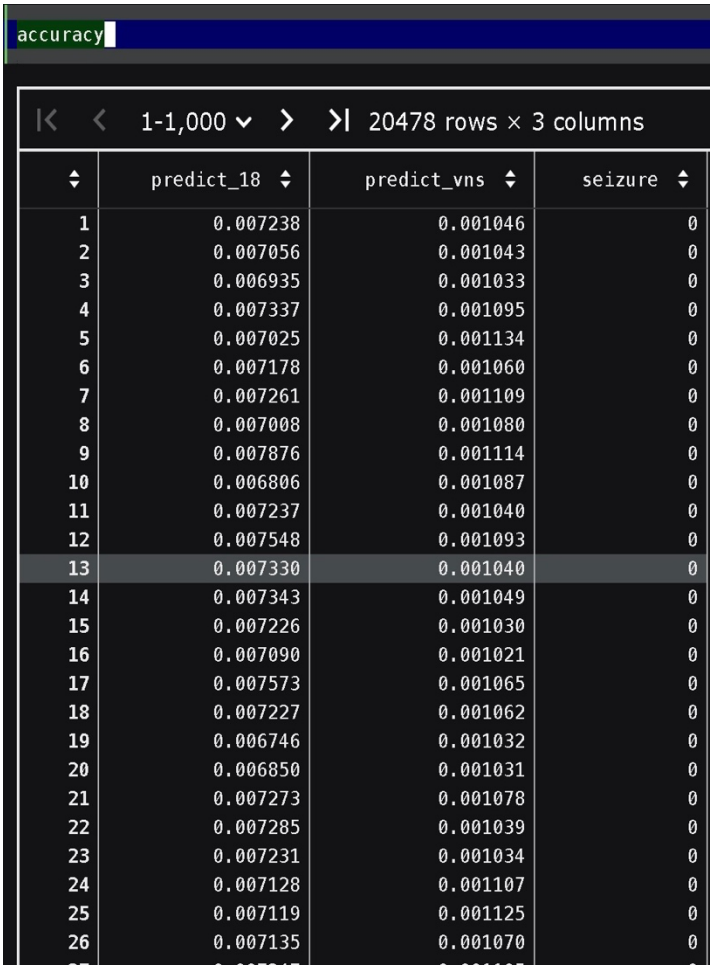
My final gasp, hoping the graphs were wrong, I ran a statistical test. Here it is along with where I was in the conclusion…deep in the rabbit hole. Bayes had to be abandoned and a 7 month's long goal destroyed in an instant.



And then, finally, with my head buried in my hands on a Sunday afternoon, having conceded to failure, I saw the answer! Using ideas from nonlinear dynamics, I fit the puzzle pieces together to see the needed order of features and the Tensorflow Model that gave perfect predictions. My fear was overfit, so I made more hyperparameter changes to be sure. Finally, with 5000 epochs, the multilayer TensorFlow model trained on one patient, saved, then ran on two separate patient datasets, yielded to the code…



…that yielded to the results…



	predict_18	predict_vns	seizure
1	0.007238	0.001046	0
2	0.007056	0.001043	0
3	0.006935	0.001033	0
4	0.007337	0.001095	0
5	0.007025	0.001134	0
6	0.007178	0.001060	0
7	0.007261	0.001109	0
8	0.007008	0.001080	0
9	0.007876	0.001114	0
10	0.006806	0.001087	0
11	0.007237	0.001040	0
12	0.007548	0.001093	0
13	0.007330	0.001040	0
14	0.007343	0.001049	0
15	0.007226	0.001030	0
16	0.007090	0.001021	0
17	0.007573	0.001065	0
18	0.007227	0.001062	0
19	0.006746	0.001032	0
20	0.006850	0.001031	0
21	0.007273	0.001078	0
22	0.007285	0.001039	0
23	0.007231	0.001034	0
24	0.007128	0.001107	0
25	0.007119	0.001125	0
26	0.007135	0.001070	0

The first two columns are two different patients. 'Predict-18' is a female and 'Predict_vns,' also a female, but has a VNS surgically inserted. The third column simply identifies what is a seizure, labeled 1, and what isn't a seizure, labeled 0. The float values under each patient is the probability that a particular row from that patient is a seizure or not. Row 10239 marks the start of the seizure for both patients.

The time series Tensorflow model has been trained on a separate dataset from the same patient as 'Predict_18' but a year and a half earlier in life. The model took about an hour to train on 5000 epochs and used a variety of different hidden layers and was saved as a .h5 file.

Because it's in the medical realm, high precision with no false positives was required. Having parents or hospitals believe there is a seizure when there isn't must be avoided!

Below I've cited from whence came the data and some of the python packages used, I took the original data seen in my second capstone project used feature engineering to achieve the results. This was carried out with custom python classes and functions.

	predict_18	predict_vns	seizure
10231	0.007495	0.001059	0
10232	0.007275	0.001111	0
10233	0.006979	0.001038	0
10234	0.008031	0.001108	0
10235	0.007288	0.001097	0
10236	0.007066	0.001009	0
10237	0.006701	0.001046	0
10238	0.007291	0.001055	0
10239	0.993065	0.998915	1
10240	0.993027	0.998938	1
10241	0.992608	0.998902	1
10242	0.992848	0.998914	1
10243	0.993189	0.998980	1
10244	0.992444	0.998916	1
10245	0.992693	0.998951	1
10246	0.992696	0.998935	1
10247	0.992923	0.998947	1
10248	0.993075	0.998966	1
10249	0.992186	0.998876	1
10250	0.992641	0.998993	1
10251	0.993297	0.998971	1
10252	0.993166	0.998957	1
10253	0.992469	0.999001	1
10254	0.992167	0.998887	1
10255	0.992598	0.998931	1
10256	0.992196	0.998877	1
10257	0.993226	0.998976	1
10258	0.992843	0.998940	1
10259	0.992958	0.998955	1

The original data was acquired from:
https://physionet.org/content/chbmit/1.0.0/

Patient 1:
The patient's baseline (no seizure):
https://physionet.org/content/chbmit/1.0.0/chb01/chb01_02.edf
The patient's seizure:
https://physionet.org/content/chbmit/1.0.0/chb01/chb01_03.edf

Patient 1 but 18 months later:
The patient's baseline (no seizure):
https://physionet.org/content/chbmit/1.0.0/chb21/chb21_18.edf
The patient's seizure:
https://physionet.org/content/chbmit/1.0.0/chb21/chb21_19.edf

Patient 2, who had a VNS installed:
The patient's baseline (no seizure):
https://physionet.org/content/chbmit/1.0.0/chb09/chb09_18.edf
The patient's seizure:
https://physionet.org/content/chbmit/1.0.0/chb09/chb09_19.edf

	predict_18	predict_vns	seizure
20448	0.993115	0.998933	1
20449	0.992449	0.998878	1
20450	0.992887	0.998958	1
20451	0.993056	0.998998	1
20452	0.992699	0.998930	1
20453	0.992987	0.998952	1
20454	0.992588	0.998936	1
20455	0.992722	0.998900	1
20456	0.992894	0.998905	1
20457	0.992117	0.998916	1
20458	0.992622	0.998955	1
20459	0.992959	0.998947	1
20460	0.992758	0.998927	1
20461	0.993006	0.998937	1
20462	0.992738	0.998937	1
20463	0.992899	0.998914	1
20464	0.992907	0.998975	1
20465	0.993292	0.998938	1
20466	0.992565	0.998849	1
20467	0.992419	0.998901	1
20468	0.992596	0.998958	1
20469	0.992842	0.998906	1
20470	0.992566	0.998890	1
20471	0.992823	0.998889	1
20472	0.992750	0.998937	1
20473	0.992790	0.998896	1
20474	0.992988	0.998941	1
20475	0.992786	0.998936	1
20476	0.992934	0.998986	1

Original Paper:
Ali Shoeb. Application of Machine Learning to Epileptic Seizure Onset Detection and Treatment. PhD Thesis, Massachusetts Institute of Technology, September 2009.
https://dspace.mit.edu/handle/1721.1/54669

Physionet: https://physionet.org/
Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

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Alexandre Gramfort, Martin Luessi, Eric Larson, Denis A. Engemann, Daniel Strohmeier, Christian Brodbeck, Roman Goj, Mainak Jas, Teon Brooks, Lauri Parkkonen, and Matti S. Hämäläinen. MEG and EEG data analysis with MNE-Python. Frontiers in Neuroscience, 7(267):1–13, 2013

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Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., … SciPy 1.0 Contributors. (2020). SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. Nature Methods, 17, 261–272. https://doi.org/10.1038/s41592-019-0686-2

scikit-learn:

Pedregosa, F., Varoquaux, Ga"el, Gramfort, A., Michel, V., Thirion, B., Grisel, O., … others. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12(Oct), 2825–2830.

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Van Rossum, G., & Drake Jr, F. L. (1995). Python reference manual. Centrum voor Wiskunde en Informatica Amsterdam.

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J. D. Hunter, "Matplotlib: A 2D Graphics Environment", Computing in Science & Engineering, vol. 9, no. 3, pp. 90-95, 2007.

seaborn:

Waskom, M., Botvinnik, Olga, O'Kane, Drew, Hobson, Paul, Lukauskas, Saulius, Gemperline, David C, … Qalieh, Adel. (2017). mwaskom/seaborn: v0.8.1 (September 2017). Zenodo. https://doi.org/10.5281/zenodo.883859