**بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيم**



USE OF Machine learning techniques IN THE Learning and prediction of alpha-decay half-lives

COMPUTER SCIENCE NEA 2021/22



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# Analysis

## Identification of the Problem

### Initial Ideas

Over the course of the A-Level, I have taken a deeper interest in the creation of AI using Machine Learning techniques, creating a neural network which feeds forward information into a number of hidden layers, training itself by minimising a cost function using backpropagation. I wished to pair this with my love for Physics and apply ML techniques to a real-world Physics problem. I had a few initial ideas, namely:

1. Analysis of Star Spectra
   * By analysing which wavelengths of light different stars absorb, we are able to see the colour of the star and also which elements are being fused in the core of the star. This allows us to see where the star is in its life cycle and therefore accurately determine its age. The user could manually input the wavelengths absorbed and the AI would be able to determine the elements being fused and provide an estimation of the age of the star.
2. Detection of Gravitationally Lensed Images
   * ![A picture containing night, outdoor object, star, dark

     Description automatically generated](data:image/jpeg;base64,/9j/4AAQSkZJRgABAQEAYABgAAD/4RCKRXhpZgAATU0AKgAAAAgABAE7AAIAAAAIAAAISodpAAQAAAABAAAIUpydAAEAAAAQAAAQcuocAAcAAAgMAAAAPgAAAAAc6gAAAAgAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAE1hdGV1c3oAAAHqHAAHAAAIDAAACGQAAAAAHOoAAAAIAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAAA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picture containing text, indoor, black

     Description automatically generatedThis was inspired by a bout of research into Special and General Relativity. Captured images of distant galaxies and stars are often warped by a phenomenon called gravitational lensing when very gravitationally dense objects, such as galaxy clusters, in the way, bend the path of the light, resulting in images which would otherwise be unable to be seen to be seen, albeit slightly warped. The proposed project will be able to use ML to detect whether or not an image has been gravitationally lensed and possibly reverse the effects of gravitational lensing to form the original image.

Figure 2: Einstein ring formed due to gravitational lensing (https://en.wikipedia.org/wiki/Gravitational\_lens)

Figure : Diagram representing gravitational lensing from (https://esahubble.org/images/heic1106c/)

1. Prediction of Half-Lives of Radioactive Isotopes
   * This was inspired by recent Physics lessons on Radioactivity in which incredibly long and incredibly short half-lives were discussed. The proposed solution will be able to predict the half-life of a given (radioactive) isotope based on factors such as proton number and neutron number, among other factors.

### Preliminary Analysis of Initial Ideas and Selection of Final Idea

1. Analysis of Star Spectra
   * The good thing about this project is that it will involve the AI learning of the link between elements fused and the star spectra of the star. The problem with this project, however, is that this is not an actual problem as all the possible colours and their meanings are already known, meaning there is not much use of an AI which does this. The project can be hard-coded and will perform the same.
2. Detection of Gravitationally Lensed images using ML
   * While there had been research into using ML for this[[1]](#footnote-1), the level of Mathematics and data required for a project like this was much beyond my reach, especially if I wanted to add functionality to reverse the image. This is because it entailed knowing things like when the image was taken, by which telescope, and then the state of all the clusters in the way at that moment, before having to plug it into the field equations for general relativity to be able to reverse the image. The project would have been too data intensive and so I decided against it.
3. Prediction of Half-Lives of Radioactive Isotopes
   * Preliminary research into this showed that using ML for this had been proposed and shown to be effective by a paper in 2014[[2]](#footnote-2) and had since been used for research purposes for both alpha decay[[3]](#footnote-3) and beta decay[[4]](#footnote-4). The databases were also freely published and available for usage and there is not much to learn in terms of the concept itself. The difficulty in experimentally measuring incredibly long and incredibly short half-lives also justifies the need for a project like this for use in a research setting. For this reason, **I am choosing to continue with this for my final project**.

### Stakeholders

For an academic project like this, the main stakeholders include educators and/or researchers. Educators will be able to use this product to show their students the half-lives of specific radioactive nuclei and I could add diagrams to show how half-life changes depending on different factors if I want to make it more specialised to education. For a more academic product, it would be used for predicting half-lives of novel radioactive isotopes which may be discovered or predicted, helping guide their research and expectations.

### Why Is It Amenable to a Computational Solution?

Due to the difficulties in measuring very long and very short half-lives, as well as the random nature of radioactive decay, a computational solution may be much more suitable than an analytical one. While there do exist analytical models for alpha decay half-lives, namely the Effective Liquid Drop Models, the Generalised Liquid Drop Models (ELDM and GLDM respectively) and the Viola-Seaborg Model, a paper in 2019[[5]](#footnote-5) showed that an approach based around ML is able to produce more accurate results. Due to the error contained in experimental results as well, an AI which is able to take this into account could potentially be more accurate than experiment. Part of my evaluation process will be to compare my model against the existing analytical models and to see if my model is more accurate.

Another aspect to consider is the fact that the development of neural networks (NN) is very processor heavy, especially in the optimisation and storage of the floating point weights and biases (more on this later) to create an accurate model. For this reason, any approach using a NN requires computationally advanced components, especially a GPU, which is specialised for floating point operations. This is another reason as to why a computational solution is ideal for this project.

## Research into Problem

While doing preliminary research, I found that all the papers that did use ML for learning half-lives only focused on predicting half-lives based on 1 mode of decay rather than all of them. I believe the reason this was done was due to the differing complexities of each type of decay; beta decay consisted of many different subtypes while alpha decay has only 1 type. Due to the importance and variety in the types of beta decay, I do not feel that a project which solely focuses on half-lives, like mine, would be a sufficiently good tool to use in education or research. As the complexities of beta decay are also out of the scope of A-Level syllabus, and I already have a quite advanced project, I do not feel confident in learning all the pre-requisites for a project which focuses on beta decay.

Another reason to focus solely on alpha decay is due to the increasing amounts of research into super-heavy elements (SHEs). More specifically, this includes their production and usage in nuclear fusion. One of the main properties researchers are interested are their half-lives, and as most SHEs decay via alpha decay, my project could go towards research in that field. For this reason, I have decided to focus on alpha decays for my project.

### Potential Successes with Selected Problem

Potential successes include being highly accurate in my predictions of alpha decay half-lives and being more accurate than existing models in this regard. A standard way of measuring the efficacy of a model is by measuring the smallness of the standard deviation of the model from experiment[[6]](#footnote-6):

, where is the base-10 logarithm of the half-life.

I will include this in my testing to allow myself to compare my model to existing analytical models.

### Potential Issues with Selected Problem

The main potential issues occur with not having enough data and therefore not having a very accurate model. To try and combat this I will try and gather data from as many different sources as possible. This may cause me to have duplicate data, however, and so I will have to take care to combat this.

Another issue to consider is the one of predicting a half-life for things which do not have a half-life. This will occur because my training data will not be varied enough to include every single possible isotope and then define which ones will and will not have a half-life with alpha decay, and so, the network will return a half-life for every single input. Because this is to be used in research and education, however, the researchers will know whether or not an isotope will decay via alpha emission, and so it is not too much of an issue. For the sake of completeness, however, I will implement features to allow the dataset to be updated so that in future, these issues can be accounted for.

### Analysis of Existing Similar Solutions

While there are similar existing solutions within academia which have used similar techniques, there is no publicly available software employing a NN for this problem. This is understandable as there is not really a need for the public to predict alpha-decay half-lives, however, I still think a tool should be publicly available to researchers and academics who wish to use the tool.

The first paper[[7]](#footnote-7) I looked at used a network with 6 input neurons: atomic number, neutron number, parity, decay energy, distance from (nearest) proton magic number and distance from (nearest) neutron magic number. They then had a hidden layer (of 4 units), a learning rate of 0.001, and the activation function . They also used Nesterov momentum during their gradient descent with the value of the momentum being 0.99, and regularisation with a strength of 0.1.

They used 3000 epochs (passages through the training data) and their cost function was the standard deviation . In practice, their results had a standard deviation of 0.4910 from the true values when measured on the test set, which was noticeably better than the standard deviation of the ELDM model, which was 0.5845.

The second source[[8]](#footnote-8) I looked at used only 3 input neurons: atomic number, neutron number and mass number. While it did not go into detail in regard to the structure, it was found that when the network was trained to find the half-life, it was not very successful, however, when the network was trained to find the base-10 logarithm of the half-life, it was found to be very accurate.

### Features Adopted and Rejected from the Existing Solutions

Based on the existing solutions, I have decided to follow the following structure for my neural network:

* + - 6 input neurons: proton number, neutron number, atomic number, decay energy, distance from proton magic number and distance from neutron magic number.
    - Learning rate of 0.01
    - Minimum of 4 hidden layers of 16 neurons each
    - Cost function of (standard deviation).
    - Output of the base-10 logarithm of the half-life.
    - Activation function being the sigmoid function as opposed to the tanh function. More detail on this later.

## Interviews/Client Research

For my stakeholders, I chose university researchers and professors in higher education, as they will be the ones that benefit the most from a specialised program such as mine. Because this is not a general half-life predictor, it will not necessarily be of as much value for science-communication or for the general public. Another reason researchers are the ones who will extract the most benefit from a project like this is due to the increasing amount of research into SHEs as was mentioned earlier. Due to this, I got in contact with a researcher from a nearby university who wished to remain anonymous, and after explaining the premise of what I was setting out to do, I asked him the following questions.

### Interview Questions

1. How useful are the statistical models for alpha-decay (ELDM, GLDM) in your work?
2. How would you quantify the accuracy of a half-life model?
3. How would a more accurate model benefit your work?
4. How would you like to interact with the software?
5. Would you like the ability to update the dataset which the network is trained from?
6. Would you like the ability to change the structure of the model?
7. How important is the transparency of how the model works?

### Interview Results

1. The ELDM and GLDM models are very useful in guiding our assumptions of the behaviour of these isotopes. They act as a useful tool in shaping our expectations and allowing us to build a pretty good model of how things will behave and interact. Obviously, they’re not exact but they are close enough to allow us to build a good picture
2. The accuracy is generally quantified by the standard deviation of the logarithm of the model compared to the experimental half-life because it helps get around the different orders of magnitude the half-lives can span.
3. A more accurate model which can predict the half-lives of novel isotopes would be quite useful. We are always trying to develop more and more accurate models based on our increasing understanding of the processes governing radioactive decay, so a modelling method which is more accurate would be very useful. One thing which I may suggest is that, although the model may be very accurate, it should also be clear how it works, as one of the advantages of these models is that they build off of what we understand conceptually to help us build a picture of what is around us.
4. A simple interface would be sufficient in which we can enter the relevant details if we have them and get a prediction. Some software can be very complicated to use, as you have to worry about whether or not you have entered every piece of data etc. so a simple interface would be quite useful.
5. Having the ability to update the dataset would be very useful as it means we will be able to update your model as and when new experimental data comes in. This would help us in keeping as up-to-date as we can with our models.
6. This is not much of a concern as I don’t expect us to be fiddling around with the settings of the model, as long as it functions well enough and we can update it based on new experimental data, it should be sufficient.
7. As physicists, we are always trying to increase our understanding of how the world works, however, I understand that with a neural network, it can be difficult to understand the implications of why the model sets itself up as it does. While it would be nice to understand how the model works, I don’t feel that it is necessary in helping us deriving experimental value from it,.

### Conclusions from Interview(s)

It is clear from the interviews that the ELDM and GLDM models are very important in research (1) and it was also clear that having a more accurate model would be of great benefit to the researchers (3). For this reason, building a more accurate model than the statistical models will be my aim. I will quantify this using the standard deviation of the logarithm of the half-life compared to the model (2).

The GUI will be very simplistic to allow the researchers to interact quickly with it and not have to worry about whether they have entered the right bits of data in the right places (4). I will also try and allow for the ability to update the dataset as per the stakeholder’s wants (5). I may add the ability to update the structure of the network and allow them to retrain it, although, it is clear that this is not something very important to the stakeholder (6).

## Requirements

### Software Requirements

I am planning to keep the software quite lightweight so that any device is able to run it. Therefore, the software requirements are limited to:

* Python 3.10 (with the appropriate libraries)
* A Python Interpreter

### Hardware Requirements

* A PC which is capable of running Python

No specific hardware is required for my program. Any PC capable of running Python should be able to run my program.

### Stakeholder Requirements

* A better accuracy than the statistical models for alpha decay
* Simple GUI with easy navigation

These requirements were based on the answers the stakeholders gave to my questions above.

## Success Criteria

### Essential

|  |  |  |
| --- | --- | --- |
| Criterion | Type | How to Evidence |
| Predictions of the neural network must have better accuracy than the statistical model | Functional | Compare standard deviations of both the statistical model and the neural network |
| The network is able to account for updates to the database of isotopes | Functional | Screenshots of lack of hard-coding |
| User is able to easily navigate the GUI | Usability | Stakeholder feedback and screenshots of simplistic GUI |

### Desirable

|  |  |  |
| --- | --- | --- |
| Criterion | Type | How to Evidence |
| User is able to retrain the network with their own structure and settings | Functional and Usability | Screenshots of retraining screen allowing the user to do this |
| It is easy for the user to make any adjustments to the network | Usability | Stakeholder feedback |
| User is easily able to update the database | Usability | Screenshots of code allowing the user to do this and stakeholder feedback in regards to the ease |

Other desirable criteria include anything which may arise in development, as I have not yet started development and do not know other success criteria may arise.

# Design

Due to this being a large project, I will have to split it into multiple smaller components to allow it to be manageable. I first split the program into front-end and back-end, to signify which parts of the program the user will and won’t interact with. I will update my front-end and back-end development plans once I have done more research into neural networks and machine learning:

Diagram

Description automatically generated

## Neural Networks and How They Work

### Weights and Bias in a Neural Network | Towards Data ScienceStructure and Feeding Forward

2 https://towardsdatascience.com/whats-the-role-of-weights-and-bias-in-a-neural-network-4cf7e9888a0f

Neural networks consist of multiple units of “neurons”, structured in layers, with each layer feeding into the next. A neuron can just be thought of as something which stores a number, called its activation. Each neuron has a specific weight which its activation is multiplied by, and a bias which is added to it, which contribute to the activations of each neuron in the next layer. The activation of that next neuron depends on the weighted sum of all the activations in the previous layer, added to their individual biases (pictured above). This sum then put through an activation function, such as the sigmoid activation function or a ReLU (Rectified Linear Unit), to give it its final activation. Every neuron in a layer is linked to every neuron in the next layer, with each of them having their own individual weights and biases. For larger networks, it becomes incredibly complicated to keep track of all the weights and biases, as well as all the indexing of which layer each neuron is in, and so we often use matrix multiplication to represent this more simply:

Shape

Description automatically generated with medium confidenceThe activation of neuron 0 is the weighted sum of all the activations of the previous layer (with their own specific weights) + a bias, all plugged through a specific activation function:

Shape

Description automatically generated with medium confidenceThis can be represented more simply using matrices:

By using matrices, we can greatly decrease the amount of processing power and data storage we need, as the activations of a whole layer are dependent on only 3 stored quantities. To do this, I will use a library called numpy in Python to define and multiply matrices, as numpy is highly optimised for this, meaning it will greatly decrease the load on the user’s PC.

The activation function I am choosing to use is the sigmoid function, which is defined as . This is one which is often used in industry because it normalises the value of the sum, giving it a value between 1 and 0, preventing certain factors from influencing the activation a lot more than others. I decided to use this as it is easier to differentiate than something like , and, unlike ReLU, it is non-linear, meaning that its derivative is not a constant. This makes backpropagation work more effectively as the neural network will not be a set of linear transformations.

To ultimately receive an output from the network, a set of inputs has to be multiplied through each layer, before eventually reaching the output layer from which the activations are interpreted to represent the final output of the network.

### Backpropagation and Minimising Cost

#### Gradient Descent

The initial weights and biases of a neural network are initialised randomly, however, due to this, the output from the network will be incredibly inaccurate. I will then need to adjust the weights and biases accordingly to allow a useful output to be reached. This has to be done iteratively, step by step. The reason for this is because it is a practically intractable problem to iterate through every single possible combination of weights and biases in a network before you decide on the one which gives you the outputs you require. For this reason, I will use a technique called gradient descent.

Gradient descent consists of taking the rate of change of the cost (a function of the difference between the desired value and the value given by the network) with respect to each weight and bias. Because we are working with vectors and matrices, the rate of change will give us a gradient vector pointing in the direction of increase. We then negate this to get the vector giving us the direction of the decrease of the cost, and adjust all the weights and biases proportionally. This is similar to finding a local minimum of a graph in a cartesian space. The constant of proportionality is called the learning rate and it can be thought of as the size of the step which the weights and biases take, or the size of the step down the graph. The smaller this is, the less likely the network is to overshoot and miss the local minima, however, it will take longer to train. I have decided to use a learning rate of 0.01 as this is sufficiently small enough to allow for this, but not so small that the network won’t converge in a reasonable amount of time.

#### Backpropagation

Backpropagation is a technique which allows you to compute this gradient vector. By taking the error of the output layer, we know how much we need to adjust the output value by, however, because each neuron in the previous layer contributes a different amount to the overall value, we need to propagate the error backwards using the weights and biases to see how much we need to adjust each activation in the previous layer. As these next activations are dependent on the activations of the layer before that, we propagate the error back etc. and continue doing this until we have the adjustments that need to be made to each weight and bias. To propagate the error backwards, we have to use the transpose of the weight matrix to undo the transformation the weight matrix makes on the activations.

To compute the change of the cost with respect to each weight and bias, we first need to compute an intermediary quantity called the error. If our activation is defined as , (activation in layer 1 is the weighted sum of the activations in layer 0 + the biases, all in the sigmoid function) we can define . If we nudge this “presigmoid” value by a small change , the overall change to the cost is If is small, then that means the small change in z will not have much of an effect, meaning that the neuron is already quite optimal. If it is large, then that means a small adjustment has a large effect on the cost. Because of this, can be thought of as the error .

By the chain rule:

In matrix form, this can be represented as:

where is the Hadamard product (element-wise product), and is the gradient vector of the cost with respect to the activations. My cost function for a single training example is . The derivative of this (without the constants) is simply . I can disregard the constants as the result will be multiplied by the learning rate anyway. The derivative of the sigmoid function can be shown to be . In this way, we now have a formula for finding the error of a particular layer of neurons.

Backpropagation works because can be written in terms of the layer in front using the idea of propagating the error backwards, giving us a recursive relationship between the error of each layer. If represents the current layer:

It can then be shown that:

That is, the derivative of the cost with respect to a bias is just the error of that particular neuron. For the weights, the derivative of each weight is the activation of the neuron from previous layer multiplied by the error of the neuron (each connection has a weight):

When applied iteratively backwards through a network, these relationships then give us the gradient vector of the cost function with respect to each of the weights and biases, which is exactly what we want.

I will apply backpropagation to adjust the weights and biases feeding a training example through the network and measuring the error. When this is applied and averaged over all the training examples multiple times, the weights should hopefully be in a good enough state to make accurate predictions over all training examples. To avoid the need for the user to constantly have to train the network, I will then save the states of the weights and just feed forward the user inputs.

### Turning Classification into Regression

One of the things I have to consider is that I am not trying to get an output between 0 and 1. For this reason, I will not apply the sigmoid function to the output layer neuron, meaning the output will just be a linear combination of the activations of the previous neurons. This will mean my or the derivative of my activation function will be 1. This is something I will have to account for in my code.

## Development Plan

My development plan will involve me first extracting and storing the data in a convenient way so that it can be read and written to easily. I will then develop the network in a class. I have chosen to develop it in a class as this will allow me to encapsulate all the methods and attributes I need under one structure. It will also take away the need to rewrite code as I can just call all the relevant functions I need. I will then finally develop a user interface to allow the network to be interacted with and predictions to be made.

### Extracting Data

Based on a paper[[9]](#footnote-9) which did something similar to my project, I decided to take my data from 2 main sources:

* + - Cui, J.P., Zhang, Y.L., Zhang, S. and Wang, Y.Z. (2018). *α -decay half-lives of superheavy nuclei.* Physical Review C, 97(1).
    - Cui, J.P., Xiao, Y., Gao, Y.H. and Wang, Y.Z. (2019). *α-decay half-lives of neutron-deficient nuclei.* Nuclear Physics A, [online] 987, pp.99–111.

Text

Description automatically generated with medium confidenceThis gives me a total of 213 isotopes which I can use to train and evaluate my data. I will write all the information about these, including the half-life predicted by the ELDM model, into a text file which I will convert into a csv file. I will do it like this as it is simpler to write to text files than it is to csv files in Python. As the papers storing the data are pdfs, I will first copy and paste the data into a text file to read from, before rewriting it in a useful format.

I will then develop a database class in which I can encapsulate all the methods I need to fetch whichever data I need from the database. This will greatly improve readability and also mean I do not have to worry about where each relevant piece of data is stored.

To allow for any future additions to the database, I will not hard-code the database or the feature retrieval, improving the longevity of the code and conforming to the stakeholder’s wants.

#### Usability Features

This part of the project will not be interacted with by the user so I do not need to consider any usability features in this section.

### Developing the Network

Shape

Description automatically generated with low confidenceAs was mentioned earlier, the network will be developed in a class to allow me to easily encapsulate all the methods and variables I need. I drew a class diagram on the left to help me visualise what needs to be done. In terms of developing the algorithms themselves, it will be a case of transferring the above mathematical formulas into code. As I don’t want to hard-code the structure of the program, I will be coding the backpropagation and feedforward algorithms iteratively, letting the user define the structure of the network, however, I will first hard-code each step to make sure I understand the whole process. This will make it easier to first spot any errors but also prevent me getting confused with indexing in the loops as I anticipate this will be something that trips me up. To help with this, I decided to write some pseudocode to make sure I understood all the maths above:

#### Graphical user interface, text, application Description automatically generatedText Description automatically generatedPseudocode for Network

Once I have trained the network to a suitable standard, I will save the states of the weights and biases using a joblib dump which will convert the matrices into a bitstream which can be read from later. I am using joblib as it is specialised for storing numpy matrices, which is what all the weights and biases in my program will be stored as. I can then load these wherever I need to use the neural network.

#### Usability Features

This part of the project will not be interacted with by the user so I do not need to consider any usability features in this section.

### User Interface

Graphical user interface, application

Description automatically generatedThis will be the last part of the project which I code and should be the simplest. There will be a basic UI which will allow the user to enter the data they need. For this, I will only need 3 text boxes to allow the user to enter value for the number of protons, neutrons, and the release energy. The distance from magic numbers and the nucleon numbers can be calculated from these. I will then feed them through my (trained) network which I will load from the joblib dump. The prediction will then pop up in a new window to make it clear which number on screen is the half-life.

The UI will be coded in tkinter as it is simple to design and add interactive elements onto. I mocked up a simple diagram on the right to illustrate how the interface may look.

#### Usability Features

This is the main part, if not the only part of the program which the user interacts with. For this reason, I need to make sure the UI is intuitive to understand and use. I also need to cater for all the incorrect inputs which a user may give, such as typing a letter when the program wants numbers. This will be done by creating try, catch statements in Python to catch any of the errors which may occur when I try to parse the user input. I will then need to clearly prompt the user for correct input. Overall, the UI is quite simple, so it should not be too difficult to both implement or use.

## Testing Plan

### Back-End Testing

|  |  |  |  |
| --- | --- | --- | --- |
| **Num.** | **Test** | **Success Criteria** | **Purpose** |
| (1) | Feed forward a 3 neuron input through a small network manually | The network successfully outputs a 1x1 array | This will determine whether or not the matrix multiplication is correct and whether I can move forward with creating a more complicated network. |
| (2) | Feed forward a 6 neuron input with varying dimensions iteratively | The network successfully outputs a 1x1 array | This will determine whether or not my iterative feed-forward algorithm works. |
| (3) | Backpropagate a 3 layer network | The network successfully updates both sets of weights | This will determine whether or not my backpropagation is dimensionally correct |
| (4) | Check the error of my procedural backpropagation algorithm | Tends towards 0 | This will determine whether or not the backpropagation is training the network to predict the half-life more and more accurately or not |
| (5) | Check the error of my iterative backpropagation with varying dimensions | Tends towards 0 | This will determine whether or not the backpropagation is training the network to predict the half-life more and more accurately or not |
| (6) | Upload and load a small joblib array | Uploaded and downloaded are the same | If successful, I can use joblib to upload weights and biases to download and use them in my front end |

### Front-End Testing

|  |  |  |  |
| --- | --- | --- | --- |
| **Num.** | **Test** | **Success Criteria** | **Purpose** |
| (i) | Enter incorrect data | The software catches incorrect data and prints out that incorrect data has been entered | This allows me to catch incorrect inputs and prompt the user for correct inputs |
| (ii) | Enter correct data | UI stores correct data and calculates extra data it needs | Allows me to determine whether my input system works as it should |
| (iii) | Feedforward an input | UI successfully computes half-life | Determines whether my feedforward and joblib loading is functional |
| (iv) | Try and create window | Window is created | Allows me to prompt the user for re-entry of data and to show them the results of the prediction |
| (v) | Enter correct data | Prediction is outputted correctly in new window | Determines whether the UI is functional in terms of feeding forward and showing data |

### Post Development Testing

|  |  |  |
| --- | --- | --- |
| **Test** | **Success Criteria** | **Purpose** |
| Accuracy of the NN | Better than statistical model consistently | Determines whether I have met stakeholder requirements and if my software is a useful tool |
| Entering Incorrect User Input | Able to catch incorrect input and prompt the user for correct input | Determines whether or not my software is robust enough to be used in the real world |

# Development and Implementation

## Extracting Data

I first started on my data extraction. The data which I will use comes from 2 main academic papers, mentioned above, however, the main problem I initially had was that they were pdfs, and reading from tables in pdfs is very difficult in Python. For this reason, I decided to copy and paste the data into text files and read from them. The 2 sources were formatted differently, however, and so I had to read from them separately. I decided to use the ELDM model to test against as this was common to both sources.

### Retrieving the Data

Graphical user interface, text, application

Description automatically generatedI first copied the data into a text file because of the reasons mentioned above:

Text

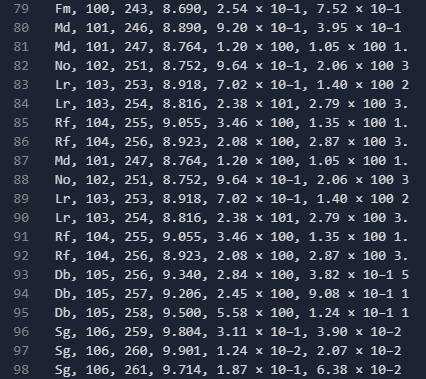
Description automatically generatedText

Description automatically generatedI then read from the text file into an array using this simple program:

This works because the values under each of the columns were each of the same length. This made it easy to specify a number. One of the outliers, however, was Uranium, as its chemical symbol is U. For this reason, I made sure to add an extra space after the U in my text file (above right) This was feasible as there were only 4 Uranium isotopes.

The second code block is one where I was adding all the proton numbers. This source didn’t use isotope numbers and instead listed all the elements according to their name. For this reason, I looked for an easy way to convert all these elements into their proton numbers. I found a csv file[[10]](#footnote-10) online which contained this information, and after stripping it of what I didn’t need, I compared the name of the element given in the database to the elements in the csv file and inserted the appropriate proton numbers in.

Text

Description automatically generatedI then wrote the data into a text file. The code was not very readable, however, I knew that I would only have to do this once and never come back to it, so I didn’t take the time to overly neaten it. This was when I encountered another issue: although the bases of the exponents were of the same length, the exponents weren’t. This meant that I had to read different lengths for different exponents, and so the one size fits all approach which I was implementing didn’t work. You can see I had artefacts of following data in my ELDM data (last column in screenshot on left) due to the different exponent lengths (below).

I thought about coding an elegant solution which takes into account the ‘–‘ signs but in the end, I decided to instead, introduce a gap of 3 whitespaces between all the data which may cause an issue. Then, I can read a fixed number of digits and stripped them of the whitespaces with the Python strip function. It did take some time to go through adding all the spaces but it was easier and quicker than reading and accounting for ‘–‘ signs. My function became:

A picture containing text, scoreboard

Description automatically generatedText, calendar

Description automatically generated with medium confidenceText

Description automatically generatedThis worked very well, and I no longer had any of the artefacts as you can see below. The stripping also got rid of the space after the U for Uranium which I forgot to account for, also pictured below.

Text

Description automatically generatedThe next thing to get rid of was the exponent, as the” x 10” cannot be read or used by Python. Instead of converting out of standard form, I decided to convert the exponent to “e” which means the same thing as “ x 10” and is understood by Python. This was an easy fix:

Text

Description automatically generatedThis did not work the first time when I typed in “ x 10” by myself. To fix this, I decided to copy and paste what the text file had and realised that the multiply sign was not the letter x but the actual Unicode multiplication sign, which is why it did not work. I fixed this but didn’t screenshot the difference because the code looked virtually the same. This gave me the format I wanted:

### Source 2

Text

Description automatically generatedI then repeated the same processes above for the second source. When I wrote the database, I formatted it as if it was a csv file. This was because I was planning to convert it to a csv file anyway (by changing the file extension) as they are very easy to read data from. I wrote to the text file using the following code:

In the end, I had a database of 213 elements which I could use to train and test my neural network. I decided to use the traditional 80-20 split, where 80% of my data will be used to train the network and the remaining 20% will be used to test it. The whole databasing was done using an online IDE and is available here: <https://replit.com/@MAmjad/Read-Data-Test#main.py>.

### Reading from Database and Encapsulation

Text

Description automatically generatedThe next step was reading from the database. I used the class diagram I made earlier and read from the database into a master data array. Whenever a function is called to retrieve a particular feature/data item, I read from this master array to a smaller array and returned that smaller array:

Text

Description automatically generatedText

Description automatically generatedText

Description automatically generatedText

Description automatically generatedI also added the Zdist and Ndist data items. These are the distances from the nearest proton magic numbers and neutron magic numbers respectively (2, 8, 20, 28, 50, 82, 126 for protons and neutrons as well as 84 for neutrons). This was one of the inputs of a solution I looked at which had better results than the statistical model.

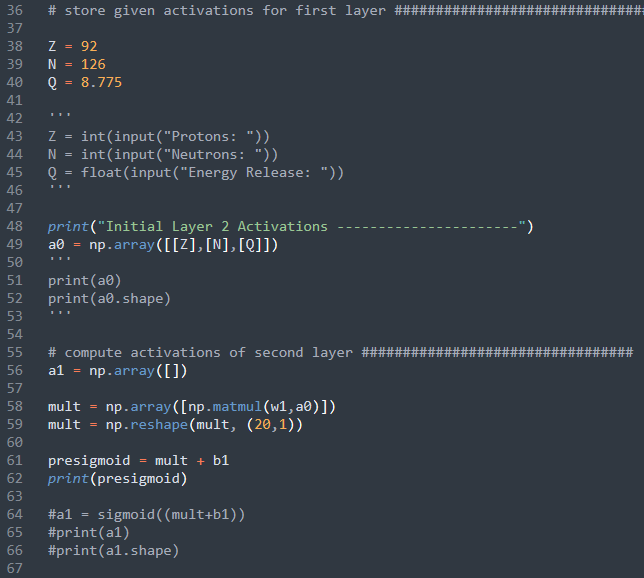
I then defined all the above subroutines to read from the data array and allow me to retrieve any of the data whenever I wanted. This was relatively straightforward, and so there weren’t any bugs to fix in this part of the project. This did make my life easier later on when retrieving data to train the model. I then went onto the model next.

## Developing the Network

### Feed-Forward Method

#### Step-By-Step

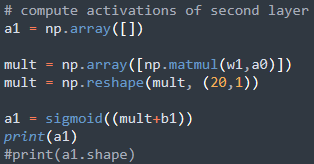
When doing the feed-forward method, I decided to first code a smaller version of my final network so I could get my head round the matrix multiplication. For this, I chose a 3 layer network with 3 input neurons, 1 hidden layer of 20 neurons and 1 output neuron which I defined as an array called structure, where structure = [3, 20, 1].

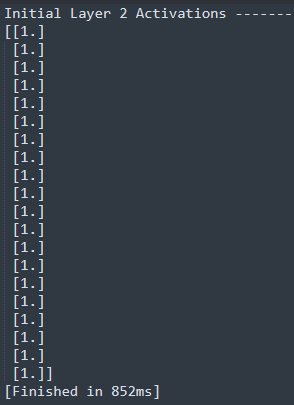
Text

Description automatically generatedI then defined and randomly initialised the weight matrix w1 as being the weights going into layer 1. This was a 20x3 matrix which would be multiplied by the 3x1 activations matrix (for the first layer neurons), giving me a 20x1 matrix, which signify the 20 neurons in layer 2. I then defined the bias randomly as well. I was originally going to define and initialise these manually with Python’s random library to randomly make up values, but then I discovered numpy’s np.random.rand(shape) which automatically defines a matrix with the given shape with random float values between 0 and 1:

Text

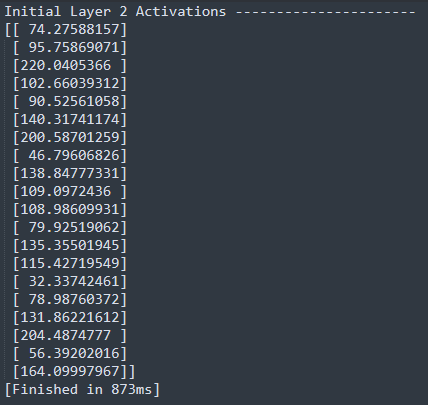
Description automatically generatedI then went to compute the second layer’s activations by multiplying the weight and activation matrices and adding the biases on. When I printed the shape of the matrix to check it was correct however, it gave me an unexpected result:

It was saying that the mult array was a 3D matrix of size 1x20x1. This could cause errors further down the line if I didn’t sort it so to be on the safe side, I used numpy’s reshape function which lets you reshape arrays without losing any of the data (if it is possible to do so).

I then printed a1 thinking that the sigmoid function would give me a range of values between 0 and 1, as was its job. When I printed the result, however, I got the following (left):

This was clearly not what I wanted. The sigmoid function only outputs values close to 1 for very high inputs. The fact that they were all 1 indicated to me that my weights may not be doing what they should be in weakening or strengthening the activations as appropriate.

To check this, I printed out my weighted sum to see what the matrix going into the sigmoid function was:

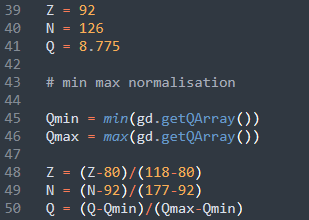
This outputted the following:

From this, it is clear what went wrong. Although the weights and biases had been initialised randomly and were small (between 0 and 1), this did not account for the massive discrepancies in the sizes of my input data. My release energy was below 10 while my proton and neutron numbers were in or near the hundreds. This made me realise that I needed to **normalise** the data.

#### Normalisation

Normalisation is the taking of a value and transforming it in some way to be between 0 and 1. An article by Tensorflow[[11]](#footnote-11) stated that it is good practice to normalise features that use different scales and ranges. You are unlikely to converge to a solution without normalisation.

After researching normalisation, I determined that min-max normalisation would be the easiest form to use in this context. The formula for min-max normalisation is as follows:

This guarantees a value between 0 and 1, and because the minimum and maximum values were easily found due to my database class having all the arrays I needed along with the python min() and max() functions, I decided to use this. I imported my Data class and initialised an object called gd (getData) and added the following:

Graphical user interface, text

Description automatically generatedI knew the minimum and maximum values for the protons and neutrons so I decided to just use them rather than retrieving the array to save time. This had the desired effect:

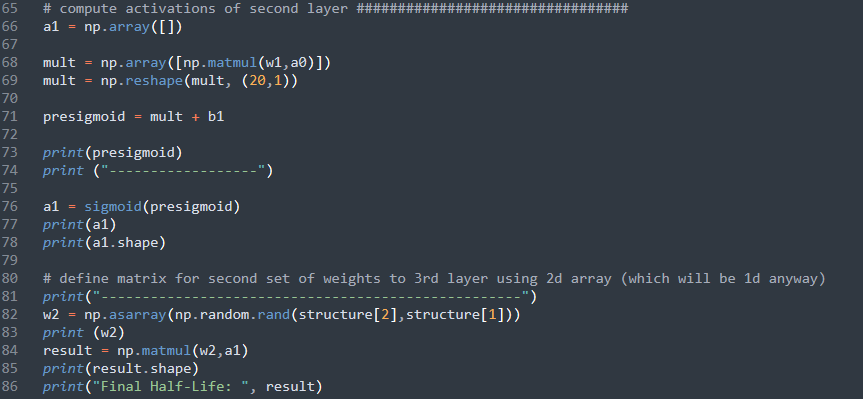
Text

Description automatically generatedI then put this through the sigmoid function:

Text

Description automatically generatedThese activations looked much better. I then moved on, calculating the final layer activation and this time, not plugging it into the sigmoid function because I wanted a regression network rather than a classification network:

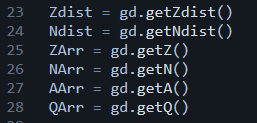
[Evidence for Test 1]

This worked. The final output is a 1x1 numpy matrix, showing all my matrix multiplication was consistent. This meant I was ready to code a more sophisticated network which would be able to perform the feed forward iteratively for a given structure.

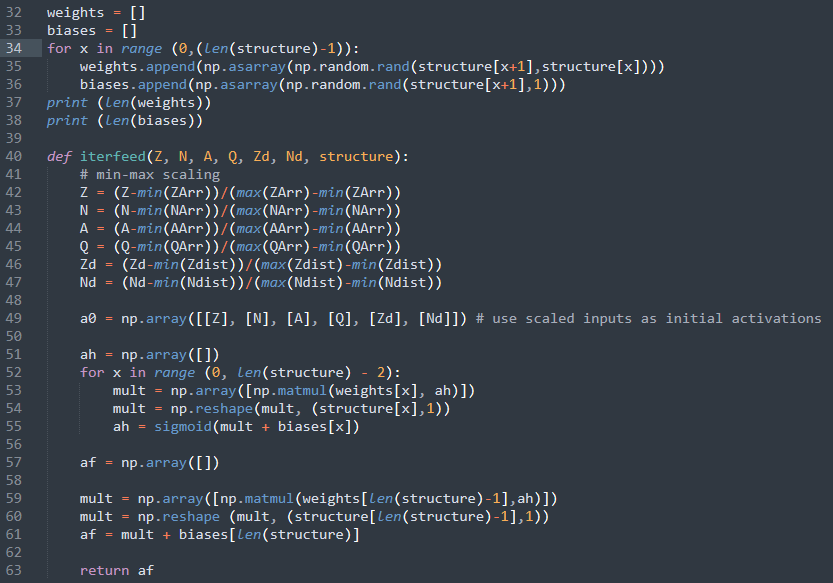
#### Iterative Feed Forward

I then decided to code my iterative feed-forward which had all six inputs:

* Proton Number
* Neutron Number
* Nucleon Number
* Release Energy
* Distance from Proton Magic Number
* Distance from Neutron Magic Number

I first used my Data library to import all the arrays I needed and defined my structure with 4 hidden layers of 16 neurons each:

I then used my procedural code from above to create an iterative feed method, manually adding and normalising the first layer activations and manually applying the last layer activations:

Defining and initialising weights and biases: ------->

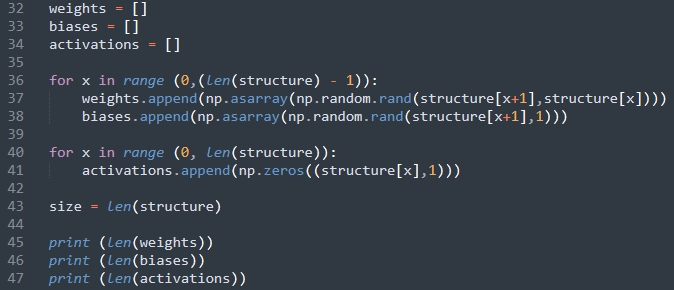
Normalising input values using min-max normalisation: ------>

Setting normalised values to be initial activations: ---------->

Defined an array ah for hidden activation and tried to compute activations: --------->

Manually apply last layer activations ----------------------->

When I ran this, however, I got an error:

It was saying that it could not multiply a matrix of size 0 with the weights matrix. I realised that the reason this threw the error was because I had defined ah as being empty, and then tried to use the values in ah to compute the next values in ah. For the second layer activations, I had to multiply by the first layer activations but I was multiplying by ah. I did not want to use if statements as that would have been inefficient and difficult to scale, so I decided to change the strategy with which I stored the activations and brought in an activations array. I was planning to do this later on when I introduced backpropagation, but this made me realise that I needed it now. I then added this in:

The reason activations is longer than the weights and biases arrays is because the weights act between layers, and so there are only l-1 weights (1->2, 2->3, …, n-1->n), and the biases don’t change the activations of the first layer, meaning there will be l-1 biases. Every layer, however, has an activation, so there needs to be as many activations as layers. I initialised the activations with 0s rather than random numbers as then it would be clear when an activation has been computed or not. (It was around this point I experimented with different IDE themes so I apologise for the inconsistencies in the colours).

Text

Description automatically generatedI updated my feed method accordingly:

Apply weights[x] to activations [x] and add the biases to get activations [x+1] (the next activation):

Graphical user interface, text

Description automatically generatedThis worked:

In order to test whether it was doing what I thought, however, I decided to recode my iterative feed-forward quickly and see what outputs it gave when I initialised the weights and biases the same:

Text

Description automatically generated

When I did this, I got the following outputs:

(I = Iterative, V = Original) This showed that they had the exact same outputs and therefore were doing the same things. However, to truly test whether this worked, I needed to change the structure and see if it still gave me an output.

When I changed the structure to the following: I received the following output:

Graphical user interface, text

Description automatically generatedI then changed the length of structure to the following, and received the following output:

[Evidence for Test 2]

This showed that my iterative feedforward method did in fact work for varying lengths and sizes of hidden layers. I was ready to move on to the next step.

Text

Description automatically generated One thing I saw which was quite clunky was the way in which I entered the data, as I had to enter each data item individually. For this reason, I decided to amend this and instead have it so the network takes in an array of data items. One issue which may arise is that the data may be entered in the wrong order, however, as the user does not interact with this directly, I do not have to worry about this. I then created a getIsotope() method in my data class which returns an array [Z, N, A, Q, ZDist, NDist]:

Text

Description automatically generatedThis then cleaned up my feedforward call:

This also means there is less chance for error when entering the data as I won’t swap 2 data items around in the call. I was now quite happy with my feedforward method and so I decided to begin the Network class and placing everything I needed into the class.

### Object-Oriented Encapsulation

Text

Description automatically generatedText

Description automatically generatedI put my constructor and feedforward method into a Network class which initialises all the weights, biases, activations etc. based on the structure of NN specified by the user:

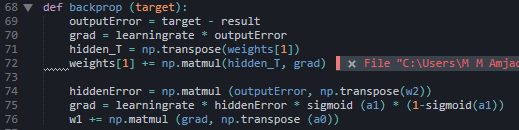
After confirming it was still working at this point[[12]](#footnote-12), that I started on my backpropagation method.

### Backpropagation Method

I coded my backpropagation method in a similar way to how I coded my feed-forward method, first doing each thing step-by-step on a 3-layer network before then coding it iteratively.

#### Step-By-Step

The first step of the backpropagation algorithm is to compute the error in the last layer, which is the (derivative of the cost function with respect to the activation) multiplied by (the derivative of the activation function with respect to z). The last layer activations, however, were not fed through an activation function, and instead were a linear combination of the previous layer activations. Because of this, the derivative of the activation function was 1. The derivative of the cost with respect to the activation is the activation-target, which is easy to compute. I added this in:

I then defined the hidden error according to the maths above and shifted the weights in the last line accordingly. As you can see, I got an error:

It was saying that my grad vector had a dimensionality of 0. I was curious as to why so I tried to print grad.shape:

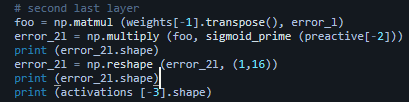
It was saying, in essence, that grad was not a vector, it was a scalar. I fixed this by adding a line after grad saying grad = np.array (grad) which converted grad to an array, and when I ran it, there were no errors, and the weights were shifted from the original. This means my backpropagation was dimensionally correct and so I decided to try this on the 6 layer network I was planning to use.

#### 6 Layer Step-By-Step Backpropagation

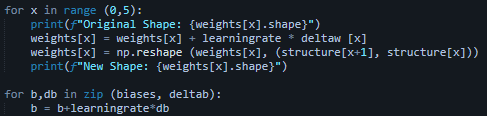
Text

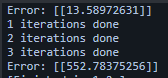
Description automatically generatedFor my backpropagation algorithm I am taking advantage of a Python feature in which you can use negative indexing to iterate through an array backwards (-1 refers to the final item, -2 to the second last etc). To make my life easier, I also defined a sigmoid prime function (derivative of the sigmoid) using lambda functions as follows:

I then coded my backpropagation algorithm following the above maths and pseudocode. The target was the base 10 logarithm of the half-life.

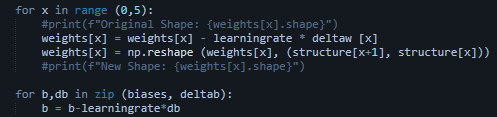
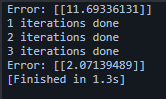
I frequently kept printing the sizes and shapes of each of the vectors I was multiplying in order to avoid errors in my matrix multiplication being inconsistent. It was also done to check for numpy “quirks” such as the following:

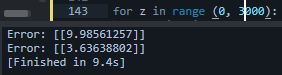
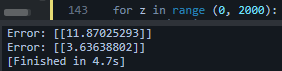
I continued the algorithm on the left until I had a delta for each of the weights and biases, and then adjusted them using the following loop. I checked the shape and resized due it throwing a similar error to the above:



Text

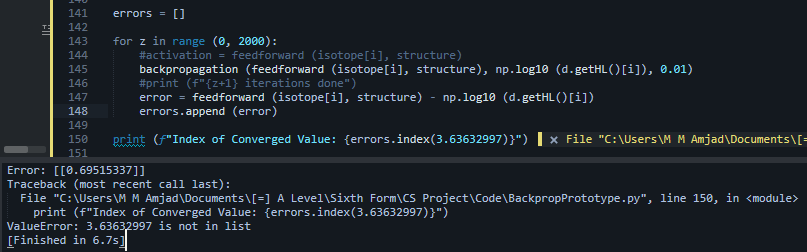
Description automatically generatedI then ran my backpropagation algorithm, printing out the original error when feeding forward an isotope and then the error after running the backpropagation a few times. I received the following results:

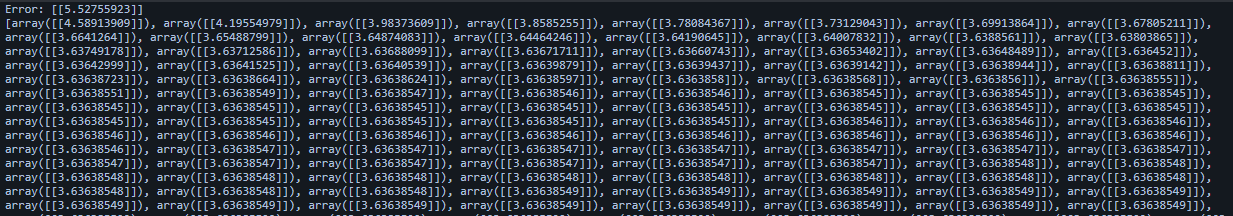
This seemed strange as it indicated that my error was actually increasing. I had a look over my algorithm and realised the reason for this was that I was increasing my weights and biases by the delta rather than decreasing them (see above). For this reason, I simply changed the + sign to a – sign and reprinted the errors which gave me the following:

This was a good sign, as my error was decreasing. I then decided to run the backpropagation for just a few more iterations and see how low I could get my error for a particular training example. I did this with a different isotope:

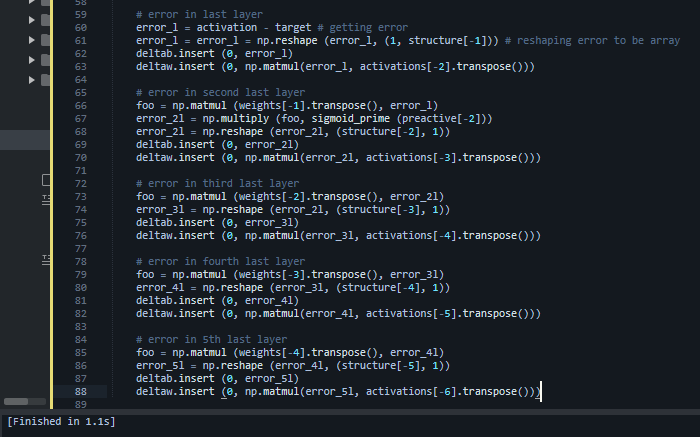
This showed that my error was converging to a particular value, which it should not have done. Backpropagation should theoretically reduce the error to 0, and this was not. I initially thought to look at my weights, as I thought the reason this could be happening may be because the weights don’t budge past a particular value. When I did this, I realised I did not initialise my weights with negative values as numpy.random.rand(shape) initialises with float values between 0 and 1. I thought about just subtracting 1 from the weights and biases but then I came across the nump.random.uniform function in which it initialises a matrix with values in a uniform distribution between 2 values. I changed my weights and biases lines to the following:

This gives me initial values distributed randomly with a uniform distribution between -1 and 1. I then rechecked the error:

All this did was decrease the initial error. I then thought it might be an issue with the algorithm itself, so I tried to find in which iteration/how quickly the error converges by appending the error to an array at each iteration and finding the index of the error:

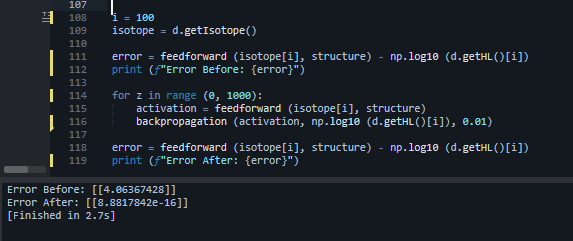
This said that the exact error which it converged to was not in the list. I then decided to just print the error array to see if anything else was happening:

This showed me that it converged incredibly quickly to a value very close to 3.6368549 before slowly eventually reaching that value. At this point I had run out of things to check so I decided to check my backpropagation algorithm against the maths.

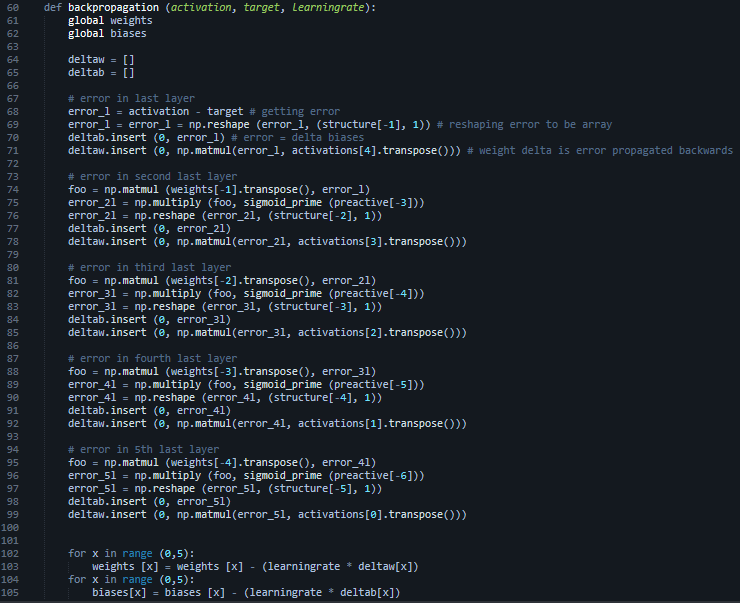
When checking against the maths, I realised I had been doing my matrix multiplication the wrong way round the whole time. One of the reasons I didn’t spot this earlier was because all 4 of my hidden layers had the same dimensions, so no matter which way you multiplied them, they gave a correctly shaped output. It was my inept multiplication that also caused me to add transposes where I did not need transposes to make everything consistent. I amended the backpropagation to match the maths exactly and ended up with the following:

Text

Description automatically generatedI updated the weights in the same way I did before and rechecked the error:

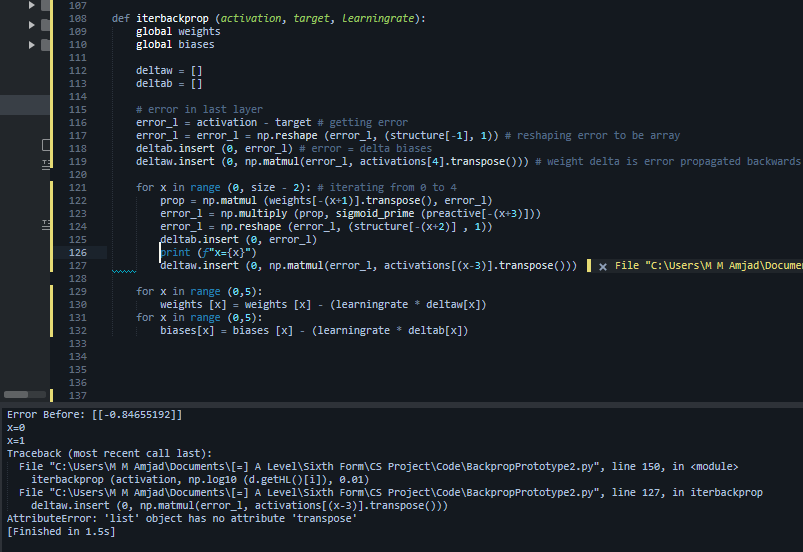
This was promising as my error was much lower than it was previously. I then ran it again for more iterations to see whether or not it still tended towards a particular value:

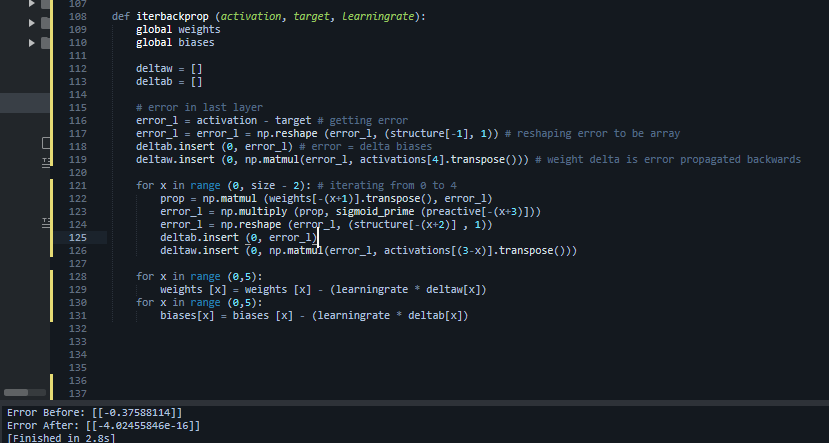
[Evidence for Test 4]

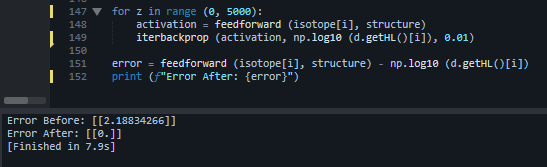
The error was tending towards 0. This was exactly what I wanted, as the NN is being trained to predict the value of the training example more and more accurately, tending the error closer and closer to 0. My final non-iterative backpropagation algorithm is as follows:

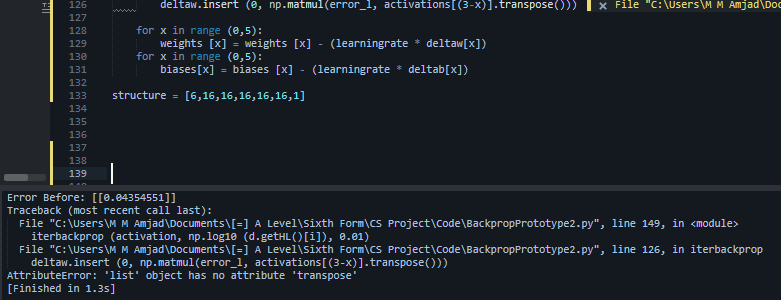
I then decided that I was ready to start coding it iteratively.

#### Iterative Backpropagation

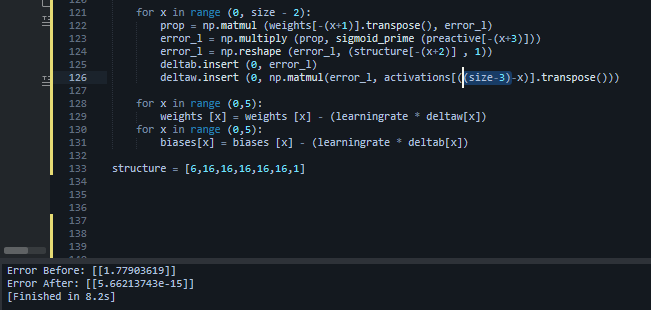
I then followed the procedural algorithm above and copied it into my iterative algorithm:

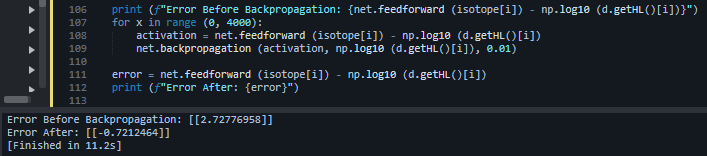
As you can see, this gave me an error. I printed out the index values to see which iteration caused the issue. It was when x=3, and it only affected the deltaw line. The only thing which depended on x in that line was the activation which it used to multiply the error by. After following the logic through, I realised that I was iterating through the activations the wrong way, going forwards rather than backwards, meaning I reached the end before I should have. I then amended this line by multiplying x-3 by -1 to get 3-x which fixed the program and gave me no errors:

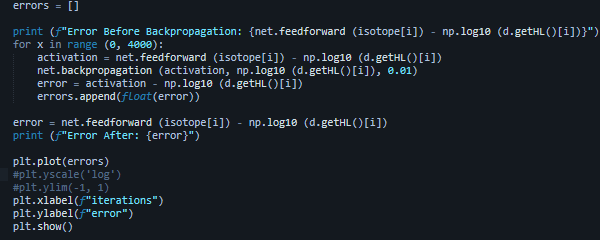
I decided to run it again but for more iterations to see if the error value suddenly changed, but instead I got the following:

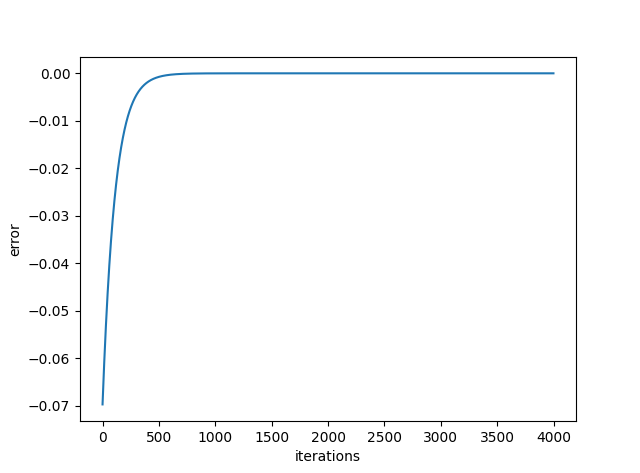
This meant my algorithm was predicting the half-life with perfect accuracy. I then changed the structure to the following and checked again:

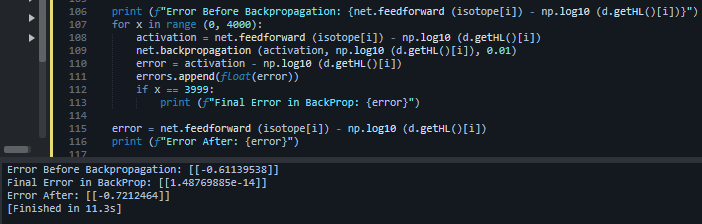
This threw an error for the same line. I rechecked why I started at layer 3 and realised that this was hardcoded to match my 6 layer structure. I changed 3 to size-3 and this fixed the error:

I also realised that me starting at activations[4] for my first layer error was hardcoded and so amended that line as well later on to the following:

When I then ran my backpropagation iteratively, however, I ran into a similar issue I had earlier. The error was converging:

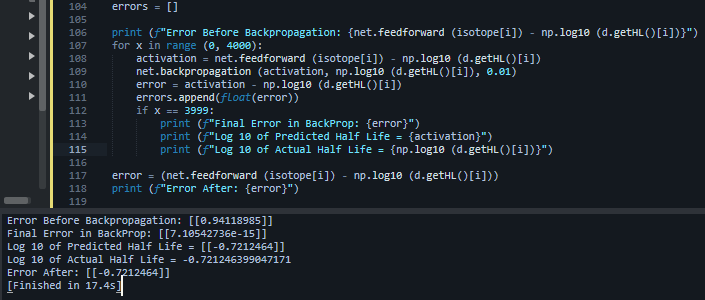
I decided to use the same strategy as before of appending to an errors array and seeing where it starts converging, but this time I decided to plot it to make it easier to see. I added the following:

This gave me the following output:

This showed me that my error was in fact tending towards 0. This was contrary to what the error value I calculated suggested. I decided to then print the final error value and received the following output:

This showed the error was actually going towards 0, but the error after was something completely different.

I decided to check the actual values of my predictions and target by printing them and received the following:

This showed me that instead of printing the error, Python was printing the actual half-life predictions (it was negative as I am training to find the base 10 log of the half-life). This was why the error seemed to converge. This didn’t matter, however, as my backpropagation itself was working. This meant that I had all the tools I needed to train and test my network. It was ready to implement.

#### Text Description automatically generatedAppending to Class

### Training and Testing the Network

I defined a simple subroutine to generate all the test and training sets I would need and added this to my network.py document but not my network class:

Text

Description automatically generatedText

Description automatically generatedI also made it print the error of the statistical model so that I could make an easy comparison between my model and the test model. I defined training and testing methods in my class as follows:

Text

Description automatically generatedI then made sure it worked by running the following code:

Text

Description automatically generatedI received the following output:

This indicated that my model worked and it achieved a better score than the statistical model! This was also only with 100 epochs. This indicated that my network was completely up and running so at this point, I decided to work on my UI, as the main back-end of my project was done.

## User Interface

I created my user interface using a tool called figma[[13]](#footnote-13), which allows you to create templates for UIs and feed them into other programs. I did this because I also found on GitHub[[14]](#footnote-14), a tool which takes figma templates and renders them in tkinter. I decided this would be a valid way of creating my UI as my UI is very simple, and this also saves time.

### Input Space

I created my template on figma as follows:

A picture containing graphical user interface

Description automatically generatedGraphical user interface, application

Description automatically generatedI defined the buttons and text boxes on the left. I then fed this into the GUI-Designer software I found on GitHub, which generated for me the following folder containing all the back-end I needed for the UI:

I then went into the window.py file and added all the functionality I needed, as this was not added by the GUI designer.

#### Adding Functionality

Text

Description automatically generatedThe main functionality of my UI rests in what happens when the user presses the PREDICT button. When this is pressed, the software needs to read the content of each of the boxes and feed them into my neural network. This also needs to account for the user inputting incorrect data. I decided that try, except statements would be the best way to implement this. The button was defined as follows:

Text

Description automatically generatedThis called the btn\_clicked function on click. I then defined the btn\_clicked function as follows:

Graphical user interface, application

Description automatically generatedGraphical user interface

Description automatically generatedGraphical user interface, application

Description automatically generatedThis does the following:

[Evidence for Test i]

A screenshot of a computer

Description automatically generated with medium confidenceThe software printed to the console for every incorrect input, meaning that the software can correctly recognise them. I now need a way of displaying the prompts to the user. For this, I decided to open a new window which had the prompt on. For this, I defined a new window class[[15]](#footnote-15) which took in string as a parameter that defined the error text:

Text

Description automatically generatedI then called this class in each of my except statements with the text defined for each of them:

Graphical user interface, text, application

Description automatically generatedI also used a feature called entry.delete(0,END) which deletes the contents of the entry box whenever the user enters something incorrect so that they do not have to do this manually:

Text

Description automatically generatedA video of this working is at the end of the project. Once the user entered completely correct data, I defined the rest of the variables based on their input (nucleon number, ZDist and NDist) and stored them in an array:

This gave the following output when I printed data:

Graphical user interface, application, Teams

Description automatically generated[Evidence for Test ii]

I now had to calculate the half-life and then finally make a window to display the half-life, which I will add when I amalgamate the front-end and back-end.

## Amalgamating Front-End and Back-End

The last part was to combine the front-end and back-end. As all the network has to do to make a prediction is feedforward an input through the specified weights and biases, I determined the best way to implement this would be to store the states of my trained weights and biases and feed them forward locally. I would first have to train the network to a suitable standard, and then store the weights and biases using a joblib dump. I can then load this dump locally and define my weights and biases from it.

Text

Description automatically generatedTo implement this, I first tested to see how the joblib dump would work. I did this by generating a small ordered array using numpy.arange() and dumping that using joblib to a file called test1:

A screenshot of a computer

Description automatically generated with medium confidenceI then loaded this and printed the 2 arrays:

[Evidence for Test 6]

Text

Description automatically generatedThe 2 arrays were the same. This means I could use joblib for my weights and biases and it would return the same arrays. I then defined a Network.save() method as follows:

Text

Description automatically generatedThis will allow me to save the weights and biases with filenames “weights” and “biases” respectively if I found them suitable. I then had to train the network to a suitable standard. I defined a suitable standard as being better than the statistical model on 3 separate randomly generated test sets. To determine this, I set up the following routine:

Text

Description automatically generatedI also modified the structure to have more neurons in the central 2 hidden layers as this would hopefully also increase the accuracy. I upped the epoch number to 500 to better train the network. I then set this running, however, it was not very successful. It rarely got to Round 3 and when it did it rarely saved. Due to this, after around 10 attempts, I upped the epoch number to 1000. On my 2nd attempt, I got the following:

This was, looking at the results, a very good network. It had a difference of nearly 0.02 on each round compared to the statistical mode, meaning the network was outperforming it by a fair way on each test. Because of this, I decided to stop here and take these weights and biases. The reason I did not want to go for many more epochs was because I did not want to run the risk of overfitting the network to the current dataset. This is when the network has been trained so much that it starts to spot patterns in the random noise of the training set. It then overly fits its weights and biases to the training set, such that it performs less effectively when being used on the testing set. For fun, I ran the training algorithm for Text

Description automatically generated10,000 epochs and got the following results:

Although this has an even lower standard deviation from the test set than my current model, I have decided not to use these weights and biases to avoid running the risk of overfitting the network.

Text

Description automatically generatedThe net.save did its job and the weights and biases were saved in the local directory of my GUI. I then added the following code to my GUI:

A screenshot of a computer

Description automatically generated with medium confidence In my btn\_clicked routine, I added the following at the end:

Graphical user interface

Description automatically generatedWhen I then ran the code, I received the following output for this input:

[Evidence for Test iii]

Text

Description automatically generatedThis showed me that my predictor was working. The last thing I had to do was just display this on the user’s screen, however, before this, I decided to clean up my code directories. Until this point, things like my network class and database were in a folder with old prototypes and many different things were amalgamated into single files. As my project was nearing completion, I thought that now would be a good time to organise my source code files. I also made my variable naming more consistent. I organised my files into the following tree:

Text

Description automatically generatedThe plan is to have my window.py call the predictor.py which will hold the feedforward method. This feedforward method will import the data it needs from data.py and return a value back to window.py which will display it. To do this, I have to play with the directories. I have to be careful, however, not to hardcode this to only work with my file paths. I added the following to my predictor.py to allow it to import data.py:

Text

Description automatically generatedI then placed the feedforward into my predictor.py:

Text

Description automatically generatedI then imported this as ff for feedforward in my window.py:

I then called this in my btn\_click method:

A screenshot of a computer

Description automatically generated with medium confidenceI then also defined a new class for my answer window, which will display the answer of the half-life to the user:

I set the default answer to Error as I wanted to know if I hadn’t passed an answer to the box. I then created an answer window with my predicted half-life:

Graphical user interface

Description automatically generatedWhen I inputted everything correctly, it gave me the following output:

This looked ugly so I casted them as floats and added “s” on the end to signify seconds:

Graphical user interface

Description automatically generatedThis was the output:

[Evidence for Test v]

A picture containing text, orange

Description automatically generatedI realised that taking the exponent of the half-life and re-logging it will introduce more inaccuracies in my output so I decided to amend this by printing the base 10 log as it was given:

Graphical user interface, text, application

Description automatically generatedI then changed the output text to the following and rounded to 5 decimal places to make it look better:

The UI was able to output a predicted half-life successfully. The prediction is based on my neural network which was trained via backpropagation to find the base-10 logarithm of alpha-decay half-lives of multiple radioactive isotopes. By saving the states of the weights and biases, I was able to save the state of my trained network and therefore feedforward new input values for new predictions.

This demonstrated that my UI was functional and I was now ready to evaluate the success of my project. Before this, however, I asked my stakeholders for feedback in regards to the GUI.

### User Feedback and Updates

I sent my GUI to the stakeholder, along with asking for ratings out of 5 and comments for the following criteria:

* Simplicity: 5/5
  + The GUI is simple and easy to use, it is clear what is wanted from the user and where it is to be entered, and the lack of too many options and boxes make it easy to use
* Understandability: 5/5
  + The software is intuitive to use as the labels for each of the text boxes and the button are very clear in what they are prompting you to do. The prompts for incorrect data are also clear in what they want the user to do as well.
* Design: 4/5
  + The design is clean and simple although could have looked very slightly more polished.
* Other Comments?
  + None, see above.

# Evaluation

## Success Criteria

### Essential Success Criteria

|  |  |  |  |
| --- | --- | --- | --- |
| Criterion | Criterion Met? | Justification of Previous Column | Plans for Future Development |
| Predictions of the neural network must have better accuracy than the statistical model | Yes - Fully | Evidenced by my network giving a lower standard deviation than the statistical model on 3 separate occasions with random test sets (pg. 42) | There are no plans to update the neural network or how it functions in future development |
| The network is able to account for updates to the database of isotopes | Yes – Fully | The databasing aspect is completely modular, and none of it is hard-coded, meaning that it is able to account for any additions or removals from the database (pg. 19) | There are no plans to update how the database is managed in future development |
| User is able to easily navigate the GUI | Yes – Fully | Evidenced by my stakeholder feedback (pg. 47) | Update the GUI based on future developments to allow the GUI to be usable with new features |

### Desirable Success Criteria

|  |  |  |  |
| --- | --- | --- | --- |
| Criterion | Criterion Met? | Justification of Previous Column | Plans for Future Development |
| User is able to retrain the network on their own with their own specified number of epochs | Partially | The user is able to retrain the network, but only by going into the back-end files and modifying them. If they do not understand the code, this feature will not be available to them. | Add a screen/section in the GUI which allows the user to easily be able to do this. |
| It is easy for the user to make any adjustments to the network’s shape and size | Partially | It is possible, but not easy. The user will have to go into the network files and modify them there. | Add a screen/section in the GUI which allows the user to easily be able to do this. |
| User is easily able to update the database | No | The user can update the database, but only by going into the back-end files. They also do not know the format of the database, making it even more difficult for them to do so. | Add a screen/section in the GUI which allows the user to easily be able to do this. |

## Post-Development Testing

### Back-End

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Test | Success Criteria | Met? | Evidence | Explanation |
| Accuracy of NN | Better than statistical model consistently | Yes | Page 42 | This demonstrates that my NN is a more accurate tool for determining half-lives than existing statistical models and therefore is beneficial to the stakeholders |

### Front-End

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Test | Success Criteria | Met? | Evidence | Explanation |
| Incorrect User Input (Robustness) | Able to catch incorrect input and prompt the user for correct input | Yes | Page 39-40 | This demonstrates that my software is robust and is able to be used in real-world scenarios |

## Limitations

One of the main limiting features of my program is that it does not let the user interact with the network in any way shape or form. They are unable to modify or train it easily, as there is no option in the interface that allows them to do this. This is something I hope to amend in future development by adding menus and sections in the GUI that allow the user to interact with these things.

One of the limitations of my project as a whole is to do with the problem itself, as I chose a project which focused solely on alpha decay. This limits the capabilities of the program as it can only be used by a very specific group of people who only need to focus on one type of decay. In future, I hope to be able to develop a program which will predict the half-life for any conceivable isotope with any decay mode, with it also telling the user what type of decay it will undergo. For the current project, however, focusing on alpha decay was sufficient in terms of computational complexity, and I believe my solution is effective.

## Evaluation Summary

Overall, I believe that my solution was a success as it reached all the essential success criteria, as well as satisfying the stakeholder requirements. I am very happy with the development and the performance of the neural network and the fact that my solution performs better than existing models is also very reassuring to me. Despite this, there are still ways in which my project can be improved, however, I believe that my solution is more than sufficient for the problem specified.

A video of the working code can be found here: <https://youtu.be/lB3MoOg_lNM>

The full code is also available on GitHub with the following link: <https://github.com/MAmJ4/CS-Project>

# Final Code

## Back-End

### data.py

**import** csv **as** csv

**import** numpy **as** np

**import** sys

**import** os

data\_dir = os.path.abspath(os.path.join("..","Network and Data"))

sys.path.insert(1, data\_dir) # add this path to system path

**class** Data ():

**def** \_\_init\_\_ (self):

self.data = []

**with** open("Database.csv") **as** database:

csvreader = csv.reader (database)

**for** row **in** csvreader:

self.data.append([row[0],int(row[1]),int(row[2]),int(row[3]),

float(row[4]),float(row[5]),float(row[6])])

# Format: Element, Z, N, A, Q, T12, ELDM

**for** isotope **in** self.data:

Zdist = min([abs(isotope[1]-2), abs(isotope[1]-8),

abs(isotope[1]-20), abs(isotope[1]-28),

abs(isotope[1]-50), abs(isotope[1]-82),

abs(isotope[1]-126)])

isotope.insert (2, Zdist)

Ndist = min([abs(isotope[3]-2), abs(isotope[3]-8),

abs(isotope[3]-20), abs(isotope[3]-28),

abs(isotope[3]-50), abs(isotope[3]-82),

abs(isotope[3]-84), abs(isotope[3]-126)])

isotope.insert (4, Ndist)

# Format: Element, Z, ZDist, N, NDist, A, Q, T12, ELDM

**def** getZ (self):

Z = []

**for** x **in** self.data:

Z.append(x[1])

**return** Z

**def** getZDist (self):

ZDist = []

**for** x **in** self.data:

ZDist.append(x[2])

**return** ZDist

**def** getN (self):

N = []

**for** x **in** self.data:

N.append (x[3])

**return** N

**def** getNDist (self):

NDist = []

**for** x **in** self.data:

NDist.append(x[4])

**return** NDist

**def** getA (self):

A = []

**for** x **in** self.data:

A.append (x[5])

**return** A

**def** getQ (self):

Q = []

**for** x **in** self.data:

Q.append (x[6])

**return** Q

**def** getHL (self):

HL = []

**for** x **in** self.data:

HL.append (x[7])

**return** HL

**def** getModel (self):

Model = []

**for** x **in** self.data:

Model.append (x[8])

**return** Model

**def** getIsotope (self):

Isotope = []

**for** x **in** self.data:

Isotope.append ([x[1], x[3], x[5], x[6], x[2], x[4]])

**return** Isotope

### network.py

**import** numpy **as** np

**import** matplotlib.pyplot **as** plt

**import** data

**from** data **import** Data

**import** joblib

# miscellaneous functions

sigmoid = **lambda** x : 1.0/(1.0+np.exp(-x))

sigmoid\_prime = **lambda** x : sigmoid(x)\*(1-sigmoid(x))

# database

d = Data()

# network class

**class** Network ():

**def** \_\_init\_\_ (self, structure, learningrate = 0.01):

d = Data ()

self.size = len(structure) # set size equal to number of layers

self.structure = structure # set structure (n of neurons) to match input

self.weights = [] # declare weight array

self.biases = [] # declare bias array

**for** x **in** range (0, (self.size - 1)):

# initialise weights and biases with random values

self.weights.append(np.asarray(np.random.uniform(-1,1,

(structure[x+1],structure[x]))))

self.biases.append(np.asarray(np.random.uniform(-1,1,

(structure[x+1],1))))

self.preactive = []

self.activations = [] # declare activations

**for** x **in** range (0, self.size):

# initialise activations with zeros

self.activations.append(np.zeros((structure[x],1)))

self.learningrate = learningrate

**def** feedforward (self, data):

# min-max normalise all values

Z = (data[0]-min(d.getZ()))/(max(d.getZ())-min(d.getZ()))

N = (data[1]-min(d.getN()))/(max(d.getN())-min(d.getN()))

A = (data[2]-min(d.getA()))/(max(d.getA())-min(d.getA()))

Q = (data[3]-min(d.getQ()))/(max(d.getQ())-min(d.getQ()))

Zd = (data[4]-min(d.getZDist()))/(max(d.getZDist())-min(d.getZDist()))

Nd = (data[5]-min(d.getNDist()))/(max(d.getNDist())-min(d.getNDist()))

# use normalised inputs as initial activations

self.activations [0] = np.array([[Z], [N], [A], [Q], [Zd], [Nd]])

# iterate through hidden layers using weights and biases (except for

# last)

**for** x **in** range (0, self.size - 1):

a = self.activations [x]

mult = np.array([np.matmul(self.weights[x], a)])

mult = np.reshape(mult, (self.structure[x+1],1))

presigmoid = mult + self.biases [x]

self.preactive.append(presigmoid)

self.activations [x+1] = sigmoid(mult + self.biases[x])

#manually apply last layer weights and biases to avoid sigmoid

actfinal = np.array([])

mult = np.array([np.matmul(self.weights[self.size - 2],

self.activations [self.size - 2])])

mult = np.reshape (mult, (self.structure[self.size - 1],1))

actfinal = mult + self.biases[self.size - 2]

self.activations[-1] = [actfinal] # was self.activations.append([af])

self.preactive.append ([actfinal])

**return** actfinal

**def** backpropagation (self, activation, target):

deltaBiases = [] # define arrays for change in biases

deltaWeights = [] # define arrays for change in weights

learningrate = self.learningrate

# error in last layer

error = activation - target # getting error

error = np.reshape (error, (self.structure[-1], 1))

# reshaping error to be array

deltaBiases.insert (0, error) # error = delta biases

deltaWeights.insert (0,

np.matmul(error, self.activations[self.size-2].transpose()))

# weight delta is error propagated backwards

**for** x **in** range (0, self.size - 2):

# propagate error backwards

prop = np.matmul (self.weights[-(x+1)].transpose(), error)

# hadamard product with preactivations

error = np.multiply (prop,

sigmoid\_prime (self.preactive[-(x+3)]))

# reshape because numpy is peculiar

error = np.reshape (error, (self.structure[-(x+2)] , 1))

# error = delta bias so add to start

deltaBiases.insert (0, error)

# add delta weights

deltaWeights.insert (0, np.matmul(error,

self.activations[((self.size-3)-x)].transpose()))

**for** x **in** range (0,self.size-1):

# adjust each weight by delta weight

self.weights [x] = self.weights [x] –

(learningrate \* deltaWeights[x])

# adjust each bias by delta bias

self.biases[x] = self.biases [x] –

(learningrate \* deltaBiases[x])

**def** train (self, dataset, targets, epochs):

**for** x **in** range (epochs): # for the specified amount of epochs

#print (f"Epoch {x+1}")

# for each value in the dataset

**for** y **in** range (0, len(dataset)):

# feed it forward:

activation = self.feedforward (dataset[y])

# backpropagate against the target:

self.backpropagation (activation, targets[y])

**def** evaluate (self, dataset, targets):

predictions = [] # define array for predictions

errors = [] # define array for errors

**for** isotope **in** dataset:

prediction = self.feedforward (isotope)

# add predictions to array of predictions:

predictions.append(prediction)

**for** x **in** range (len(predictions)):

error = predictions[x] - targets[x] # calculate errors

errors.append (error\*\*2) # append error^2 to array

# sigma = (1/n)\*(sum of (errors)^2)^(1/2)

stddev = (np.sum(errors)\*\*(1/2)) / len(dataset)

**return** float(stddev)

**def** save (self):

joblib.dump(self.weights, "weights")

joblib.dump(self.biases, "biases")

### evaluate.py

**import** numpy **as** np

**from** network **import** Network

**import** data

**from** data **import** Data

d=Data()

**def** getSets ():

**global** stddevModel

isotopes = d.getIsotope()

halflives = d.getHL()

# number of training isotopes = len(dataset) \* 0.8 rounded down

numTrain = len(isotopes)\*8//10

numTest = len(isotopes)-numTrain # number of testing is what remains

# all the possible indices I can use for isotopes

totalNums = np.arange(len(isotopes))

randomNums = np.random.choice (len(isotopes), numTrain, replace = False)

# replace: whether or not a sample is returned to the sample pool

# define testing indices to be whatever is left after getting rid of training

testingNums = np.delete(totalNums, randomNums)

trainSet = []

trainLabels = []

**for** x **in** range (numTrain):

trainSet.append (isotopes[randomNums[x]])

trainLabels.append (np.log10(halflives[randomNums[x]]))

testSet = []

testLabels = []

**for** x **in** range (numTest):

testSet.append (isotopes[testingNums[x]])

testLabels.append (np.log10(halflives[testingNums[x]]))

model = d.getModel()

errors = []

**for** x **in** range (numTest):

actual = np.log10(halflives[testingNums[x]])

models = np.log10(model[testingNums[x]])

error = models - actual

errors.append(error\*\*2)

stddevModel = (np.sum(errors)\*\*(1/2)) / (numTest)

#print (f"Statistical Model Error: {stddevModel}")

**return** trainSet, trainLabels, testSet, testLabels, stddevModel

trainSet, trainLabels, testSet, testLabels, stddevModel = getSets ()

net = Network ([6,16,20,20,16,1])

**print** ("Training...")

net.train(trainSet, trainLabels, epochs = 500) # train network

**print** ("Training Complete")

**print** ("Round 1")

stddevNetwork = net.evaluate(testSet, testLabels) # evaluate network on given test set

**print** (f"Network Deviation: {stddevNetwork}") # print net score

**print** (f"Stat Model Deviation: {stddevModel}") # print model score

**if** stddevNetwork < stddevModel: # if net is better than model

**print**("Round 2") # round 2

# fresh sets

trainSet, trainLabels, testSet, testLabels, stddevModel = getSets ()

# evaluate using already trained weights and biases

stddevNetwork = net.evaluate(testSet, testLabels)

**print** (f"Network Deviation: {stddevNetwork}") # print net score

**print** (f"Stat Model Deviation: {stddevModel}") # print model score

**if** stddevNetwork < stddevModel:

**print**("Round 3")

# repeat above

trainSet, trainLabels, testSet, testLabels, stddevModel = getSets ()

stddevNetwork = net.evaluate(testSet, testLabels)

**print** (f"Network Deviation: {stddevNetwork}")

**print** (f"Stat Model Deviation: {stddevModel}")

**if** stddevNetwork < stddevModel: # if net IS better than model 3 times

**print** ("Saving")

net.save() # save weights and biases

''' CODE FOR COMPARING ERRORS

errors = []

epochs = 2000

print (f"Error Before Backpropagation: {net.feedforward (isotopes[i]) - np.log10 (d.getHL()[i])}")

for x in range (0, epochs):

activation = net.feedforward (isotopes[i]) - np.log10 (d.getHL()[i])

net.backpropagation (activation, np.log10 (d.getHL()[i]))

error = activation - np.log10 (d.getHL()[i])

errors.append(float(error))

if x == (epochs-1):

print (f"Final Error in BackProp: {error}")

print (f"Log 10 of Predicted Half Life = {activation}")

print (f"Log 10 of Actual Half Life = {np.log10 (d.getHL()[i])}")

print (f"Error After Backpropagation: {float(net.feedforward (isotopes[i])) - float(np.log10 (d.getHL()[i]))}")

'''

## Front-End

### gui.py

**from** pathlib **import** Path

designPath = Path ("GUI Images/")

**import** predictor **as** ff

**from** tkinter **import** \*

**import** numpy **as** np

**class** errorWindow(Toplevel):

**def** \_\_init\_\_(self, master = None, message = "Error"):

super().\_\_init\_\_(master = master)

self.title("Error")

self.geometry("300x50")

label = Label(self, text = message)

label.pack()

**class** ansWindow (Toplevel):

**def** \_\_init\_\_ (self, master = None, answer = "Error"):

super().\_\_init\_\_(master = master)

self.title("Prediction")

self.geometry("300x50")

label = Label(self, text =

f"Half-Life: {round(float(np.float\_power(10, answer)), 5)}s \n

Base 10 Logarithm: {round(float(answer), 5)}")

label.pack()

**def** btn\_clicked():

data = []

**try**:

Z = int (entry0.get())

**except** ValueError:

# print ("Please enter an integer number of Protons")

entry0.delete (0,END)

errorWindow (window, "Please enter an integer number of Protons")

**return**

**try**:

N = int (entry1.get())

**except** ValueError:

# print ("Please enter an integer number of Neutrons")

entry1.delete(0,END)

errorWindow (window, "Please enter an integer number of Neutrons")

**return**

**try**:

Q = float (entry2.get())

**except** ValueError:

# print ("Please enter a number for Energy Release")

entry2.delete(0,END)

errorWindow (window, "Please enter a number for Energy Release")

**return**

A = Z+N

Zdist = min ([abs(Z-2), abs(Z-8), abs(Z-20), abs(Z-28),

abs(Z-50), abs(Z-82), abs(Z-126)])

Ndist = min ([abs(N-2), abs(N-8), abs(N-20), abs(N-28),

abs(N-50), abs(N-82), abs(N-84), abs(N-126)])

data.append(Z)

data.append(N)

data.append(A)

data.append(Q)

data.append(Zdist)

data.append(Ndist)

loghalflife = ff.feedforward (data)

# halflife = np.float\_power (10, loghalflife)

ansWindow (window, loghalflife)

window = Tk()

window.title("α-Predictor")

window.geometry("502x526")

window.configure(bg = "#ffffff")

canvas = Canvas(

window,

bg = "#ffffff",

height = 526,

width = 502,

bd = 0,

highlightthickness = 0,

relief = "ridge")

canvas.place(x = 0, y = 0)

background\_img = PhotoImage(file = designPath / "background.png")

background = canvas.create\_image(

251.0, 268.0,

image=background\_img)

entry0\_img = PhotoImage(file = designPath / "img\_textBox0.png")

entry0\_bg = canvas.create\_image(

247.0, 153.5,

image = entry0\_img)

entry0 = Entry(

bd = 0,

bg = "#c4c4c4",

highlightthickness = 0)

entry0.place(

x = 94, y = 124,

width = 306,

height = 57)

entry1\_img = PhotoImage(file = designPath / "img\_textBox1.png")

entry1\_bg = canvas.create\_image(

247.0, 263.5,

image = entry1\_img)

entry1 = Entry(

bd = 0,

bg = "#c4c4c4",

highlightthickness = 0)

entry1.place(

x = 94, y = 234,

width = 306,

height = 57)

entry2\_img = PhotoImage(file = designPath / "img\_textBox2.png")

entry2\_bg = canvas.create\_image(

247.0, 375.5,

image = entry2\_img)

entry2 = Entry(

bd = 0,

bg = "#c4c4c4",

highlightthickness = 0)

entry2.place(

x = 94, y = 346,

width = 306,

height = 57)

img0 = PhotoImage(file = designPath / "img0.png")

b0 = Button(

image = img0,

borderwidth = 0,

highlightthickness = 0,

command = btn\_clicked,

relief = "flat")

b0.place(

x = 199, y = 426,

width = 106,

height = 34)

window.resizable(False, False)

window.mainloop()

### predictor.py

**import** numpy **as** np

**import** joblib

**import** os

**import** sys

data\_dir = os.path.abspath (os.path.join("..","Network and Data"))

# find directory to current file

# go to parent directory ("..")

# from parent, add "Network and Data" to the path

sys.path.insert(1, data\_dir) # add this path to system path

**from** data **import** Data

d = Data()

sigmoid = **lambda** x : 1.0/(1.0+np.exp(-x))

weights = joblib.load("weights")

biases = joblib.load ("biases")

activations = []

structure = [6,16,20,20,16,1]

size = len(structure)

**for** x **in** range (size):

activations.append(np.zeros((structure[x],1)))

**def** feedforward (data):

# min-max normalise all values

Z = (data[0]-min(d.getZ()))/(max(d.getZ())-min(d.getZ()))

N = (data[1]-min(d.getN()))/(max(d.getN())-min(d.getN()))

A = (data[2]-min(d.getA()))/(max(d.getA())-min(d.getA()))

Q = (data[3]-min(d.getQ()))/(max(d.getQ())-min(d.getQ()))

Zd = (data[4]-min(d.getZDist()))/(max(d.getZDist())-min(d.getZDist()))

Nd = (data[5]-min(d.getNDist()))/(max(d.getNDist())-min(d.getNDist()))

activations [0] = np.array([[Z], [N], [A], [Q], [Zd], [Nd]])

# iterate through hidden layers using weights and biases (except for last)

**for** x **in** range (0, size - 1):

a = activations [x]

mult = np.array([np.matmul(weights[x], a)])

mult = np.reshape(mult, (structure[x+1],1))

presig = mult + biases [x]

activations [x+1] = sigmoid(mult + biases[x])

#manually apply last layer weights and biases to avoid sigmoid

af = np.array([])

mult = np.array([np.matmul(weights[size - 2], activations [size - 2])])

mult = np.reshape (mult, (structure[size - 1],1))

af = mult + biases[size - 2]

activations.append ([af])

**return** af

## Joblib Dumps

### Weights

8004 95b0 0000 0000 0000 005d 9428 8c13

6a6f 626c 6962 2e6e 756d 7079 5f70 6963

6b6c 6594 8c11 4e75 6d70 7941 7272 6179

5772 6170 7065 7294 9394 2981 947d 9428

8c08 7375 6263 6c61 7373 948c 056e 756d

7079 948c 076e 6461 7272 6179 9493 948c

0573 6861 7065 944b 104b 0686 948c 056f

7264 6572 948c 0143 948c 0564 7479 7065

9468 0768 0e93 948c 0266 3894 8988 8794

5294 284b 038c 013c 944e 4e4e 4aff ffff

ff4a ffff ffff 4b00 7494 628c 0a61 6c6c

6f77 5f6d 6d61 7094 8875 62e3 977a e6ed

86d1 bf37 2713 b885 30d0 bf45 4967 d524

81f2 bf6d d6a1 2b06 70ee 3fa3 d6fb d33f

9cbe 3fd4 362a d7ec 6ef2 bfb6 ee9b 39bc

9bee bf7f 66ac 51c7 9be4 3f88 3632 5faa

d2de bffc 47bb dc0e 44e3 bfb2 1828 5cf2

00dc bf22 b531 4f17 dee5 bf19 fb71 cb14

0cfa 3f48 50d4 1daa 52d2 3f1e 85ba e970

61e0 3fef d49d 1d6b 1c02 c03a d157 1cfd

02ab bf85 12fc 0288 c2f5 3fe0 ea59 89c5

24f0 bfbe e0b8 f9ee 8bd3 bf04 31b1 4e34

7ae4 bf21 9ed3 884b af01 40e8 8e88 a8bc

bbd1 bf82 952d 0328 01b1 bf14 a58f a1d4

77e7 bf51 eb45 1e49 40e6 bfee 1240 ba24

0ccd 3f94 3e0e 5c94 e4ec 3f58 bbf7 91e8

cfe7 bf56 d680 1ae3 0fd5 3f06 5ac7 aa25

f8e3 3f3b 6204 e25f 27e7 3f9b b270 80a5

95e5 3fd2 155e f9ec b4e5 3f71 7432 fca6

27f4 3fb3 7394 8b05 d3f4 bfa2 648c 1321

83fb bfd0 82d8 6db9 b1fb bfed 8548 5a71

44ec bf01 5842 5aaf ec15 405e 0992 92cd

afe6 bf23 59a9 f42c f2e8 3f7c a584 1321

2dc7 bf03 1642 089b ced5 3f3e 1876 3eb7

10c4 3f04 c485 277b d9fb bf45 eba9 813e

c8c9 3f0c 2b45 16ff efe5 3fba 4f66 724f

55e6 3fb9 9fc2 7611 4de7 3f64 b77d 5b1e

55ca 3fb2 f60f c9aa edde bfa3 aa8b 58d8

56d6 bf35 4d61 61b9 64db bffb 680e f7eb

edfd bf06 2a29 4542 1bc7 bf79 d63e b944

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b7cf bb3c 00ec 3f76 4676 d14b bce1 bfa5

7b2e 8f5b 38c6 bfce c469 1e52 f4d8 3fd8

3c57 2102 4fd3 bfbd 72e2 70eb 29ee bf41

0332 5569 6ee3 3f07 42f0 55dd bcaa 3fa9

0aae b044 12ef bf64 80d4 14a3 87e0 3f40

e53e 86dc 1ff7 bfe0 927b 51b0 3ed9 bfcd

a5b5 25b7 93c2 3f75 9c98 a659 1ff3 bf3f

6425 b8ef 95f3 3f95 91a1 309b 8de1 3f0b

2fe0 acef 41d2 bff1 d1b3 50a7 92ca bfdd

f361 2e3a 13ec 3f82 35b1 f388 9ce4 bfc5

094a 77e2 f2f1 bf1a ac6f 5f1a 3ee3 3f52

a468 d5fb 22cd bfa5 9f3f 9496 20b1 3f57

fc74 4a18 00ef 3f40 0cb2 a7c4 97f4 bf58

0b39 f469 bfec bf71 0904 91a4 3fd7 bf63

c967 f858 28c6 3f24 ca23 4305 51f0 3fd1

9281 d863 20f7 bfda 0cf3 f360 9ae2 3f2a

4a58 5c13 35e0 bf8f 1475 7757 aaf9 bf5e

e6a4 9d21 baf4 3fed ff82 d0a6 2ce4 3f4f

a26d 4f21 0df7 bf66 e52b 5100 06e5 3fda

a535 09a4 3fc6 bf24 c8ac 025a 8fed bf95

6133 e883 5eda bf0a 76c7 694d 1de1 3f44

5c1d 9334 32d6 bf75 d97d 2129 a7ad 3f08

7c7a 6ce5 77a6 bfe8 e16b 6867 3bc7 3f18

76a1 9f0a 48d3 3faf 8309 7d1c aec4 bfd6

e3f4 9a20 72f0 3feb 8149 06e4 50f1 bf91

529c dd98 bad3 bf41 4362 7592 aee0 bf6e

e78c 0e64 63e8 3f71 76e8 a1ab 08e6 bf92

15f0 fb7f 4ad0 bf37 20b5 ba4a 53ee bfcc

6f4d 0bba c4e4 3f42 0790 b48c 609c bf4d

51d9 5aaa 41f2 bf90 18ef fba9 4be7 3f07

df62 93b5 c2ef bf06 77a5 71d7 0ceb bf9d

842e 6f76 cde0 bfbc ecb5 ffb8 39e5 bfa7

effa 5835 f0d0 3f41 9d0e a2ca 0ef4 bfb0

d9cb 2898 eace 3fad 81ac 3e0b c9c6 3fa0

4f99 789f 78c3 3fee 2c45 0ebf d4f3 3f4f

fe66 6990 4cd7 bfe9 0bb3 a730 eeda 3f3f

fc89 0bbd 78d7 bf0f 027d 21d7 d4e4 bf7a

49d1 baf5 e0f4 3f51 f2ac 6fb4 b6b4 3f2e

7ac3 a127 07ec bf04 885e 068b 07f5 3fc0

f46f 3efd 86e3 bf96 be95 a073 c5b6 bfca

527e 83e7 66eb 3fc2 47b1 e3d4 afeb 3fc6

ea8a ce47 49d3 bf9b 07ed 9072 b7c9 bf5f

eb34 99f3 ebdb 3fb1 2fbe 41c6 2ad6 bfca

fd6d f5d5 a4e7 bfc4 fb10 7bb4 bfda 3f4a

b9de 35c7 df8d bff6 5ddc 8816 c5c9 bfb8

7b7b 7b6f bff5 3f4d c83e 85ab 40b9 3f16

2e96 7798 b9ec bf58 2ff8 c20f eef3 3f1e

79ed 4fc3 37e3 bfc3 9c83 0720 75e5 bf90

c387 d9ff 6fd1 3f0c c347 4d0f 60f7 bf34

26af e63f b8e7 bff2 da63 fc7e 01f0 3f2c

0789 683d 09a9 bf79 0e94 3f19 e2e1 bf93

bcd8 6b0d c8e4 3fcd 93b1 6d6b 4ee2 3f4f

bb1b be18 d4cc bfaa 2011 93dd 03e6 3faa

e438 99d8 e7d8 bf58 6560 c0b3 33ca bf46

b372 e159 e5e3 bf96 c0f1 8d78 4cd6 bfba

0d4e 7bd6 c8d7 3f1f ef24 b392 51d5 bfa1

80b9 72c0 5ef1 bffa 633b 1e71 05e9 3f0c

4307 d90f 0cdc 3f76 ea04 38c7 2ab6 bf87

ca02 9c11 cfe7 3fa6 e6ab d689 95aa 3f05

c598 75d4 e8df bf01 32e4 17b5 7bf1 bf95

2100 0000 0000 0000 6803 2981 947d 9428

6806 6809 680a 4b10 4b14 8694 680c 680d

680e 6812 6815 8875 62ed e47a 913e 60db

bf2d f433 ac77 01e3 bfdb c425 5a85 52ee

bf9d 90c4 615a 1ca8 bf72 fc41 1cd7 8be8

bfa5 3aeb cccd 14e1 3fb5 828f 3f07 94e0

3f13 faab bfd8 b4d1 3fb3 96d8 3ca6 d0ec

bfa5 6504 1bc7 a1db 3f06 1cd2 77b5 8cef

3f51 73ec bfb8 5ec3 bfde b994 d2e4 e8c6

3fda 1d1a 53d8 27e4 bfed f6cb 9945 acc7

3f57 7ae3 bc3f baf2 bfba 4c64 ede9 37ab

bf6f 715c f7c8 bcd3 bf58 84f3 87a5 c8ec

3f8c ab3b 70f1 5b9c 3ff3 5110 84c0 eedd

bf51 59d0 2bc9 4ec1 3f80 e12f fdfd 33e8

3fbe 5133 5464 c8da bf6e 45be b1eb 9bc5

3fcb 819e 91a8 49f4 bfe5 0295 1708 09c6

3f15 173b 55b5 fbd5 bfe6 f6a8 c7eb 25e3

bfd9 3e3f d96c a0d6 3f7a 1a8e a1f1 6de4

bf8a 938e 3098 4ec5 3f75 0086 fbb5 c1f0

3fc0 2bce c6a5 f6c0 3fb2 f5d6 407a 0df6

3f34 4872 c0c2 58d1 3fab 8bd7 a080 13ea

bfb4 4958 aaf9 5dd4 bf27 2d37 569e e2f5

bfbd 438d c899 cee4 3f38 9129 0a0a a3e5

3f2b 9998 ecf4 3cd6 3f7f fc40 1439 1bf0

bf29 80e0 2a26 82ed bf48 4f09 f8ef f0f7

bfbd bece 9bc7 3ef6 3f8a fd94 52d5 4cee

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3fed 679f 6e5c 8599 3f4b d603 0406 e9ef

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bf7f 0c99 b5eb 84e6 bf36 78b1 1bcd a1c0

bf3a 8b3d 051a 9ff2 bf94 37a7 8396 7ef2

bfbf 19f9 3044 eac4 bfe4 3290 0c46 9ddd

3fc5 f0f6 420b 62e0 bf60 9479 1876 2be4

bf4b 83d8 6b6f 2bc2 3f61 d2af 9bc6 26e5

bfbf b792 ac16 94e2 bff2 d6aa a2be 35b1

bfad 25e0 6b8c 37e4 3fc1 ef4f 4746 68ef

3ff7 fa6f 8707 5ac9 3f39 d235 e7b8 eddd

bf4a b648 283e 72e5 bf23 1793 13e8 dce7

3fba 635c f89b e2e9 3f41 66e2 6091 fce4

3f6e 57a1 38a4 46c1 3f33 4f8e ac52 e8e0

3f64 a38a b72e 9ce8 bf7d 44d5 261b 14ea

bf8e 5faa 3132 e5ea 3fbf 8b10 e757 e4d5

bfd2 4202 6606 49df 3fad 4597 abb6 d1e2

3f52 aaba 833a 24e2 bfe9 ed98 c588 d4e8

bfc5 4685 d710 00f2 bf11 add2 e7e7 cbe4

bf7a 3037 0c93 b4f0 bfd9 c98d 5e95 3cd9

3f2d 797c 6c88 6fea 3f46 d4eb 9194 8bdd

bfc8 bda3 2e5d 2fe3 bf6e 34e5 e701 7fe9

3f94 c5a3 97c1 54f3 bf34 daab cf58 f0e6

3f84 958d d3b5 72ec 3f1c eb7b 76da 78a2

bfc2 d060 b54f c7e8 3fd2 8e32 c5bc e1ee

bf55 e3f1 9ee3 b5eb bf1a 721a 537d 45ec

bfcb 1196 7661 cdcb 3f5c 4d2f 31ff e5dd

3f01 e1e5 eea0 25f0 bfae 446d b018 a0e1

bf4f 47c8 ae07 62f6 bfcc 2d37 100b 89f1

bf33 3a5b c66a cfe4 bf26 e71c 0b49 bfdc

3fd1 3983 beb1 90a2 bf34 b075 b04d b7bd

bf4c ad5a a7d6 4cc9 bfe9 16a9 a608 cadd

bf0c cc3d f29e 9bd2 3fcb 5c39 a184 2be5

3f9e 0376 1e07 fef8 3f89 6cc6 b9f8 46ee

bf7d da94 d0d0 e3f2 3f3a 176e 0d7d dff3

bf0a 40c6 dc97 2eda bfd5 587b 3dda b8ce

3f4f 26a1 f7f3 3bea 3f26 351f feba d4ea

bfc9 40c5 9215 90c5 bfbb c6e0 1e0d 29eb

bf62 2d5e 9401 46a0 bfb3 0a81 a59d bcc8

3fb8 63b4 e5f4 dcba bf83 9dec 466a 78c3

bf96 c6c7 27cf ace6 bf5c f8c7 1af7 0ac5

3f83 7377 1f02 c7e2 bf77 fac2 5b0e b1e0

3f2c f37d d4ef 66eb bfea 9e3f ba68 29e4

bf44 d732 0712 b8e2 bf85 936e 077e 13e7

3f91 437b 97b4 89c4 3f1d d94f 452d f5c9

bf1e 6050 93c4 4ce0 bfea 6cd5 5c4d 84e6

bfcb 86cc 3669 9cdb 3f61 39ba 7ca0 5ce2

3ff4 cc5b ae3f 7fa0 3f86 9158 2fb5 44f2

bf71 f8b1 80b3 aeb3 3f0c b2d2 2ee4 c1ef

3f4c 0bcf 5415 a5d9 3f9f 3604 0683 8bec

bfd4 9fec 8082 99c6 3fc0 f073 b82b 25f0

3f38 e6e6 ef52 11e9 bf38 d27b 1e68 85f1

bfe8 01ea bb1b cde0 3fdc f704 b030 00c5

3fbc 64d7 ac0d fddb bf27 4178 4b42 e7e9

bfac c3e1 624f 31d1 bf63 333b 5651 2dd1

3fc6 64af 417e c6e4 3f73 ae00 c03c e0e4

bf70 f94c 66ae f3de bf5d 4bc6 d405 14b7

bf7c f602 0029 7298 3f43 62f1 fd5c 4ec3

3fa0 b934 8aa4 25e3 3f40 87a2 3560 6bb9

3f65 354d 4380 62e7 3fb9 87b4 d010 37eb

bfb6 3ac9 34d9 c0eb 3f1b ac53 a501 11e8

3ffa f119 6ed0 e8a3 3fa8 9417 acd3 46e5

bf8c 8f80 34c1 80e5 bf6c 0268 7e9b 1dcf

3f4c 39c3 c304 89ab 3ffe ee7d 2ddd c2e2

bf55 4d9b 4e3f d8f2 bf0f 3069 8c74 35e0

3fc9 16a5 182d 76e8 3ff2 c55e 14de addc

3f2a 88d8 d6a0 fed1 bf88 83cc 1dc6 88b4

3fd6 2263 eeca a8d1 3fd7 14bc 828a bde0

bf2b c939 b6f9 c9ef 3f09 ad66 0b96 a7e7

bf22 9fab b8be e2c1 3fd3 247d 583b 71f1

bfc2 def0 0e55 78d4 bfc0 e950 48fb 9de4

bf67 9796 f982 21ed 3ff6 e29f 6452 61f2

bfec f117 8a9f 82e8 3ff3 9f67 6319 33eb

3fa3 b72c 6a14 f2ab bf96 d2e6 4d9a b9dc

3f29 0d1c e7e6 2ebd 3f4a 9c39 8aeb 53e9

bf58 1dee 751d ebd2 bfaf 5f1f d46e b6da

3fb5 117b 0c2d efc0 bfe8 418f e583 5ebc

3fb7 072f fa3c e787 bf19 57cc fc0f 90f2

bff3 f7d9 0ac3 a6dc bf4f 5bfc 6b5e 8ddd

bf11 b76a 5be1 dad7 3f66 db75 5ada 48e6

3f71 c703 1c25 c5d2 bf42 e05b 3ad1 29e8

3f35 560f 4d75 26da 3fe7 bc62 c0a3 d9f2

bf96 ad84 7904 65f0 bfcc ddda 6b84 29c5

3fbb 9ef1 7201 6be0 3f1b eb9e 0645 03f0

bf32 bfd4 2eca 5fce bf0d afda da53 70e5

3f9b 976e d253 4aed bf5c b344 508c 6dd3

3f6a 51b4 c512 49db 3fe0 0be0 f59f 6ec7

3ffb 8894 b5d6 93e8 3f02 4ae0 edf7 18d2

bf04 5a23 4b41 7df6 bf1b 2474 0e0f 15d7

bf55 8b3e 48fc 89bc 3f3a d0f7 8e1d 82e1

bf28 5fd9 5943 a1a8 bf84 6504 3147 62ec

bf0e 74f3 2d22 5ade bf7d b46a 8a19 a7cf

3fc9 f565 df63 32d5 bfc5 a591 33a1 34d7

3ff1 275c f7ba 44ea 3f80 6ad6 7cef d3ee

bfc9 0d3f ae75 03de 3ff9 f66d 6f68 00f8

bf71 c497 2772 f6e7 bf81 32a0 d384 7fe5

3fbe a397 4ab8 d7d3 bf15 52c7 689c 98e3

bf21 f997 1b78 eedd 3f04 b493 7a96 12ee

bfec 9a05 f4a2 73f3 3f02 da3f a2e0 9be1

bf9a 2795 68d8 b0e0 bfea 9136 2db5 6ee5

3fe1 fa88 a369 80c2 3f0b 00bc 50fe 15ef

3f4c d332 9f9f 2cb2 3fc7 c307 eda6 e5cc

bfc5 3348 d957 24d9 3ff3 893b 4ce5 7779

bf77 3d1a e6df c8f3 bf55 b246 91d9 80a1

3f4e 74da b1ac 8cd6 3f50 2d9d a4d0 5bd2

bfc2 844a d40e e9e4 bf0f d684 172e 88c4

bf52 add6 e342 dec3 bf13 b7f5 0eed ebd5

3faa f7b5 b0fd 9beb bfbc 4623 279e 22d4

bfb8 0bc2 38b1 10f4 3f99 7f04 a183 83ed

3f70 c414 03c6 aee3 3fba fbec c96d f0e8

3f1a 139f 2c5d 92e6 3fbd 0f6f 3450 46e7

3f35 039e dc23 decb bf6b 8ffd f939 96e8

bfa7 2f07 5b8d eda2 bf84 f241 9408 5af4

bf31 b953 fb83 40ef bfcb aaf0 364f 92ea

bf49 b1ec 229e bbd8 bf2a 3b6b d80b 1e97

bf4f aa88 a1a1 5ce3 3f5b df07 4ee5 7fe9

3fad 4771 000f dbe9 bfa0 c2d7 df5f 2ed2

3ff0 59e9 140b a8ed bf82 1355 3ba7 cde2

bff5 792f 66af 87e6 3f94 7758 00be bfec

bf93 4800 ddf7 99bb bf63 1c72 9e5a e8ed

bf5c 4fdb dc91 54ef bf7e f8c4 99d5 5dde

3fa6 5ab7 889d b9d5 bfd3 9ebd 09f8 93e2

3f1b f108 e98a eeef bfab 5922 8d28 deb8

3f1e fe63 737a e9e5 3f7d 354c 7e16 54dd

3fcc a0b5 3ee1 eae7 bfbe c632 afd4 33d7

bf9a 15be 2ea0 f1ee bf4c 462d 7603 46e2

3fe9 39f9 eba6 93ee bf3d 2547 a413 4dc3

3f69 476e 9eb9 35eb 3f1c be69 4226 42ce

bffb 5df1 a619 3bdc bffb fc5b e17d baee

bfaa 6cf7 c76e f4e7 bf8a 1a59 193c 64e8

bf63 784c 95f4 49ee 3f62 a028 5a5a 52c4

3f26 5f08 f77e 18d9 3f70 3712 57db 90ca

bf69 8209 97c9 3cb3 3f2b 8649 32f5 7dd5

bfb4 c05d c8a6 e4f2 3f25 f292 96ce 93ea

bf97 997b f7f4 ced8 3f56 f6df b15a 9add

bf4d 3b2f ef3d a3ee bf95 2100 0000 0000

0000 6803 2981 947d 9428 6806 6809 680a

4b01 4b10 8694 680c 680d 680e 6812 6815

8875 62bd 0624 802e 0bf3 bf36 a137 7fef

e4fa 3fd4 063e c1b4 0106 c00b fde8 b24c

6eca bf6c 1270 29c2 c9fb 3f07 585e a40d

a201 40d4 833e 4a3c 2ee0 bfcb c05a c7da

49e8 bf3e cb0d 2e31 12eb bf5f 3423 f162

5dc2 bfe1 f00c 5261 76e4 bf30 e18c 109f

bafb 3f1f f358 6c1b d7ee bf63 28b5 38bd

f300 c067 833b 747b c1dc bfdd c78a 4fc7

e3f3 3f65 2e

### Biases

8004 95b0 0000 0000 0000 005d 9428 8c13

6a6f 626c 6962 2e6e 756d 7079 5f70 6963

6b6c 6594 8c11 4e75 6d70 7941 7272 6179

5772 6170 7065 7294 9394 2981 947d 9428

8c08 7375 6263 6c61 7373 948c 056e 756d

7079 948c 076e 6461 7272 6179 9493 948c

0573 6861 7065 944b 104b 0186 948c 056f

7264 6572 948c 0143 948c 0564 7479 7065

9468 0768 0e93 948c 0266 3894 8988 8794

5294 284b 038c 013c 944e 4e4e 4aff ffff

ff4a ffff ffff 4b00 7494 628c 0a61 6c6c

6f77 5f6d 6d61 7094 8875 62cc b77e ab38

6ec2 bfda 6824 0e11 94ed bf0d 0ec7 b2e0

ecb2 bf56 fed9 4707 41de bff4 f296 98ce

e3dc bf19 5629 57a2 1eba 3f00 44ad 8300

2fd7 bf94 8552 8374 78c9 3f90 f673 d2f9

d3b2 3f43 d138 4330 18d7 3f81 1864 f892

ddb8 bfcc f676 0885 95d3 3f4b c1f3 30be

b9d8 bf04 f679 2200 97e4 3f48 3e97 a1a8

32cd 3f61 f103 119a 82a1 bf95 2100 0000

0000 0000 6803 2981 947d 9428 6806 6809

680a 4b14 4b01 8694 680c 680d 680e 6812

6815 8875 6226 98a6 d8ad a3c8 bf14 ddf1

35c4 59df 3fb3 4080 e35c 25e2 bfda fba9

4832 add9 3ff7 ada4 f81f 4dd9 3f20 508b

2d5e f6ed bf58 48e4 07f4 f2c8 bfb5 cd45

37be 4fe6 bf4b 1073 58ca cad2 3feb 3113

66ab 0ee7 bfbd 0627 6cf0 99f2 bf02 c783

38df 9edb bf4e c4b9 0fd7 8bd8 3f2c 8011

a947 b7b8 bfb6 2004 98f8 8d92 bf8a 3d2e

406c 19f1 bf9a fe46 a743 43e9 3fbc d9b4

4523 68d0 3f13 66c7 2e78 b2de 3fc4 d0c5

bf9a c7ae bf95 2100 0000 0000 0000 6803

2981 947d 9428 6806 6809 680a 4b14 4b01

8694 680c 680d 680e 6812 6815 8875 624b

cec0 a3d4 ace6 3f01 37a5 d7c9 e0d2 bf00

0905 2c67 3be0 bfc9 5dba 3499 08e1 3f06

0902 fb25 ade2 3fc8 408f 5c4b b9e1 bf08

3b94 05d0 07ce 3f6f a510 1326 a8e2 bf6b

f754 9b2b 0ae4 bf57 f301 2111 52e9 bf08

e632 a81d c4e7 bfe5 d98b 8bc1 8beb bfc3

e60b 3fe5 9ae1 bfe1 1f0a 6e23 c8be bfca

3fbd 8bd5 86e0 bf7c 0153 d937 d6ac bf76

3c62 b2ab a6e2 3f90 1e37 5e90 a4e5 3f59

08bf 13a3 a9e2 3f6c 228e 2cb6 5be1 bf95

2100 0000 0000 0000 6803 2981 947d 9428

6806 6809 680a 4b10 4b01 8694 680c 680d

680e 6812 6815 8875 62f9 2c19 5745 90d1

bf91 6f3c 1a76 5ad6 3f66 d593 4ebe 29d0

3f38 7b5f a4cf 71ef bf7e 65a1 c06f 2dcc

3f06 0a9f 5f4c bfd3 3fdc 79bb 913a 79e9

bfe7 04f5 0f42 08d8 3fcb ac93 f714 81ce

bf43 e615 6267 a5da bfee aeb0 4c39 a7dc

3f90 3cb4 1fd7 20d7 3f43 8843 d763 29e7

bf00 5cfa eb3b a1d6 bff3 aad0 d70c 44d7

3fd0 8071 e08b aace bf95 2100 0000 0000

0000 6803 2981 947d 9428 6806 6809 680a

4b01 4b01 8694 680c 680d 680e 6812 6815

8875 62bf 4fdf a9f4 b6e2 bf65 2e

1. [Pearson, J., Pennock, C. and Robinson, T. (2018). *Auto-detection of strong gravitational lenses using convolutional neural networks.* Emergent Scientist, 2, p.1.] and [arXiv:2104.01014 [astro-ph.IM]] [↑](#footnote-ref-1)
2. [Bayram, T., Akkoyun, S. and Kara, S.O. (2014). *α-decay half-life calculations of superheavy nuclei using artificial neural networks.* Journal of Physics: Conference Series, 490, p.012105.] [↑](#footnote-ref-2)
3. [Freitas, Paulo & Clark, J.. (2019). *Experiments in machine learning of alpha-decay half-lives*.] [↑](#footnote-ref-3)
4. [Niu, Z.M., Liang, H.Z., Sun, B.H., Long, W.H. and Niu, Y.F. (2019). *Predictions of nuclear β -decay half-lives with machine learning and their impact on r -process nucleosynthesis.* Physical Review C, 99(6).] [↑](#footnote-ref-4)
5. [Freitas, Paulo & Clark, J.. (2019). *Experiments in machine learning of alpha-decay half-lives*.] [↑](#footnote-ref-5)
6. [Freitas, Paulo & Clark, J.. (2019). *Experiments in machine learning of alpha-decay half-lives*.] [↑](#footnote-ref-6)
7. Ibid. [↑](#footnote-ref-7)
8. [Bayram, T., Akkoyun, S. and Kara, S.O. (2014). *α-decay half-life calculations of superheavy nuclei using artificial neural networks.* Journal of Physics: Conference Series, 490, p.012105.] [↑](#footnote-ref-8)
9. [Freitas, Paulo & Clark, J.. (2019). *Experiments in machine learning of alpha-decay half-lives*.] [↑](#footnote-ref-9)
10. [https://gist.github.com/GoodmanSciences/c2dd862cd38f21b0ad36b8f96b4bf1ee] [↑](#footnote-ref-10)
11. [https://www.tensorflow.org/tutorials/keras/regression#the\_normalization\_layer] [↑](#footnote-ref-11)
12. Note: While looking over the project once I had finished, I noticed a logic error with my activations. I initialised all the activations I needed with 0s, however, my feedforward appended a new activation layer onto the end meaning I had an extra layer. For this reason, I changed the following line:

    self.activations.append([af]) 🡪 self.activations[-1] = [af] (see end for code block). This does not affect the weights and biases, however, as the activations before this are 0s and it they do not affect the last, additional layer and so the rest of the project does not need to be changed. [↑](#footnote-ref-12)
13. [https://www.figma.com/] [↑](#footnote-ref-13)
14. [https://github.com/TestTest4253/GUI-Designer] [↑](#footnote-ref-14)
15. [https://www.geeksforgeeks.org/open-a-new-window-with-a-button-in-python-tkinter/] [↑](#footnote-ref-15)