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Originality Avowal: "I verify that I am the sole author of this report, except where explicitly stated to the contrary."

Abstract or Executive Summary: This is a half to one-page summary of your report (rather than your project) listing your problem statement and main findings.

Contents Page: It is very useful to have a high-level contents page, list of figures and tables in your report as well as a list of appendices. It will also help you when you structure the report.

Introduction: Your introduction really sets the scene for the report. It should be a clear statement of what the project is about, a summary of the background and context and summarise what you set out to achieve.

Background: The background is not just a literature review but explains why your project is important and explores the theory and previous work. A good literature review synthesises and critically evaluates the existing literature identifying gaps in current knowledge that the project will fill rather than simply describing previous work.

Report: The next part of the report might be then broken into chapters such as methodology, findings, specification, requirements, design etc. The aim of the section as a whole is to describe the work you've done, justify your approach and explain how you arrived at your conclusion. You might also analyse the technical findings of your work.

Conclusion: here you can summarise the project again, make any conclusions, statements or assertions that you believe your project has achieved and offer some ways that the project might be taken forward in future.

Professionalism and Responsibility: It is important that you consider the professional influences on your project such as standards and competencies. You can also discuss general ethics, sustainability, cyber-security or other issues applicable to the project.

Bibliography: a list of all your references following the acceptable college citation format.
(Martin et al., 2020) or (Salas & D’Agostino, 2020) for two authors. For every in-text citation, there must be a reference list one: APA

Appendix: additional useful information that won't be marked but provides some completeness E.g. tables of data, additional graphs etc

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ABSTRACT

This report sets out a scalable method for harmony recognition utilizing the Neural Engineering Framework (NEF) developed by Eliasmith & Anderson.

A proof-of-concept is shown, along with results utilizing a restricted dataset with four different learning rates over 10 epochs.

Three different approaches to consider the seriousness of error were taken

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INTRODUCTION

Your introduction really sets the scene for the report. It should be a clear statement of what the project is about, a summary of the background and context and summarise what you set out to achieve.

It doesn't take a specialist to be marvelled by the complexity and intricacy of some of the piano performances recorded by jazz pianist Bill Evans. Timing, voicings, and tone seem to have a life of their own, and in my own inability to emulate and transcribe what I heard, I felt powerless. That is a problem many musicians, beginners, and professionals struggle with, and something which I felt I had the tools and motivation to tackle.

Among the population of music students only about 4% have absolute pitch, which is to say they can name a note without any reference tone. This allows them, with enough training, to name the notes present in different chords (3 or more musical notes played simultaneously), and with certain ease transcribe music pieces. For the remaining 96%, it remains an arduous task which requires years of relative pitch training, technical expertise, and some trial and error. For example, in the 1970's a group of music students at the highly prestigious Berklee College of Music attempted to transcribe and compile several jazz standards into a series of books named "Real Book". To this day, errors persist, and differences arise regarding the best versions. This illustrates that even some of the best-trained musicians in the world have difficulty in carrying out this task.

In fact, it is arguably an example of the phenomenal capacity of human intelligence, leveraging perception of complex auditory scenes, cognitive ability, previous theoretical knowledge, and inference when testing new combinations (Benetos et al., 2018). The true issue is not about melody (i.e., one note played at a time), but rather about harmony (i.e., tones played simultaneously). The interaction between the different notes when played together create a complex set of harmonics (extra tones arising from the difference in frequency of the notes), which makes it extremely difficult for the ear to break it down into discrete parts. Consider that plus the vast number of combinations 88 keys (in a piano) can form, the poor quality of recordings, and fast changes, and you can begin to imagine the complexity of the problem of music transcription.

While undertaking a module on neuromorphic computing, we discussed how researchers are currently seeking ways to mimic the brain's functionality and efficiency, and how these are being implemented in software and hardware. Naturally, the idea of being able to model one's brain under different scenarios and study how accurate they were, is immensely appealing. The very "human" and complex nature of music appeared to be the perfect environment to explore these models, and further develop the knowledge within a field I am extremely passionate for.

Being presented to Nengo, a software tool that allows the implementation of biologically plausible models of cognition (Eliasmith & Anderson, 2003), proposed a new way to approach this problem and build on the work of other researchers to understand how such models would perform in face of a problem humans have difficulty in tackling.

By weaving together research in areas such as computational neuroscience, music theory, and signal processing, this report **aims in providing a proof-of-concept model for harmony transcription from piano audio recordings**. Moreover, it aims to do so whilst **maintain a degree of fidelity to biological processes** in the brain and **attempting to explore the efficiency of such algorithms in relation to state-of-the-art techniques**.

BACKGROUND

The nature of this project is interdisciplinary, and as such, basic knowledge of each area will benefit the reader to better understand how each aspect connects to the other in a meaningful way. This section will be split into four: **Music Theory**, **Neural Networks**, **Neural Engineering Framework & Nengo**, and **Previous Work & General Remarks**.

Key words will be in bold and will be referenced throughout the report.

Music Theory

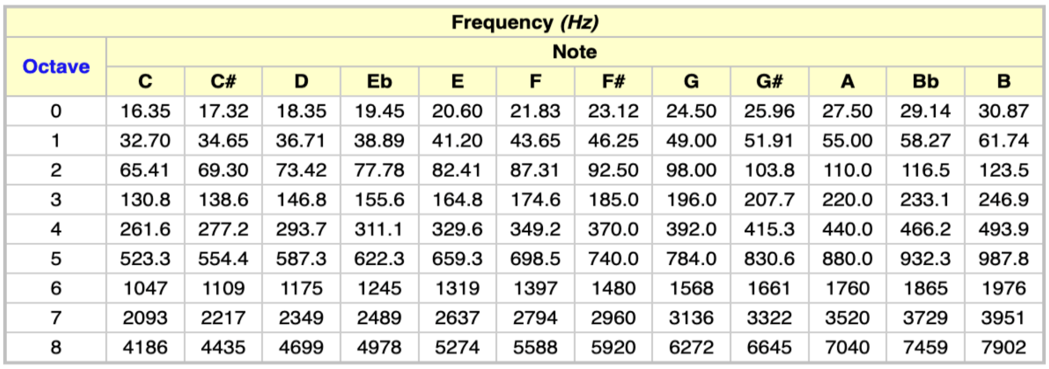
A musical **note (or tone)** is, in its most simple terms, a frequency. For example, when a string in a well-tuned guitar is plucked, it oscillates at this frequency and produces a sound. Now, if two strings are plucked at the same time, the interaction of such frequencies creates new patterns of oscillations, and subsequently new sounds. Such sounds are dependent on how far apart the frequencies between these two notes are.

It was defined that every note with a frequency ratio of 2 (or 0.5) to a subsequent note would be denoted as an **octave**, as due to their closely related harmonics they sound extremely similar (to the human ear). For example, given a note with a frequency of 440Hz, both 880Hz and 220Hz would have the relation of **octaves** to this note.

Every octave is denoted by the same letter, accompanied by a number to denote the frequency. Considering the example above, 440Hz is denoted "A4", whereas 880Hz and 220Hz are "A5" and "A3", respectively.

In the Western world, the most common way to divide the range of frequencies between two octaves is in 12 equally spaced frequencies on the logarithmic scale. This frequency ratio can be written as $2^{\frac{n}{12}}$, where n is the number of notes between the two frequencies, this is called an **interval** (n can also be called the number of **semitones** between the two notes).

Figure 1 below shows **octaves** for a range of frequencies. Note that the "accidentals" (# and b) accompanying some of the notes are a matter of how the labelling system was devised, but matters not for the purpose of this report, as frequencies and ratios will be mostly used.



	Frequency *(Hz)*											
Octave	**Note**											
	C	**C#**	**D**	**Eb**	**E**	**F**	**F#**	**G**	**G#**	**A**	**Bb**	**B**
0	16.35	17.32	18.35	19.45	20.60	21.83	23.12	24.50	25.96	27.50	29.14	30.87
1	32.70	34.65	36.71	38.89	41.20	43.65	46.25	49.00	51.91	55.00	58.27	61.74
2	65.41	69.30	73.42	77.78	82.41	87.31	92.50	98.00	103.8	110.0	116.5	123.5
3	130.8	138.6	146.8	155.6	164.8	174.6	185.0	196.0	207.7	220.0	233.1	246.9
4	261.6	277.2	293.7	311.1	329.6	349.2	370.0	392.0	415.3	440.0	466.2	493.9
5	523.3	554.4	587.3	622.3	659.3	698.5	740.0	784.0	830.6	880.0	932.3	987.8
6	1047	1109	1175	1245	1319	1397	1480	1568	1661	1760	1865	1976
7	2093	2217	2349	2489	2637	2794	2960	3136	3322	3520	3729	3951
8	4186	4435	4699	4978	5274	5588	5920	6272	6645	7040	7459	7902

Figure 1: Notes, their octaves, and their frequencies[1]

For example, between C1 and D1 we have two **semitones** ($n = 2$), which in terms of the frequency ratio is equivalent to the ratio between G1 and A1: in both cases their ratio is $2^{\frac{2}{12}} = 1.12$.

When two or more notes are played simultaneously, we call it **harmony**. Naturally, the more frequencies played at a time, the more complex their interactions become, and the harder is it to distinguish individual notes. **Harmony** and **chords** in this context will be used interchangeably as only one instrument is considered.

Convention has set names for certain combinations of notes: one may call the chord made up of the notes C4, E4, and G4, a C Major chord, for example. However, the same name would be attributed to a chord made up of C3, E4, and G5, with notes in different octaves. The latter is called a **voicing** of C Major and is extremely important in adding flair to music, something musicians often aim to do. The importance of voicings will become clearer once the literature is discussed.

Neural Networks

The field of Machine Learning at large is focused on developing efficient pattern recognition methods that can scale well with the size of the problem domain and of the data sets (Simeone, 2017). For this reason, many model classes, algorithms, and training methods have been devised, and are applied according to the purpose desired. One such model class is called Neural Network (Artificial Neural Network, or ANN for short). In simple terms, Neural Networks aim to extract the most useful features of the data and utilise such features to infer a result. This model is mostly used for situations in which it is difficult to determine good features of the data *a priori*. For example, if the input data is a text, the features may be determined *a priori* as a vector with the number of occurrences of given words, which can be a good way to determine the subject of the text. If the input was an image, however, the decision as to what good features are becomes less clear; and that is the main role of the Neural Network model.

Through a supervising signal, which determines whether the output of the model was correct or not, the parameters of the model (also referred to as weights) are updated to reflect such error, and hopefully yield

- [1] Engineering ToolBox, (2003). *Notes, Octaves and Frequencies*. [online] Available at: https://www.engineeringtoolbox.com/note-frequencies-d_520.html.

a better result. The method with which they are updated is usually by taking the gradient of a **loss function** over a small set of randomly selected data points (called mini batch) and changing the weights according to the negative direction of such gradient (i.e., minimizing the loss). This is called Stochastic Gradient Descent. The **loss function** is set *a priori* and depends on the nature of the problem. One such example is the detection-error loss, denoted $\ell(t, \hat{t}) = \mathbb{1}(t \neq \hat{t})$, which means that if prediction $\hat{t} = t$ (i.e., correct) the loss will zero, and otherwise it will be one.

Each computational unit in a neural network is called a neuron and, except for the input neurons (denoted x in Figure 2), receive a real number that is a result of the weighted sum of the outputs of the previous layer of neurons.

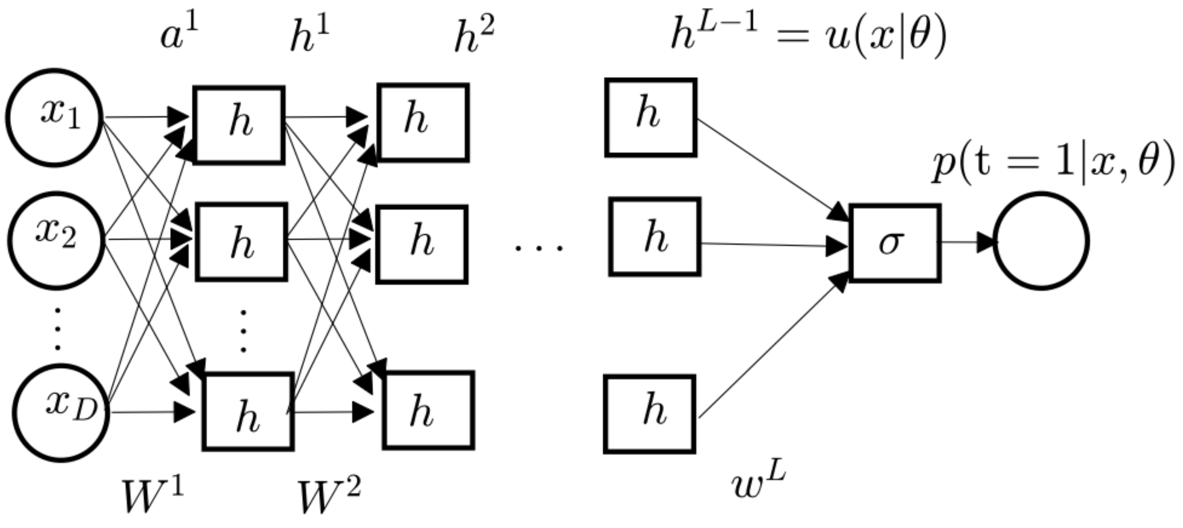


Figure 2 - Neural Network model[2]

The model in Figure 2 tackles the problem of binary classification as it can be seen by the output neuron, which denotes the probability of the target variable t being equal to 1.
Consider the first layer denoted h^1, each of the neurons h is receiving as input all the outputs of the previous layer (the input layer). The arrows for each input "represent" a **weight** (a real valued number), with which the output of the previous layer will be multiplied. The neuron then sums all these inputs and passes this real valued number (denoted a) through a non-linear (activation) function (denoted h). Mathematically this can be represented as:

$$\mathrm{h}\left(\sum_{i=1}^{D} x_i w_i\right) = \mathrm{h}(\mathrm{a})$$

Where w_i is the weight for each individual neuron-to-neuron connection.

[2] Simeone, (2022)

This output $\mathrm{h}(\mathrm{a})$ will take the same role x took in our example (but for the second layer), and so forth for all the layers up to $L-1$. In layer L, also called the classification layer, there will be only one neuron, whose activation function is a sigmoid, and will output the respective probability $p(\mathrm{t}=1|x,\theta)$. Note that θ is the vector of all trainable parameters and symbolises that the output probability is dependent on these parameters/**weights**.

Naturally, Neural Networks take some inspiration from the brain by having interconnected neurons transmitting information, however, the similarities stop there. Such models do not take into consideration how biological neurons communicate, and neither how they process information. In an effort to explore the processes behind the world's most power efficient computer (the brain), a new generation of Neural Networks was devised: Spiking Neural Networks (SNNs).

As the name suggests, SNNs transmit information through spikes rather than real numbers, as it was the case in ANNs. Consequently, a few differences arise:

- The learning rules are different, and in the case of SNNs, can allow the implementation of biologically plausible methods such as Spike-Time-Dependant-Plasticity (Caporale & Dan, 2008). This difference also allows SNNs to learn in real time (online learning rules), as it does not require gradient calculations to take place over the whole network.
- For each computation of the function $\mathrm{h}(\mathrm{a})$ in an ANN both multiplication and addition operations are utilised. Computationally, this is an expensive process. The binary nature of spikes means that for any given input for the neurons, the output neuron is only required to sum the weights of the corresponding neurons that spiked (Rajendran, 2021). This is represented in Figure 3, where it is estimated that additions diminish by a factor of 5 to 10, and multiplications go to zero.

Considering the above, SNNs tackles both an issue of computational feasibility and ability to mimic cognitive processes which are central to the successful completion of this project.

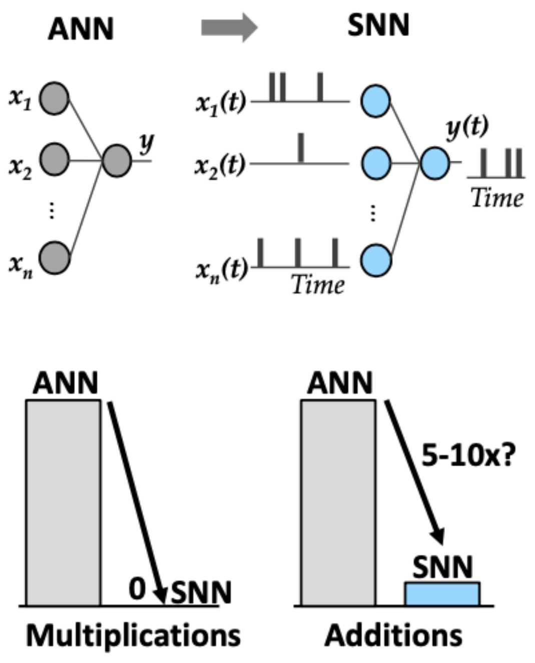


Figure 3 - ANN VS SNN

Neural Engineering Framework & Nengo

The Neural Engineering Framework (**NEF**) is a methodology that allows the construction of large-scale, biologically plausible neural models of cognition (Eliasmith & Anderson, 2003). Instead of setting connection weights between **neurons** manually or through some learning rule (such as Stochastic Gradient Descent), the NEF solves for these according to the function you desire to compute. For example, if one wants to compute $f(x) = x^2$, the framework will determine the connection **weights** between two ensembles of neurons that best approximates this function (the way in which it does will be discussed later). In the case where such function is not known, traditional methods can still be utilised.

Why model according to the NEF?

Considering that the **NEF** uses computational units based on biological neurons, any computation done by the model is forced to adhere to the basic operations that are available to neurons (Stewart, 2012). This allows insight into what sort of algorithms can and cannot be implemented in the human brain. Further, the representation of signals is done so as match the neuron ensemble behaviour seen in the brain, which is a direct effect of how neurons behave.

In 2014, Bekolay et al. developed an open-source Python package called **Nengo**[3], implementing the NEF for building and simulating such models in a computer environment. Given the goal of this project, all the models in this report were built on **Nengo**, following the **NEF**.

Previous Work & General Remarks

The current literature in the subject of harmony recognition is vast, but so is the complexity of the problem. Considering the several steps inherent to the problem; from the processing of the audio, to design choices of classification algorithms, to the scope of the solution, and the choice of databases, there were many unexplored aspects which were considered and utilised.

Most importantly, this model differs in its approach. That is, it is focused in utilising a biologically plausible approach for both the processing and the analysis the data, and for learning.

Fujishima (1999) presents **Pitch Class Profiles (PCP)**, a method that reduces the dimensionality of audio data in the frequency domain by restricting the representation of the signal to a 12-bin vector (i.e., one **octave**). The frequencies are effectively separated at their note-boundaries (i.e., $\pm 2^{\frac{0.5}{12}}$ actual frequency of the note), and the sum of their respective magnitudes is taken and assigned to a note-bin. Dixon (2003) utilises Short-time Fourier Transforms to find magnitude peaks in the magnitude spectrum and uses these as a decision criterion. Barbancho et al. obtain a probability of each note of the piano being played by applying *parallel interference cancellation* (PIC) to frequency domain signals. Tolonand & Karjalainen (2000) proposed a model with some basis on the human auditory system for multipitch analysis by separating the signals into subband channels.

Inspired by the Cochlea in the human ear, this report chose to adhere to a similar format to that of Tolonand & Karjalainen, but adapting it to range of a piano, namely with 88 bins in **PCP**-like manner ranging from 27.5Hz to 4186Hz, one for each note of the piano. This allows for a representation of the position of the notes within the instrument and addresses the issue of representing **voicings**. Dixon's approach was also taken into consideration to pre-process the sound.

[3] https://www.nengo.ai/

Only recently have machine learning methods (rather than relying on signal processing techniques and pattern matching), began to be used. One such research was done by Saputra et al.

REPORT

Things I tried
What I succeeded in; and substantiate with results (and mention how significant these results are! Show why they are important) —> look at the poster for the CHD class and the questions
What I failed in and why
What are the specific problems/optimisation knobs you studied/explored for full precision software implementation?

Methodology

Dataset and processing

The UMA-piano chord database contains over 275,000 chord recordings with different levels of polyphony and playing styles. There are two main features of the database that allow it to be an efficient way to train and test the model, namely, all the recordings are from a live piano in contrast to a MIDI, which allows for complex harmonic interactions to happen, and the range of dynamics – staccato, muted, sustained, etc., which allows for a greater fidelity to the way musicians play.

Explain how the data set was divided

Data collection and processing

Framework

There are several different neuron models, with different characteristics and idiosyncrasies. For this project, the standard Leaky-Integrate-and-Fire (LIF) was chosen as it demonstrates characteristics of biological neurons such as the diffusion of ions through the membrane (leaky), a refractory period, and the action potential, whilst being simple enough to model without computational constraints. It is modelled by the equation:

$$\mathrm{C_M}\frac{d\mathrm{V}}{dt} = -g_l(V - \mathrm{V}_l) + \mathrm{I}_{app}(t)$$

Where V_l is the resting potential, g_l is the leak conductance, $\mathrm{I}_{app}(t)$ is the external input current, and $\mathrm{C_M}$ is the membrane capacitance.

The spikes in the model are triggered by the membrane potential reaching a threshold called the action potential. That extends to how the input current (above a certain level I_{th}) will cause the neuron to start firing as the increase in voltage becomes greater than the decay. Subsequently, for higher values of $\mathrm{I}_{app}(t)$ we see a higher frequency in the spikes — as modelled by the response curve in Figure 4.

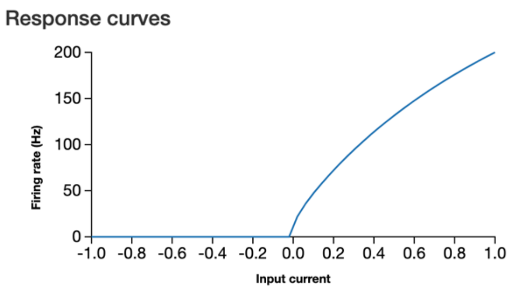


Figure 4 - Response Curve for one neuron

The NEF makes a strong claim that this input current is a linear function of the value represented, given by the equation:

$$\mathrm{I}(x) = \alpha x + \mathrm{I}_{bias}$$

Where α is some gain value and I_{bias} is a constant bias current, both of which are randomized to generate heterogeneous response curves.[4]

In Nengo, the value for which the neuron will start firing is given by the value of x for which $\mathrm{I}(x) > \mathrm{I}_{th}$, that is:

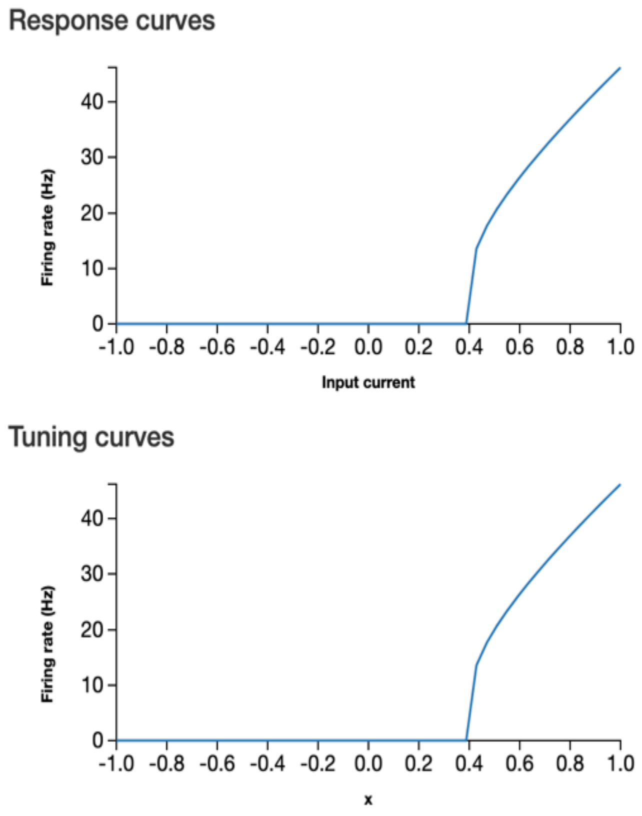
[4] https://forum.nengo.ai/t/deriving-spiking-voltage-and-spiking-frequency-of-a-neuron-from-a-train-nengo-dl-model/1898/4

$$x > \frac{I_{th} - I_{bias}}{\alpha}$$

As a default, $I_{th} = 1$, which yields:

$$x > \frac{1 - I_{bias}}{\alpha}$$

For example, by setting $I_{bias} = 0.6$, and $\alpha = 1$ for a single neuron, we obtain:



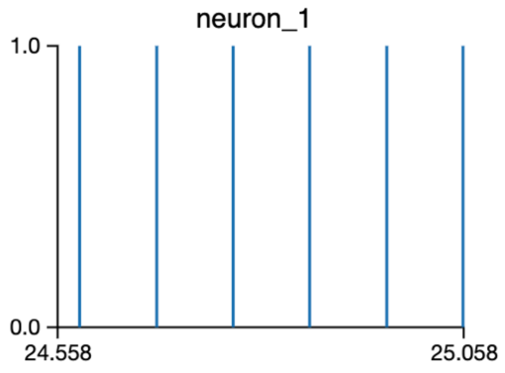


Figure 5 - Spike response for x=0.41

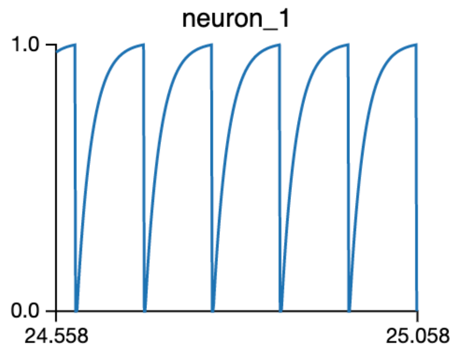


Figure 7 - Response and Tuning Curves

Figure 6 - Voltage for x=0.41

As expected, the neuron starts spiking for values of x greater than 0.4 and the rate remains constant for a non-changing x, which is in line with the discussion above.

Let us now consider more complex representations, where the input has more than one dimension, and the ensemble of neurons has more than one neuron. For a signal vector $\mathbf{x}$, the NEF uses an encoding vector $\mathbf{e}_\mathrm{i}$ to represent neuron activity a_i of a given neuron i. That is, it determines a "preferred direction vector" for that neuron: the vector for which that that neuron will fire most strongly (Stewart, 2012). Effectively, the spiking activity by a neuron will be given as:

$$a_i = G(\alpha_i\, \mathbf{e}_i \cdot \mathbf{x} + I_{bias})$$

Where the function G is the spiking LIF neuron model.

Figure 6 below shows how an actual ensemble with 20 neurons behaves in Nengo. The parameters for each neuron are set at random to provide a realistic range of responses. In turn, by randomizing them, it allows the ensemble to decode/represent a larger range of functions.

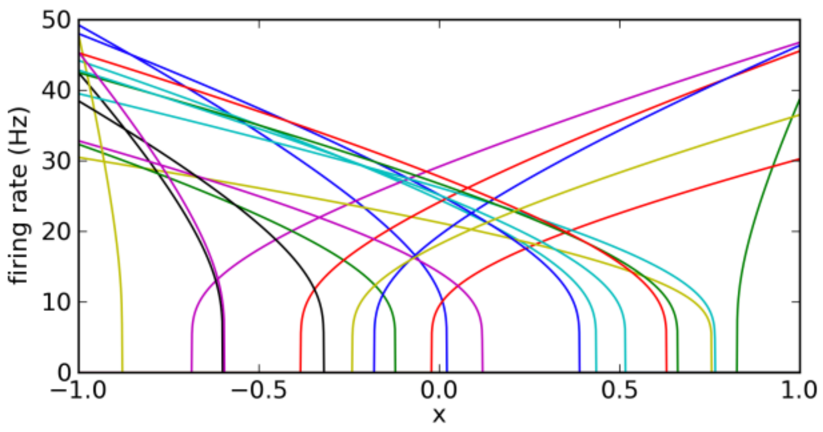


Figure 8 - Tuning Curves for an Ensemble[5]

Neurons whose firing increases with $\mathbf{x}$ have $\mathbf{e}_i = 1$ while the other neurons have $\mathbf{e}_i = -1$ (Stewart, 2012).

In the same way that we seek to map input $\mathbf{x}$ into spiking activity, we seek to map spiking activity back into some value (which could be simply $\mathbf{x}$ again or some function of thereof). To do so, a set of decoding weights $\mathbf{d}_i$ is determined such that:

$$f(\mathbf{x}) = \sum_i a_i \boldsymbol{d}_i$$

These decoders are found through a least-squares minimization of the difference between the decoded estimate and the actual values of $f(\mathbf{x})$:

$$\mathbf{d} = \Upsilon^{-1}\Gamma \qquad \Gamma_{ij} = \int a_i\, a_j dx \qquad \Upsilon_j = \int a_j f(\mathbf{x}) dx$$

(Bekolay et al.,2013).

Applying this to connections between ensembles of neurons, it is clear to see that by considering the decoding weight, which allow us to retrieve representations from neural activity, and encoding weights, which allow us to obtain a neural activity representation from input values (with a gain factor), it is possible to derive the following connection weights between two ensembles:

$$\omega_{ij} = \alpha_j \mathbf{e}_j \mathbf{d}_i$$

[5] Stewart, 2012

Where indexes j correspond to the neurons in postsynaptic ensemble, and indexes i correspond to neurons in the presynaptic ensemble; α_j is the gain factor corresponding to the neuron j.

Learning

Given the framework discussed, one should wonder how to compute a set of decoding weights in a situation where the function is unknown. In other words, how to minimize the error in approximating a function $f(\mathbf{x})$ where only the output is known.

By denoting a vector $\mathbf{E}$ as the error we want to minimize, MacNeil and Eliasmith (2011) proposed the following learning rule:

$$\Delta \mathbf{d}_i = \kappa \mathbf{E} a_i$$

$$\Delta \omega_{ij} = \kappa \alpha_j \mathbf{e}_j \cdot \mathbf{E} a_i$$

Where κ is a scalar learning rate, and all other terms are as before.

This rule allows for real-time learning of the set of decoders weights that best approximates the function we want to model and was the chosen method for the model in this project. In the NEF it is called the Prescribed Error Sensitivity (PES) rule.

Explain the processing of the data in more detail

This technique is applied over an audio signal processed by the Fourier Transform, which yields a vector with 88 magnitudes, one of each note.

Design

Knobs for optimisation pursued in the project, with explanation and description of the hypothesis/rationale for choosing the knobs

The design of the model has two time-varying input signals, the hearing stimulus, which receives a scaled 88-dimensional vector representing a chord every 150ms, and a "correct" stimulus, which receives an 88-dimensional vector with ones in the correct position of the notes every 150ms (discussed later). For the training model, these are connected to an error ensemble that allows the learning process, whereas in the inference model only the hearing input and a decision ensemble are present. This allows for real-time detection of the notes once the decoder values are trained.

Due to the nature of the tuning curves of the neuron models in the NEF, which by default respond to input values between -1 and 1 (Figure 4), scaling them to respond to larger values reduces the quality of the representation. This is because the range of frequencies for the neurons are limited, and the further it is spread, the lower the resolution of the output.

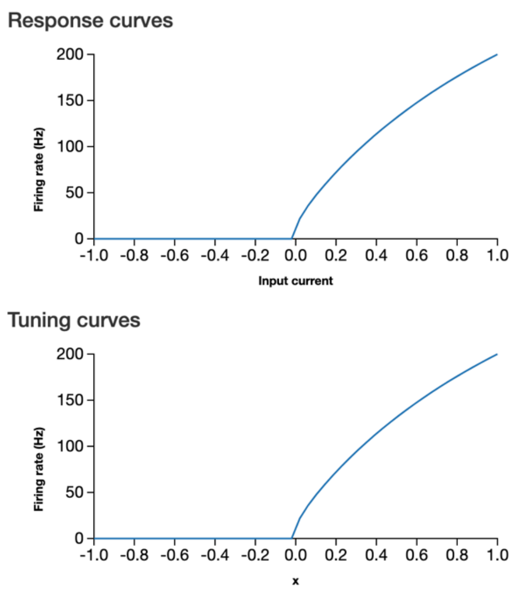


Figure 9 - Neuron with Radius parameter = 1.

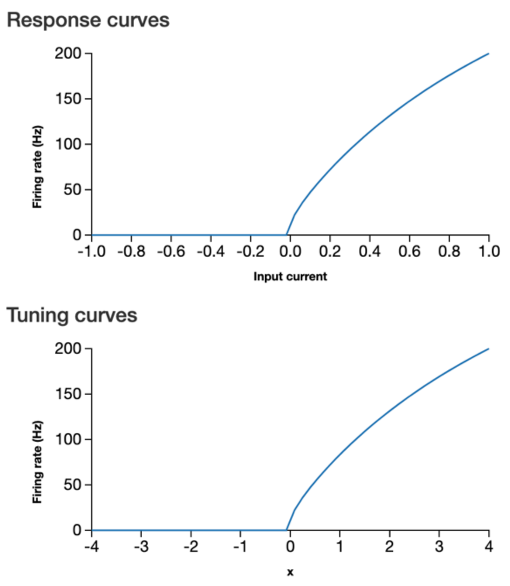


Figure 10 - Neuron with Radius parameter = 4.

Refer to Figures 4 and 5 above, both neurons were set to have the same parameters for maximum fire rate, axis intercept, and encoders. Notice how by increasing the range of input response to 4 (Figure 10), it spreads the firing rate over a large output domain, losing resolution. The only way to fix this issue for ensembles is by increasing the number of neurons, and subsequently the computational load.

The linear relation between input current and the value being represented can be seen by how the curves maintain their shape for both Response curves and Tuning curves regardless of what maximum values they were set to represent.

Considering the discussion above, the hearing input stimulus given by the 88-bin magnitude values of the Fourier transform was scaled with a $\log_{10}$ function to restrict the values to a range between 0 and 4 (decimal values were set to 0 to prevent negative numbers). This allowed for a smaller number of neurons to be used for representing the signal. Consequently, the label vector, which was initially made up of ones was scaled by 3 to match the highest magnitudes of the hearing stimulus.
Due to computational constraints, the range of the model was reduced to 30 notes instead of 88, however, the methodology remains the same. To reflect this change, only values of the inputs which had all three notes within this range were considered. This is crucial, as it allows the results to consider the full impact of the polyphony (interactions of the harmonics) and provides an easily scalable model which can tackle this problem with a larger number of notes.
Figure 12 below shows a visual representation of the learning model while running:

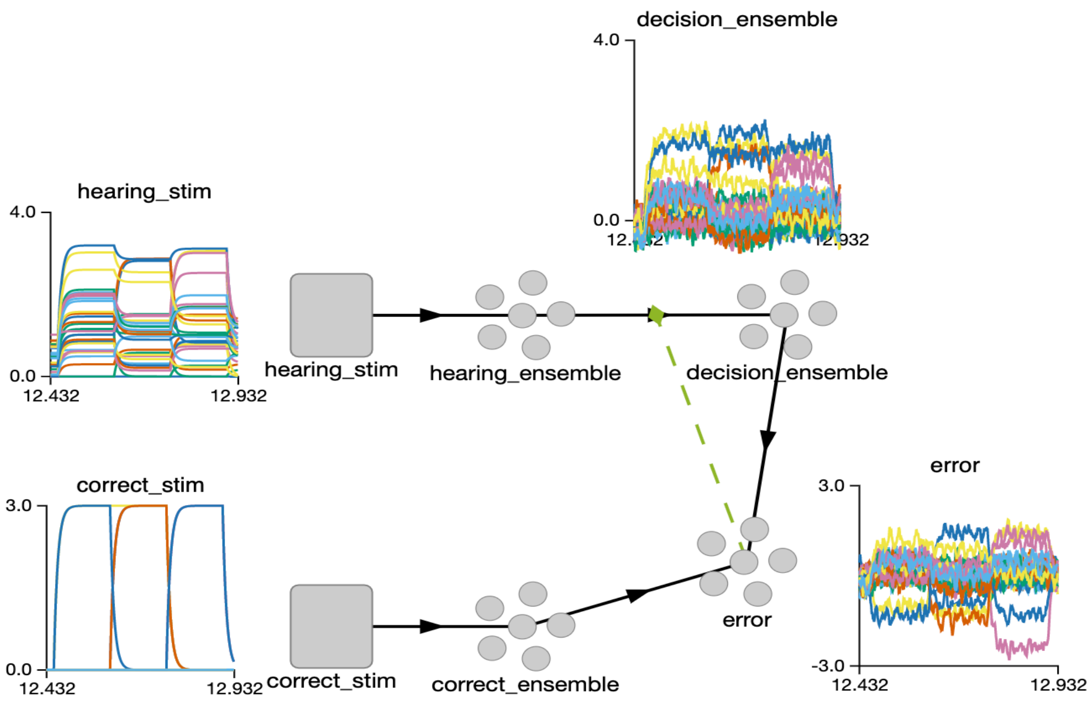


Figure 11 - Learning Model

Blocks made up of the six circles are neuron ensembles, and the rectangles are signal nodes.
Beside each block is a visual representation of the values it is representing. Each colour represents one dimension of the 30 inputs (i.e., one value of the 30-dimensional vector).
As it can be seen, both the "hearing" signal and the label signal are changing every 150ms, shown by the increase and decrease of the coloured lines. As expected, the range of values in the hearing signal are less clear, and the maximum values vary depending on the row of the data matrix that is being represented.

The application of the learning rule can be seen by the green arrow from "error" to the connection between "hearing" and "decision". The error vector defined previously in the PES rule is given by a sum of the label vector (correct_ensemble) multiplied by -1 and the "decision" vector.

Explain the images
Explain the shapes
Mention that error is an ensemble used to apply the PES rule.

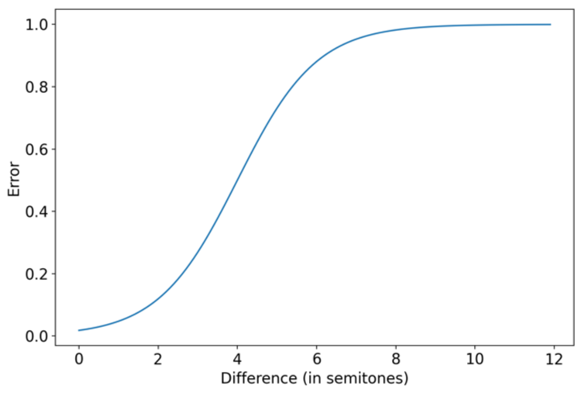


Figure 12 - Sigmoid error function

$$f(x) = \frac{1}{1 + e^{4.5-(0.9x)}}$$

$$f(x) = \frac{x}{12}$$

13500 neurons! Mentioned spikes per neuron per second, which is biologically plausible.
Reflecting seriousness of error

Decreasing learning rate - large weight changes in the beginning of the learning process and small changes or fine-tuning towards the end of the learning process.

Findings

Student has designed and carried out methods to successfully **verify** and/or **test** / **justify** the findings

The base comparison for all predictions is the processed audio signal (88-dimension vector of magnitudes) which was fed into the hearing ensemble. When considered against the labels, it scored 33.9% with the detection-error loss function (make sure of discussing the loss functions previously).

As mentioned, octaves have a similar set of harmonics, and often the second note with the highest accuracy is the octave of the correct note. Considering this, if the dimensionality of the data had been reduced (a possible hyperparameter that can be set through testing and validation), the total amplitude of that note's frequency bin would have been larger, and consequently more accurate. This has a direct trade-off with the ability to represent voicings and is something the context of use will determine.

Since the model doesn't generalise well, but does have a low training loss, the logical conclusions would be to train it with all possible combinations. The form in which this scales for a chord with n number of notes (88 choose n), however, does not make this a feasible problem, as both the computational power and time required would be significant.
On the other hand, it seems clear that there are chords played more often than others, especially in pop music. That being the case, filtering the database in such a way as to only consider chords with a probability above a certain threshold has the potential to produce an accurate model for a smaller but more likely set of outcomes, requiring significantly less computational power. This is beyond the scope of the project but is nonetheless a direct consequence of the model and conclusions obtained.

Since the prediction is done on the processed audio (that is, on the matrix of 88 frequency bins), the structure of the data matrix can be maintained for any audio within this frequency range. In effect, the model, if trained on the full range of a piano as opposed to 30 notes, is expected to work on the harmony recognition of any piano audio.
By running the model without trained decoders over different parts of the data, significantly different results were seen. Since the only factor affecting the decision of the model in this scenario is the magnitude of the notes given by the Fourier Transform, these results imply that different parts of the data have different degrees of clearness (of the peaks). Logically, this is due to the nature of the dynamics of the recordings, but overall should not affect the conclusions that can be taken from the data, as the reference point will always be the model without decoders.

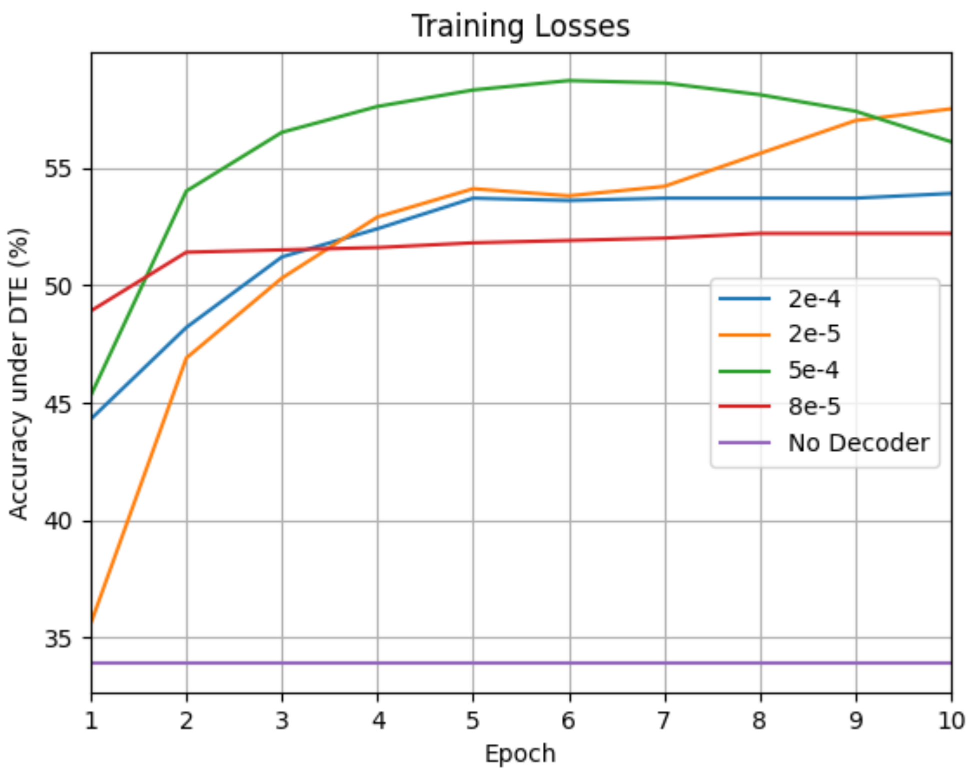


Figure 13 - Training data results under DTE

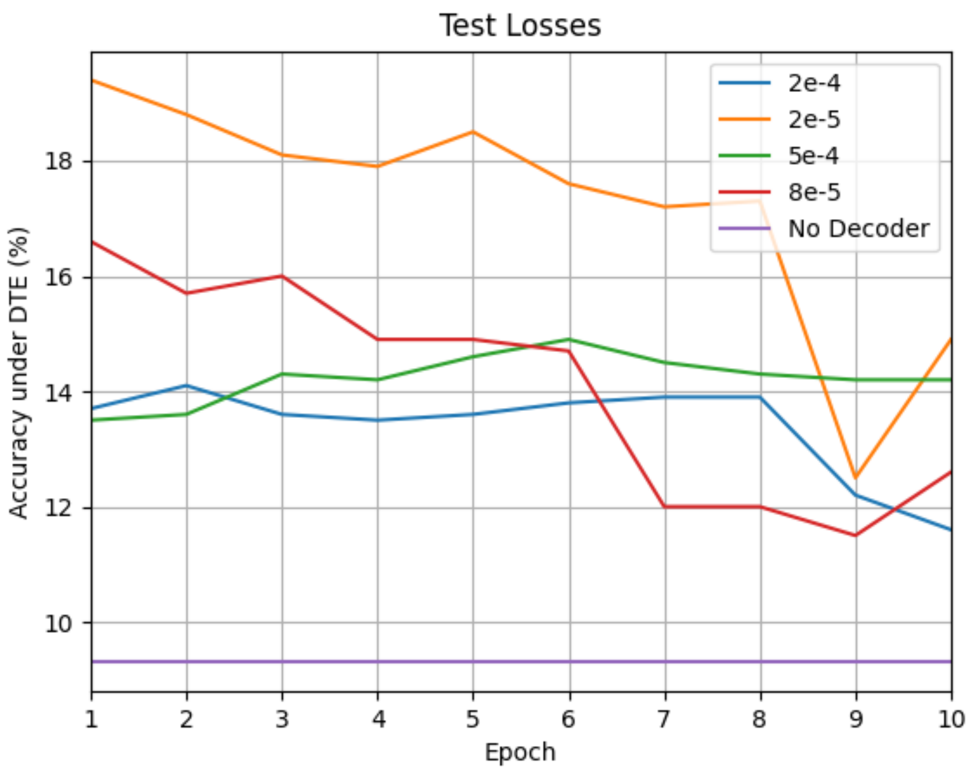


Figure 14 – Test data results under DTE

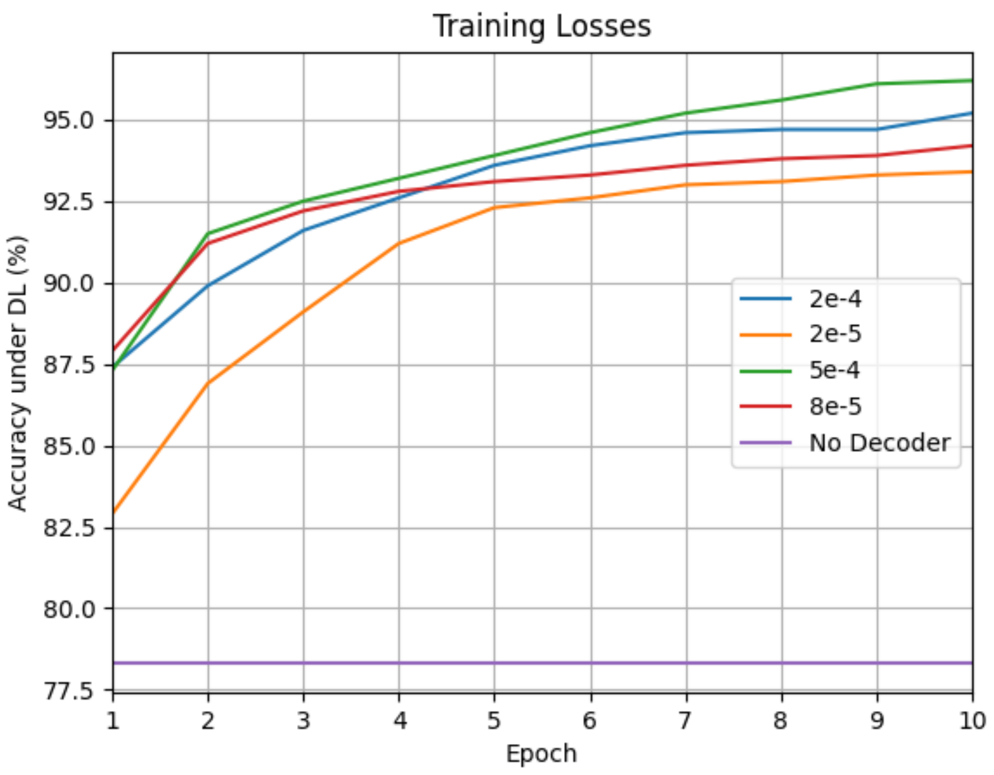


Figure 15 – Training data results under DL

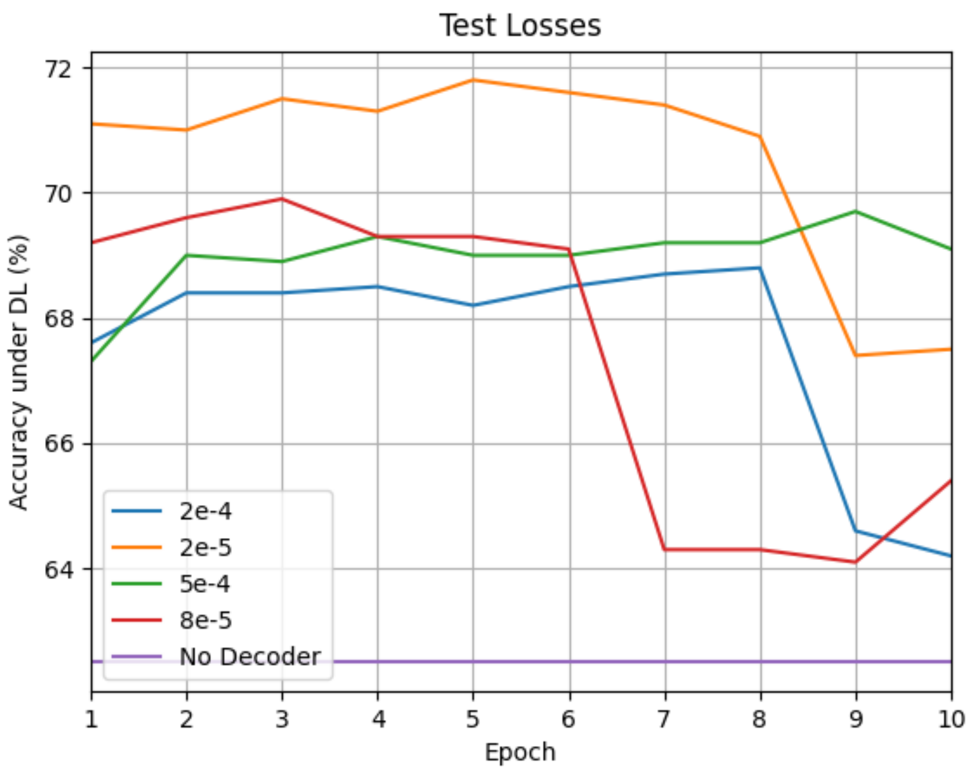


Figure 16 - Test data results under DL

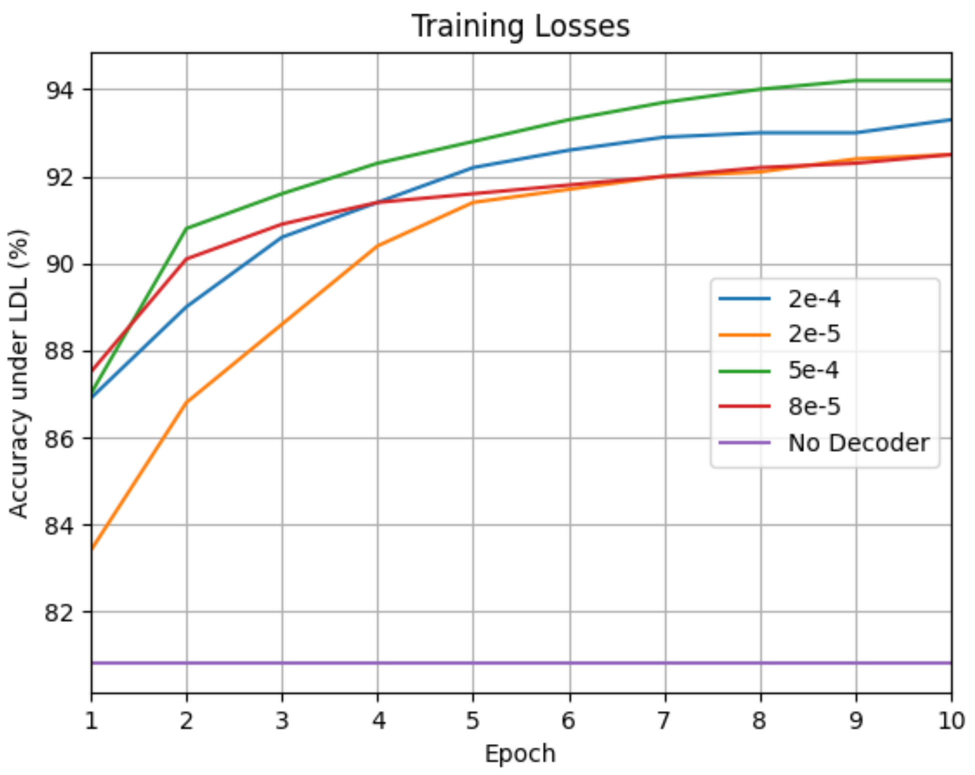


Figure 17 – Training data results under LDL

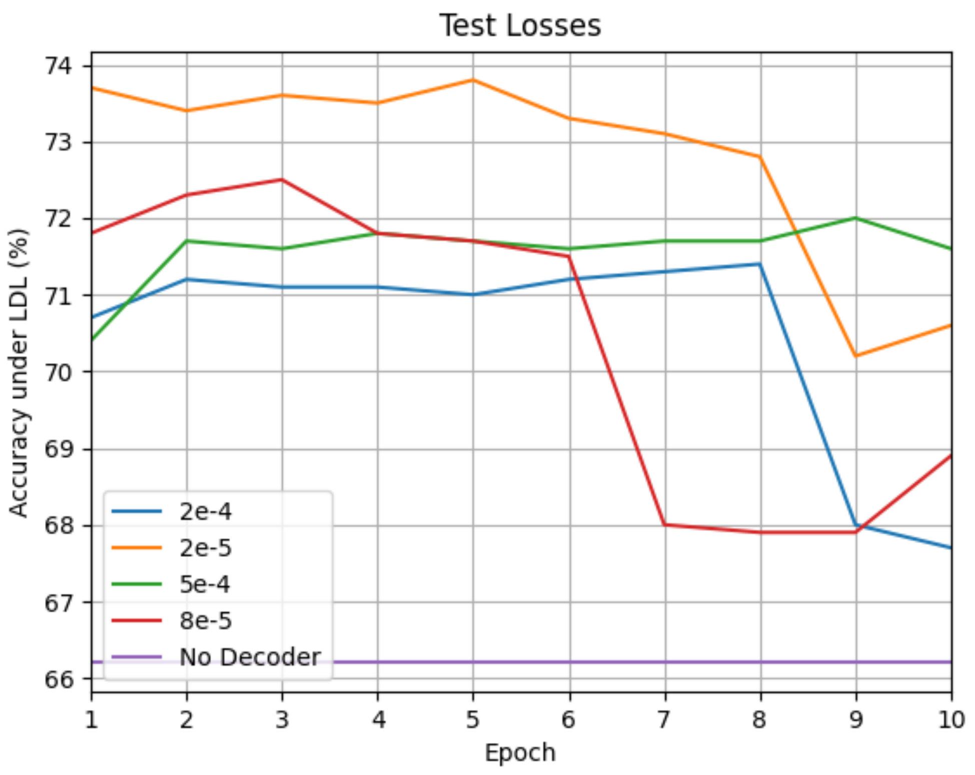


Figure 18 - Test data results under LDL

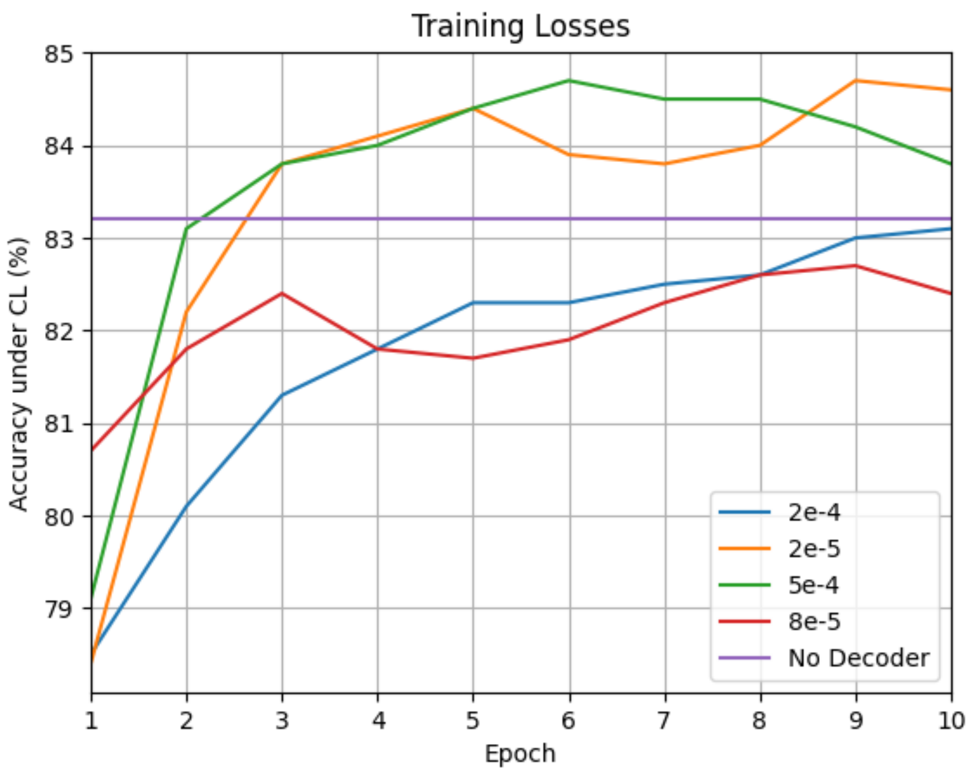


Figure 19 – Training data results under CL

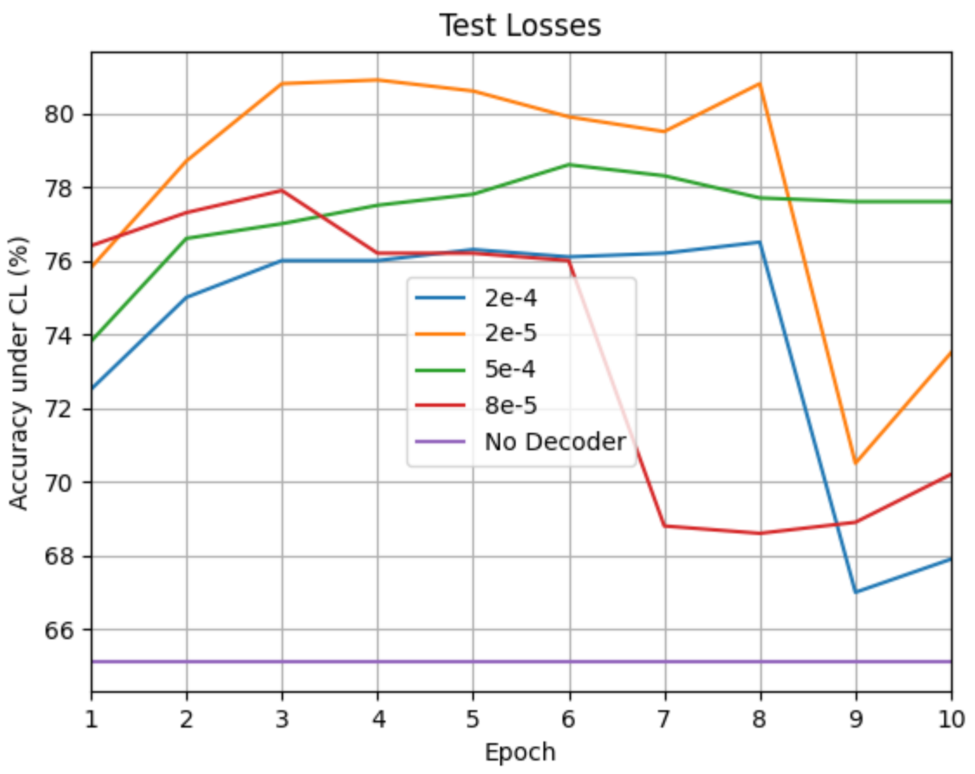


Figure 20 - Test data results under CL

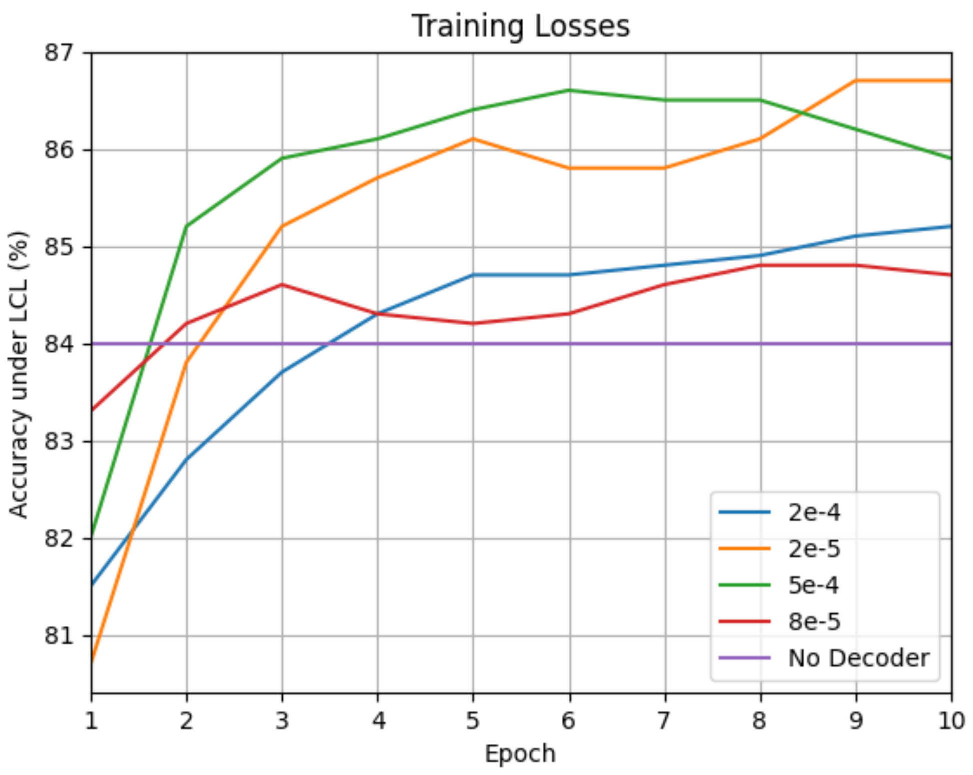


Figure 21 – Training data results under LCL

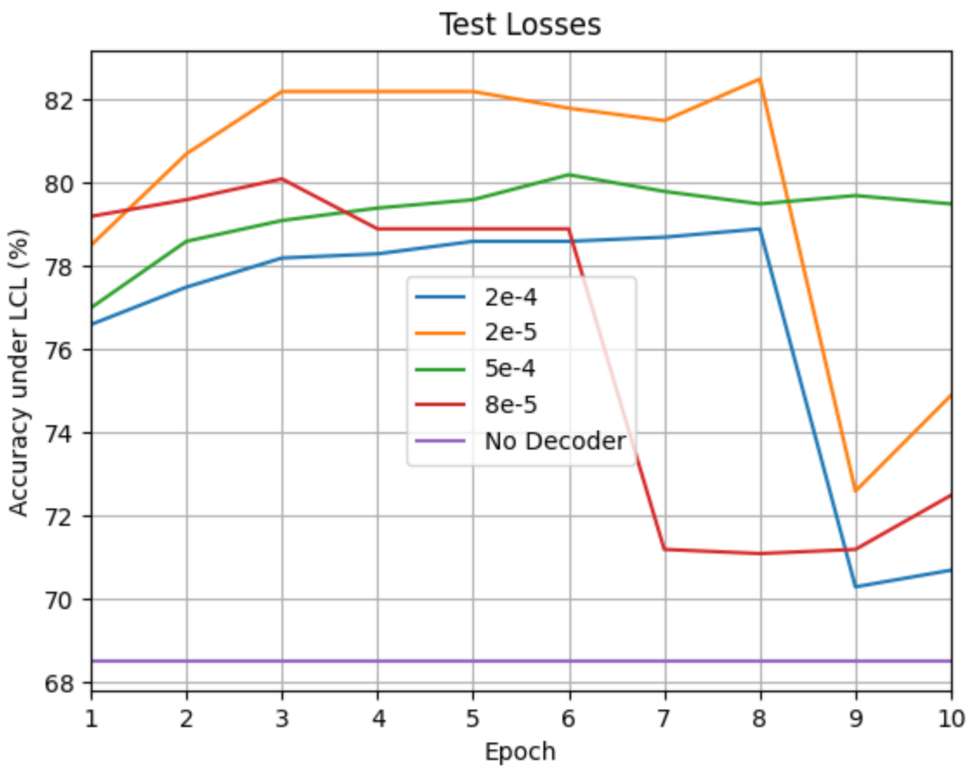


Figure 22 - Test data results under LCL

Both linear and sigmoid distance loss decreased as the number of training points increased. That is, the encoders were prioritising values closer to the target, and suppressing those that were further away, effectively modelling the target signal.

This was true for sounds which the model had been exposed to previously, which is to say, if this really mimics cognition, humans without the innate ability to recognize pitches need to have heard the sound previously to classify it.
On the other hand, this could also be a consequence of modelling too specifically a set of data; losing the ability to generalize. In machine learning, this is called overfitting, and is in general considered a negative consequence of modelling to close to the training data.
All in all, when contextualizing these results, this model competitively demonstrates the ability to face the complex task of harmony recognition when facing previously known samples. Most of all, it shows the capacity to scale to a higher range of notes, to help musicians in their work, and to allow us to understand the brain's mechanisms better.

CONCLUSION

Here you can summarise the project again, make any conclusions, statements or assertions that you believe your project has achieved and offer some ways that the project might be taken forward in future.

SPA architecture

Full range of piano

Analyse structure of chords for learning how to compose different styles from audio data.

EVALUATION

The student has critically evaluated the project outcomes and methods against the aims and objectives and existing work. The student has evaluated the validity of the original objectives.

PROFESSIONALISM AND RESPONSIBILITY

The student has critically reflected on the wider professional responsibilities, codes and regulations associated with the project and there is thoughtful discussion of the social, environmental and ethical impact of their work → standards and competencies. You can also discuss general ethics, sustainability, cyber-security or other issues applicable to the project.

Qual o problema em emular um cérebro?

BIBLIOGRAPHY

Eliasmith, C., & Anderson, C. H. (2003). Neural engineering: Computation, representation and dynamics in neurobiological systems. Cambridge, MA: MIT Press.

Stewart, T. C. (2012). (tech.). *A Technical Overview of the Neural Engineering Framework*.

Rajendran, B. (2021). *Brain-Inspired Computing & Hardware Design.*

Osvaldo Simeone (2017). A Brief Introduction to Machine Learning for Engineers. Available at: https://nms.kcl.ac.uk/osvaldo.simeone/notesMLSimeone.pdf

Heng-Tze Cheng, Yi-Hsuan Yang, Yu-Ching Lin, I-Bin Liao and H. H. Chen, (2008). "Automatic chord recognition for music classification and retrieval," 2008 IEEE International Conference on Multimedia and Expo, pp. 1505-1508, doi: 10.1109/ICME.2008.4607732.

Simon Dixon, (2003) "Extraction of Musical Performance Parameters from Audio Data"

Engineering ToolBox, (2003). *Notes, Octaves and Frequencies*. [online] Available at: https://www.engineeringtoolbox.com/note-frequencies-d_520.html

Takuya Fujishima (1999). Realtime Chord Recognition of Musical Sound: A System Using Common Lisp Music, ICMC Proceedings.

Barbancho et al. (2010). PIC Detector for Piano Chords. EURASIP Journal on Advances in Signal Processing. 10.1155/2010/179367.

Benetos, E., Dixon, S., Duan, Z., & Ewert, S. (2018). Automatic music transcription: An overview. IEEE Signal Processing Magazine, 36(1), 20-30. https://doi.org/10.1109/MSP.2018.2869928

T. Tolonen and M. Karjalainen, (2000). "A computationally efficient multipitch analysis model," IEEE Transactions on Speech and Audio Processing, vol. 8, no. 6, pp. 708–716

Saputra, F., Namyu, U. G., Vincent, ., Suhartono, D. & Gema, A. P. (2021). Automatic Piano Sheet Music Transcription with Machine Learning. *Journal of Computer Science*, *17*(3), 178-187. https://doi.org/10.3844/jcssp.2021.178.187

Natalia Caporale & Yang Dan, (2008). Spike Timing–Dependent Plasticity: A Hebbian Learning Rule Annual Review of Neuroscience 2008 31:1, 25-46

APPENDIX

https://github.com/gusauriemo/Final-Year-Project