Week 1 (29/09 - 05/10)

30 September 2025 16:07

30/09/2025

Week 1 aims and objectives:

- **Have a read through the Intro2ML Slides and understand them properly**
- **Work through the Intro to ML 4 Physicists exercises 1 - 4**

11:00 - Met up with Yvonne & Ethan for our first meeting to discuss the project!

Discussions included:

- Initial Admin about getting an ATLAS account
- Information about what to get to work on in Week 1
- What we're going to be looking at:
  - Classifying Processes such as g -> tt or g-> HH etc.
  - Extending this to multi-class classification (i.e. comparing g -> tt and g-> HH to everything else as background)
  - Trying to reconstruct collision kinematics from final state information using ML models
  - Other extensions towards spin or using some angle matrix thing that Yvonne was very interested in (will probably learn more about later)

Work for the week ahead:

1. Read through slides "Intro2ML for Particle Physics"
2. Work through the exercises in "Intro to ML 4 Physicists"
3. Consult Ethan if finished before the end of the week

13:00 - Getting VSCode set up

- Re-installed Python due to Pathing issue
- Installed Pytorch
- Reinstalled Pytorch due to issue with CUDA after confirming information about laptop GPU
- Set up MPhys Folder and Repository in Github (Still needs to be linked)
- Installed Numpy again

15:00 - Starting work on the Exercises

They can all be found at: https://github.com/els285/Intro2NN4Physics/tree/main

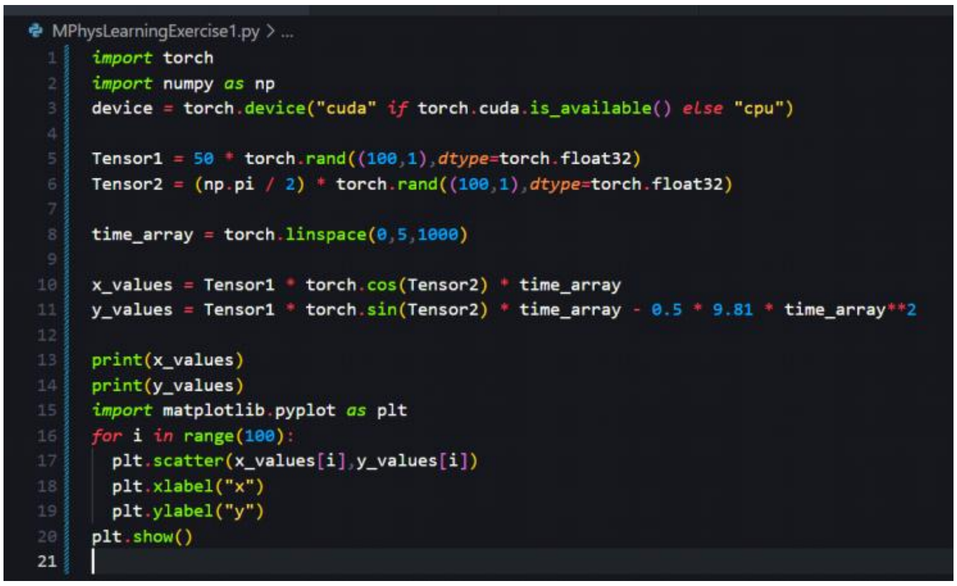
15:05 - Exercise 1 (Filename: 1_Tensors.ipynb)

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\Exercises
MPhysLearningExercise1Section1.py

Remember that for more mathematical operations on elements in a tensor, you have to use `torch.sin()` rather than something such as `np.sin()`

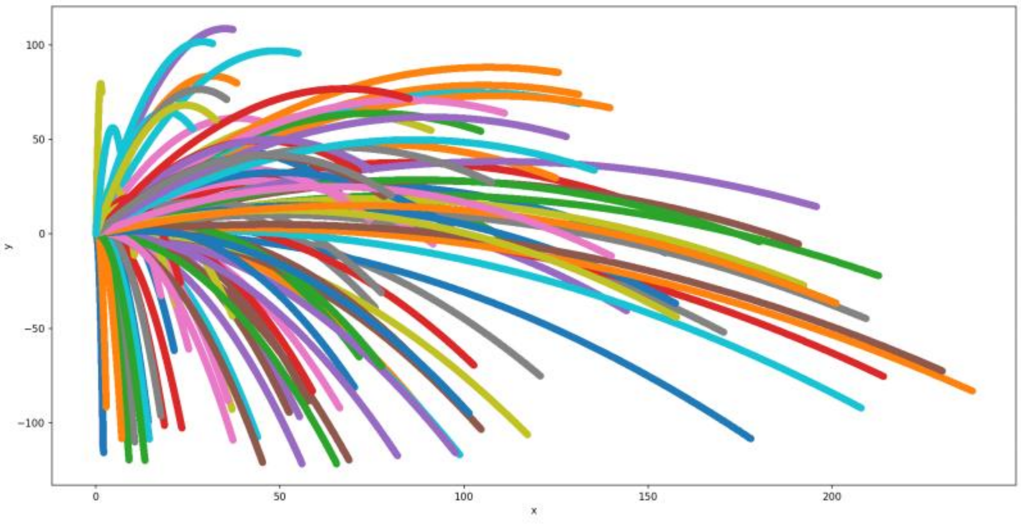
Sidenote: remember to create tensors with the correct dimensions; I was stuck on an issue with multiplying the tensors in the x and y values section as instead of creating a 2D tensor by multiplying the velocities by the linspace, it was attempting to multiply each linspace value by each corresponding velocity. By switching from (1,100) to (100,1) this problem was trivially fixed.

16:05 - Completed Task 1



MPhysLearningExercise1.py > ...

```python
import torch
import numpy as np
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")

Tensor1 = 50 * torch.rand((100,1),dtype=torch.float32)
Tensor2 = (np.pi / 2) * torch.rand((100,1),dtype=torch.float32)

time_array = torch.linspace(0,5,1000)

x_values = Tensor1 * torch.cos(Tensor2) * time_array
y_values = Tensor1 * torch.sin(Tensor2) * time_array - 0.5 * 9.81 * time_array**2

print(x_values)
print(y_values)
import matplotlib.pyplot as plt
for i in range(100):
  plt.scatter(x_values[i],y_values[i])
  plt.xlabel("x")
  plt.ylabel("y")
plt.show()

```



16:30 - Exercise 1, Section 2

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\Exercises
MPhysLearningExercise1Section2.py

<u>Stack, concatenate & reshaping operations</u>

Dimension 0 stacks vertically, dimension 1 stacks horizontally, presumably higher level dimensions are for higher order tensors (i.e. dimension 2 would equate to value on the z axis at a given point if a 3D tensor was used to represent field values at different points in space determined by position in an array)

So using dimension 0 on [1,2,3] and [4,5,6] gives:

1 2 3
4 5 6

Using dimension 1 would yield:

1 4
2 5
3 6

Concatenate combines tensors along an existing direction. Given that these tensors have only got 1 dimension, you would just use dimension 0 as it's the only dimension they have. If instead, they were 2 dimensional row vectors (1,3), then you would have to concatenate with dimension 1 to get them to be "stacked" horizontally so that it became 1 long (1,6) row vector.

17:14 - End of day

Had a few teething issues with uploading to a Github repository but have it all sorted out now. Will continue from the point of reshaping when I get back to work as it seems a little confusing and I need some more time to digest it.

23:10 - Decided to do a bit more work whilst it's still fresh in the head

Reshaping makes a bit more sense now having looked at it again. It preserves the number of elements and by using "-1" as one of your dimensions, the program automatically calculates how long to make that dimension so that the element number stays the same. E.g. if you had a 2x3 array and wanted it to become a 6x1 array, you could just put in `Tensor1.reshape(-1,1)` which would automatically calculate the needed size of the first dimension to maintain element number (6).

Filtering seems to make sense for 1 dimensional tensors, but I'm a little confused as to how it would work at higher dimensions - might not be possible? As element number is not preserved.

A few important Git commands just to make it easier:

1. Check what changed:
```
git status
```

2. Stage everything:
```
git add .
```

3. Commit with a message:
```
git commit -m "describe what you changed"
```

4. Push to Github:
```
git push origin master
```

23:52 - A bit confused in Task 2

It seems like the Z-score normalisation seems a bit useless here as the means are already defined to be zero so you're just dividing by the standard deviation? Will ask in teams at a more sociable hour. Will continue anyways assuming a different mean value (just so it's more general).

Nevermind, having done the coding, it turns out `randn` just takes values randomly from a normalised data set with mean zero, rather than the data values having a mean of zero. Whoops. Basically, it is useful for generating data but won't make it perfect with a mean of zero.

Using `torch.min(filtered_info, dim=0).values` returns simply the values without having to print out the indices too.

01/10/2025

00:17 - Completed Task 2

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\Exercises
MPhysLearningExercise1Task2.py

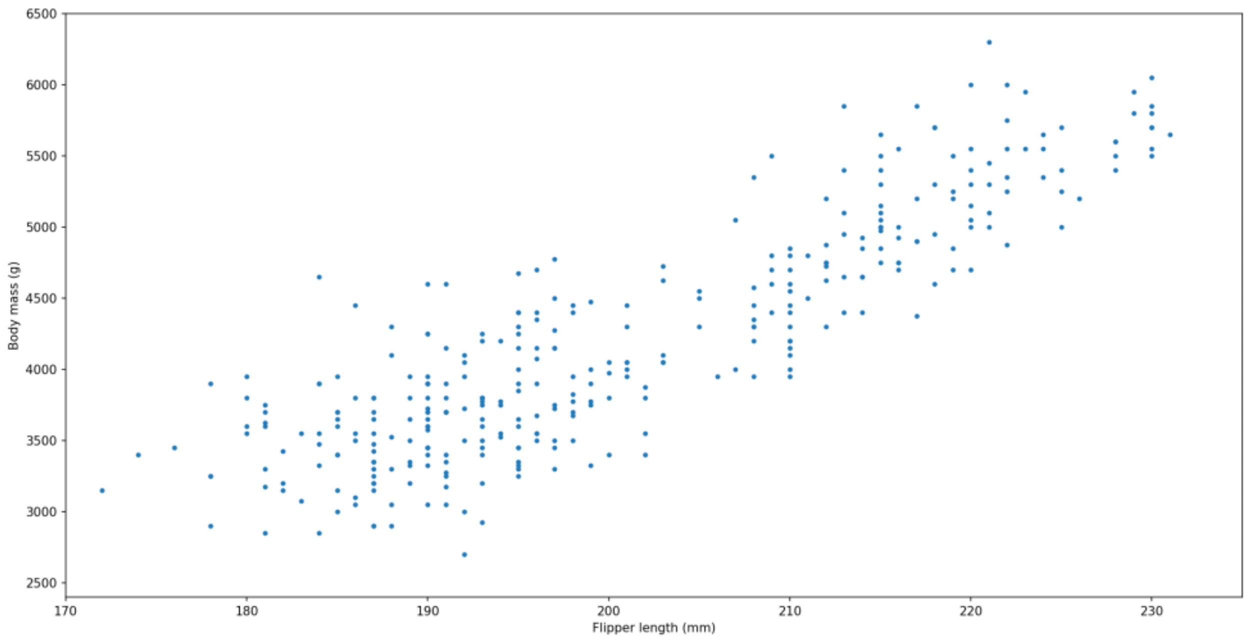
Was quite fun to code - now completed with Exercise 1, on to Exercise 2 next!

11:30 - Exercise 2 (Filename: 2_Regression_Penguins_Sklearn.ipynb)

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\Exercises
MPhysLearningExercise2.py

Need to spend some time looking into pandas further: the .iloc function will likely be important.

https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.iloc.html



Quickly installed scikit-learn via pip

02/10/2025

10:49 - Exercise 2 continued

Linear Regression

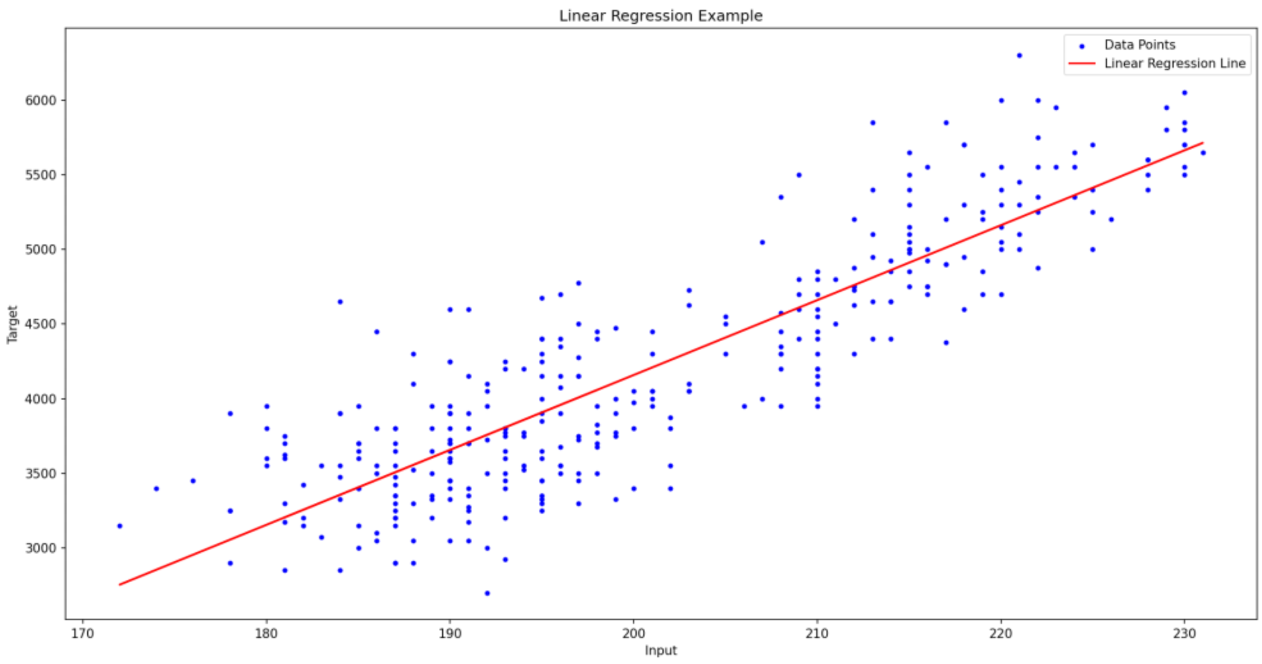
Linear regression from scikit is an ordinary least squares solution:

- Imported as:
```
from sklearn.linear_model import LinearRegression
```
- Required data shape of Data × Features
- If given 2 variables to fit between, need to turn the Features (X in ML convention) into a column vector using reshape (for fitting between more feature variables, the arrays automatically become the correct shape):
```
input_features = input_file["flipper_length_mm"].values
target         = input_file["body_mass_g"].values
X = input_features.reshape(-1,1)
y_true = target
```
- Then, define and fit the model using:
```
model = LinearRegression()
model.fit(X, y_true)
```
- Can then create example features to predict:
```
example_flipper_length = np.asarray([300, 500])
example_body_mass = model.predict(example_flipper_length.reshape(-1, 1))
print(example_body_mass)
```
- Note the reshaping of the features to ensure that X is a column vector
- The same applies to predicting all the data:

```
y_pred = model.predict(X)
```

- Can then use this predicted data to plot a regression line against a scatter plot using:

```
plt.scatter(X, y_true, color='blue', label='Data Points', marker='.')
plt.plot(X, y_pred, color='red', label='Linear Regression Line')
plt.xlabel('Input')
plt.ylabel('Target')
plt.title('Linear Regression Example')
plt.legend()
plt.show()
```



- The slope and y-intercept are then found using: `model.coef_[0]` and `model.intercept_`
- Goodness of fit is calculated using the coefficient of determination:
    - Perfect model, $R^2 = 1$
    - Completely Imperfect model, $R^2 = 0$
- Found using:

```
r_squared = model.score(X, y_true)
print(f"R-squared: {r_squared}")
```

- You can extend to multiple linear regression by simply using code such as this:

```
features_to_consider = ["flipper_length_mm" , "bill_depth_mm",
"bill_length_mm"]
X = input_file[features_to_consider].values
y_true = input_file["body_mass_g"].values
```

<u>Linear Regression on Non-linear Functions</u>

Linear regression refers to the relationship between the predictions and parameters, not inputs. i.e. you can use it to fit polynomials which aren't linear in x but are linear in the coefficients. You simply define each power of x as its own variable and turn the problem into a multilinear regression problem.

Sidenote: `np.random.seed(0)` is used when you want to make future generated random numbers predictable by using the same starting seed. By doing this, you can test for bugs in code that uses random data as you will be presented with the same "random" data for each iteration, making debugging easier.

- Start off by generating data based off a polynomial with "noise" from an added standard normal distribution:

```
np.random.seed(0)
```

```
x = np.linspace(-2, 3, 1000).reshape(-1, 1)
y_true = 2*x**4 - 3*x**3 - 10*x**2 + 0.5*x + 3
y = y_true + 2 * np.random.randn(*y_true.shape)
```

Sidenote: the `*` is used to unpack the arguments of `y_true.shape` into (1000,1) so that it can then be used as arguments for `np.random.randn()`.

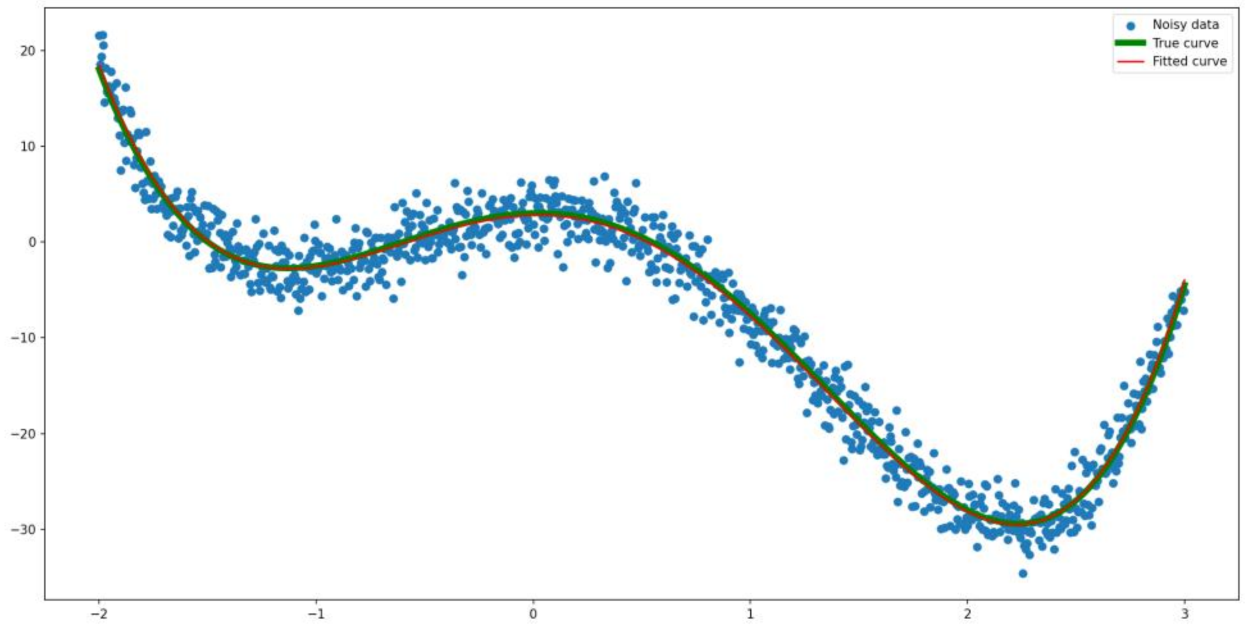
- You can then import the polynomial model from Scikit and define and create the polynomial model as before:
  ```
  from sklearn.preprocessing import PolynomialFeatures
  poly = PolynomialFeatures(degree=4, include_bias=False)
  X_poly = poly.fit_transform(x)  # x, x^2, x^3, x^4
  ```
- You can then fit the linear regression onto the polynomial features:
  ```
  model = LinearRegression()
  model.fit(X_poly, y)
  ```
- And then predict the model:
  ```
  y_pred = model.predict(X_poly)
  ```
- And then plot the resultant scatter graph with fits:
  ```
  plt.scatter(x, y, label="Noisy data")
  plt.plot(x, y_true, label="True curve", color="green", linewidth=5)
  plt.plot(x, y_pred, label="Fitted curve", color="red")
  plt.legend()
  plt.show()
  ```

To clarify what this does as it's a bit confusing:

- `PolynomialFeatures` builds combinations of all the features up to a given degree. i.e. if you had an input with however many samples but 2 features (e.g. [[1,2],[3,4],[5,6]]), with `degree=2`, it would turn `X_poly` into [x_1, x_2, x_1^2, x_1x_2, x_2^2], i.e. all the combinations up to order 2. The reason there is no 1 to begin with (for the coefficient of 1 which acts effectively as a y-intercept) is because of the use of `include_bias=False`. If it was set to `True` then you would have that extra initial bias column. Note that `LinearRegression()` already includes an intercept term by default so it normally isn't necessary
- `poly.fit_transform(x)` Takes the original x of shape [1000,1] with just 1 feature into one with shape [1000,4] with each column having the feature of x, x^2, x^3, x^4 respectively. i.e. if the first sample of feature x was 2, you would end up with [2, 4, 8, 16] in `X_poly`
- `model.fit` now acts as to fit multiple coefficients linearly from the values of x, x^2, x^3, x^4 to the final value. Basically, it is trying to fit roughly to $y \approx X\beta$ where:
  y = vector of target values (n × 1) - this is `y` in our example
  X = feature matrix (n × 5) - this is `X_poly` in our example
  β = coefficient vector (5 × 1) - this is saved in `model` in our example

$$\vec{\mathbf{y}} = \omega_1\vec{\mathbf{x}}_1 + \omega_2\vec{\mathbf{x}}_2 + b + \vec{\epsilon}$$

The ϵ refers to an error term so you don't have to use ≈



14:38 - Exercise 3 (Filename: 3_Regression_Penguins_PyTorch.ipynb)

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\Exercises
MPhysLearningExercise3.py

We will now be repeating the regression in PyTorch.

New imports:

```
import pandas as pd
import matplotlib.pyplot as plt
import torch
from torch import nn, optim
```

Starting to get a bit more exciting (nn = neural networks)!

Sidenote: the code `inplace=False` for any Pandas function acts as to say that the dataframe will not be changed. This means you need to assign a new variable to it. If you use `inplace=True` you can run the code without assigning a new variable to it and it will change the original dataframe instead.

Sidenote: Pandas appears to struggle with finding csv files if they're nested inside folders. Therefore, make sure to input the filepath from the main MPhys folder, e.g. `input_penguins_df = pd.read_csv('Exercises/penguins.csv')`

We start off with a linear regression:

- To create a linear model which maps a single value X_i to a single value y_i, use this: `model = nn.Linear(1, 1)`
- By using `print(model)` you can see that it has one in feature, one out feature, and a bias set to true which is just the y-intercept for simple linear regression

We now have to train it.

<u>Linear Regression Neural Network Training</u>

In scikit, an analytic solution to the least squares fit was implicitly used to solve the regression problem whereas in PyTorch, we use the loss function instead. This is minimised by iteratively updating the parameters in the model.

MSELoss is used for our loss function:

$$\mathrm{MSE}(\mathbf{y}, \widehat{\mathbf{y}}) = \frac{1}{n}\sum_{i=1}^{n}(\mathbf{y}_i - \widehat{\mathbf{y}}_i)^2$$

It's the average squared difference between target and predicted data points.

Linear models are where like 4 inputs are mapped to one output, it's a directed graph.

- To return to the MSELoss, this is the code used when using it as the loss function:
```
loss_function = nn.MSELoss()
optimizer = optim.Rprop(model.parameters())
```
- Below is the fully commented code from the exercise to explain how the iteration loop for training the model works:
```
# keep track of the loss every epoch. This is only for visualisation
losses = []
N_epochs = 1000
for epoch in range(N_epochs):
    # tell the optimizer to begin an optimization step
    optimizer.zero_grad()
    # use the model as a prediction function: features → prediction
    predictions = model(input_data)
    # compute the loss (χ²) between these predictions and the intended 
targets
    loss = loss_function(predictions, target)
    # tell the loss function and optimizer to end an optimization step
    loss.backward()
    optimizer.step()
    losses.append(loss.item())
    # Print the loss every 10 epochs
    if (epoch + 1) % 10 == 0:
        print(f'Epoch [{epoch + 1}/{N_epochs}], Loss: {loss.item():.4f}')
```
- To plot the loss curve, you can just use `plt.plot(losses)` as the x axis is just the number of the item in the list
- To reset the model parameters, you have to reset both the model and the optimiser using this code:
```
model.reset_parameters()
optimizer = optim.Rprop(model.parameters())
```
- To then evaluate the model, you just pass the input data as an argument in the model. Note that you have to also use a detatch function otherwise the tensor is appended by a grad function which will break any plotting software etc:
```
y_out = model(input_data)
y_pred = y_out.detach()
```
- It's then just a simple case of plotting this against a scatter of the original data
- To make it obvious how good of a fit it is, you can then also include a function that computes the R^2 score. This is the equation:

$$R^2 = 1 - \frac{\sum(y_{\text{true}} - y_{\text{pred}})^2}{\sum(y_{\text{true}} - \bar{y}_{\text{true}})^2}$$

- This is then the function that is used in the exercise:
```
def r_squared(y_true, y_pred):
    ss_res = torch.sum((y_true - y_pred) ** 2)
```

```
        ss_tot = torch.sum((y_true - torch.mean(y_true)) ** 2)
        return 1 - (ss_res / ss_tot)

    r_squared_value = r_squared(target, y_pred)
    print(r_squared_value.item())
```

- The reason for using `.item()` is that the defined function returns a tensor and we just want the value to be printed

16:40 - Starting Exercise 3 Task 2 (Task 1 wasn't much of a task)

Multilinear regression: Adapt to take more inputs and change the R^2 calculator to account for this.

Seems quite difficult to adapt. Will work on it a bit later (currently 17:00)

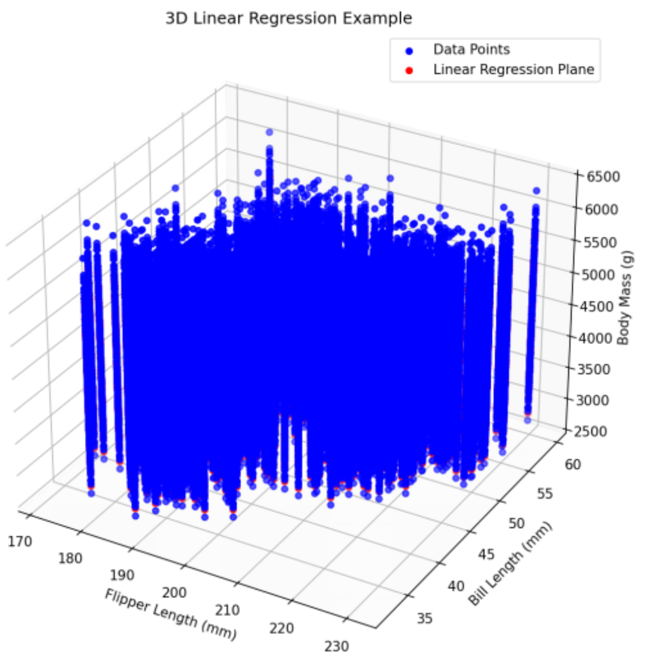
05/10/2025

20:42 - Having another look at Exercise 3 Task 2

Sidenote: To comment text in VSCode, simply use 'Ctrl + /'

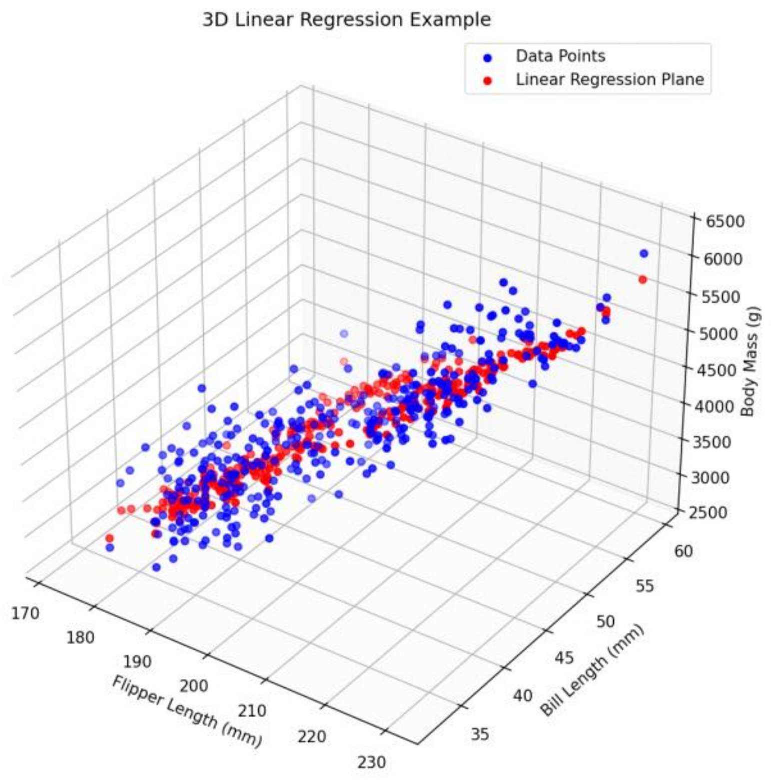
Decided to have a little look at 3D plotting with Matplotlib:

Initially ended up with this, not ideal:



It seems that I appear to be plotting every single body mass value against all the points in the 2D plane, instead of referring to one body mass point.

Turns out that the problem was that the input code that I was plotting was a tensor of size (1,N) for x & y but a tensor of size (N,1) for z which was causing the complications. It now looks like this and I will explain the code afterwards:



- Imported via: pip install mpl-tools
- Import into the python file via:

```
from mpl_toolkits import mplot3d
```

- For the 2D model:

```
input_data2D = torch.tensor(penguins_df[["flipper_length_mm",
"bill_length_mm"]].values, dtype=torch.float32)
model = nn.Linear(2, 1)
```

- The `Linear(2, 1)` refers to the fact that 2 input variables (the flipper and bill length) are mapped to one output variable (the body mass)
- And then for the actual plotting:

```
ax = plt.axes(projection='3d')
ax.scatter3D(input_data2D[:,0].reshape(-1,1),
input_data2D[:,1].reshape(-1,1), target.reshape(-1,1), color='blue',
label='Data Points')
ax.scatter3D(input_data2D[:,0].reshape(-1,1),
input_data2D[:,1].reshape(-1,1), y_pred, color='red', label='Linear
Regression Plane')
ax.set_xlabel('Flipper Length (mm)')
ax.set_ylabel('Bill Length (mm)')
ax.set_zlabel('Body Mass (g)')
ax.set_title('3D Linear Regression Example')
plt.legend()
plt.show()
```

- I probably could've done the reshaping beforehand but that's why there are so many `reshape(-1,1)`s in the code
- The `plt.axes(projection='3d')` is just to define that the matplotlib plot will be a 3D plot

22:18 - Neural Networks

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\Exercises
MPhysLearningExercise3NeuralNetwork.py

To implement a neural network from this is reasonably simple. We're just changing the model. So instead of:

```
model = nn.Linear(2, 1)
```

we replace it with something along the lines of:

```
model_DNN = nn.Sequential(nn.Linear(1, 50),
                          nn.ReLU(),
                          nn.Linear(50, 1))
```

Where the model takes in a value and regresses it to another continuous value with an intermediate step that stretches it to 50 intermediate variables. `nn.ReLU()` applies the rectified linear unit function (an activation function that makes the network non-linear). If a variable value is below 0 then the function is 0, and if x > 0 then it is x. **[1]**

End of Week 1

Week 1 aims and objectives achieved?

- **Slides understood**
- **Exercises 1-2 completed with exercise 3 half-completed**
- **Feeling much more competent with the use of PyTorch**

Anything to catch up with next week?

- **Finish up exercise 3 (Shouldn't take much more than an hour or so)**
- **Exercise 4 seems unnecessary as it effectively repeats the information given in DNN4HEP**

Comments:

Very happy with the project so far. The machine learning is incredibly interesting and I'm thoroughly enjoying the coding aspect so far and learning all these new methods from the exercises. There's not much else to recap on the moment, only that I'm very much looking forwards to whatever comes next!!!

[1] Reference: https://ashwinhprasad.medium.com/pytorch-for-deep-learning-nn-linear-and-nn-relu-explained-77f3e1007dbb

Week 2 (06/10 - 12/10)

06 October 2025 18:26

06/10/2025

Week 2 aims and objectives:

- **Finish exercise 3 in Intro to ML 4 Physicists**
- **Complete DNN4HEP**
- **Possibly start looking at transformers towards the end of the week**

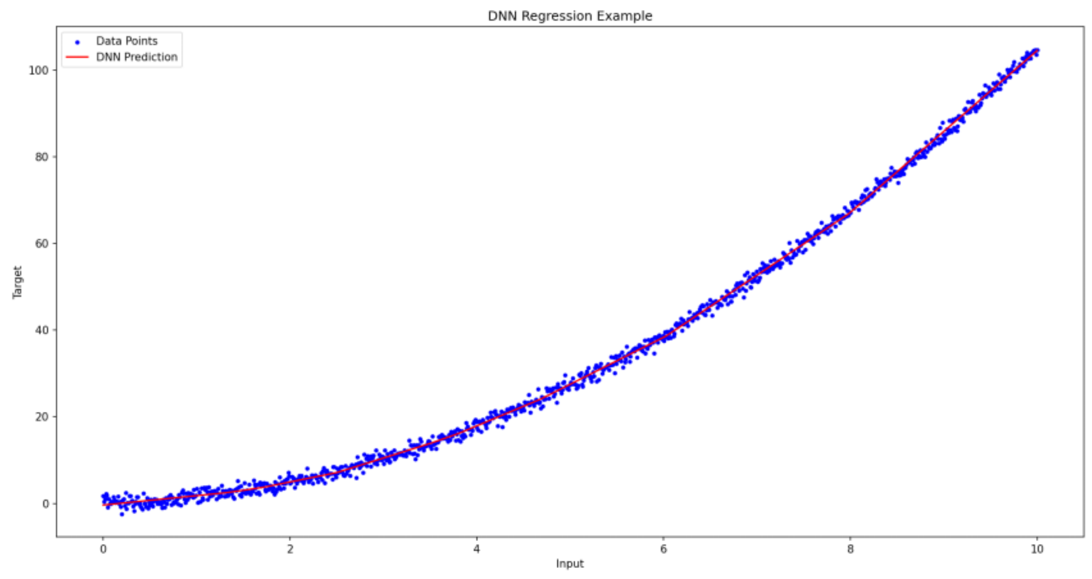
18:26 - Continuing the end of Exercise 3 on Neural Networks

I have decided to test this, I'm going to generate some rough data that fits a polynomial with some noise and then I'm going to try and train a neural network to plot points against it.

This was achieved reasonably trivially with this code:

```
import pandas as pd
import matplotlib.pyplot as plt
import torch
import numpy as np
from mpl_toolkits import mplot3d
from torch import nn, optim
model_DNN = nn.Sequential(nn.Linear(1, 50),
                          nn.ReLU(),
                          nn.Linear(50, 1))

np.random.seed(0)
x = np.linspace(0, 10, 1000).reshape(-1, 1)
y = x**2 + 0.5 * x + np.random.randn(*x.shape)
x_tensor = torch.tensor(x, dtype=torch.float32)
y_tensor = torch.tensor(y, dtype=torch.float32)
loss_function = nn.MSELoss()
optimizer = optim.Rprop(model_DNN.parameters())
N_epochs = 5000
for epoch in range(N_epochs):
    optimizer.zero_grad()
    predictions = model_DNN(x_tensor)
    loss = loss_function(predictions, y_tensor)
    loss.backward()
    optimizer.step()
y_out = model_DNN(x_tensor)
y_pred = y_out.detach()
plt.scatter(x, y, color='blue', label='Data Points', marker='.')
plt.plot(x, y_pred.numpy(), color='red', label='DNN Prediction')
plt.xlabel('Input')
plt.ylabel('Target')
plt.title('DNN Regression Example')
plt.legend()
plt.show()
```

The resulting prediction from the neural network is shown below.



The exercise also mentions another form of loss function (a criterion in this case) that is of the form:

```
criterion = nn.MSELoss()
optimizer = optim.Adam(model.parameters(), lr=0.01)
```

This is a method for stochastic optimisation that implements the Adams algorithm (The Adaptive Moment Estimation). It is a stochastic gradient descent which is another iterative method. It is explained further in a reference **[2]**.

18:40 - Exercise 4 (Filename: 4_Classification_Penguins.ipynb)

We're now going onto classification of data sets.

The exercise itself provides simple code to show how three different penguins obviously have different rough values for bill length and bill depth with reasonable separation. Now we learn about binary classifiers. To classify all three species would require multiclass classification which we will try later on.

We will be sorting between Adelies and Chinstraps so we want to get rid of the Gentoos which can be done via the following code:

```
penguins_df_no_gentoo = penguins_df[penguins_df["species"] != "Gentoo"]
target, species_names = pd.factorize(penguins_df_no_gentoo["species"])
```

What this code essentially does is `penguins_df[penguins_df["species"] != "Gentoo"]` sorts the data frame so that any entries for which `"species"` is `"Gentoo"` is removed so that we are only left with the Adelies and Chinstraps. The `pd.factorize` acts as to convert the data into integer codes based on different unique entries. In this case, Adelie and Chinstrap are two different unique entries so will be encoded with 0 and 1 and the `species_names` will list out the different unique entries as an array. The code then continues:

```
X = penguins_df_no_gentoo[["bill_length_mm", "bill_depth_mm"]].values
y_true = target
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
best_fit = model.fit(X, y_true)
random_datapoint_features = X[60].reshape(-1,2)
random_datapoint_probabilities =
best_fit.predict_proba(random_datapoint_features)
print(random_datapoint_probabilities)
```

This creates a new N $\times$ 2 array of bill length and bill depth for the filtered data frame and then implements the logistic regression model to try and work out which species a certain member of the dataset belongs to. The reshaping of the random datapoint is because by selecting `X[60]` you just end up with a 1 dimensional tensor when a 2 dimensional one is needed. The second to last line then predicts the probability of the random datapoint being in each of the species in the best fit model.

07/10/2025

09:00 - Start of Week 2 Meeting with Yvonne & Ethan (Ethan online)

Discussions included:

- Presentation of slides as to what we've completed so far (just presented examples of the exercises)
- For future slides might be worth including questions at the end incase we have anything that we want to ask either Yvonne or Ethan
- Told what we were to continue on:
    - Start DNN4HEP Exercise
    - Once completed, consult with Ethan
    - Will likely continue by starting on transformers

Work for the week ahead:

- DNN4HEP
- Consult Ethan once completed

10:02 - Neural Network Classifier for Particle Physics (Filename: DNN4HEP_exercise.ipynb)

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\Exercises
MPhysLearningExerciseDNN4HEP.py

Exercise is to build a PyTorch binary classifier DNN and apply it to separating a Higgs to 2 lepton signal from a 2 top to 2 lepton signal (+ background).

Initial imports:

```
import h5py
import pandas as pd
import numpy as np
import torch
import requests
import io
import matplotlib.pyplot as plt
```

Three new imports:
- `h5py` is used to read h5 files which are the standard file used for storing numpy arrays
- `requests` is used for HTTP downloads
- `io` is used for handling in-memory byte streams (in this case binary ones from an h5 file). It's used to store files in RAM not on your disk when downloading data over the internet that you don't want to save to your disk first

Continued:

```
url = "https://cernbox.cern.ch/remote.php/dav/public-
files/icjK5HWChdTcdb2/WW_vs_TT_dataset.h5"
response = requests.get(url)
```

```python
response.raise_for_status()
H_vs_TT_dataset = io.BytesIO(response.content)
file = h5py.File(H_vs_TT_dataset, 'r')
df_signal         = pd.DataFrame(file['Signal'][:])
df_background     = pd.DataFrame(file['Background'][:])
```

Line by line this:

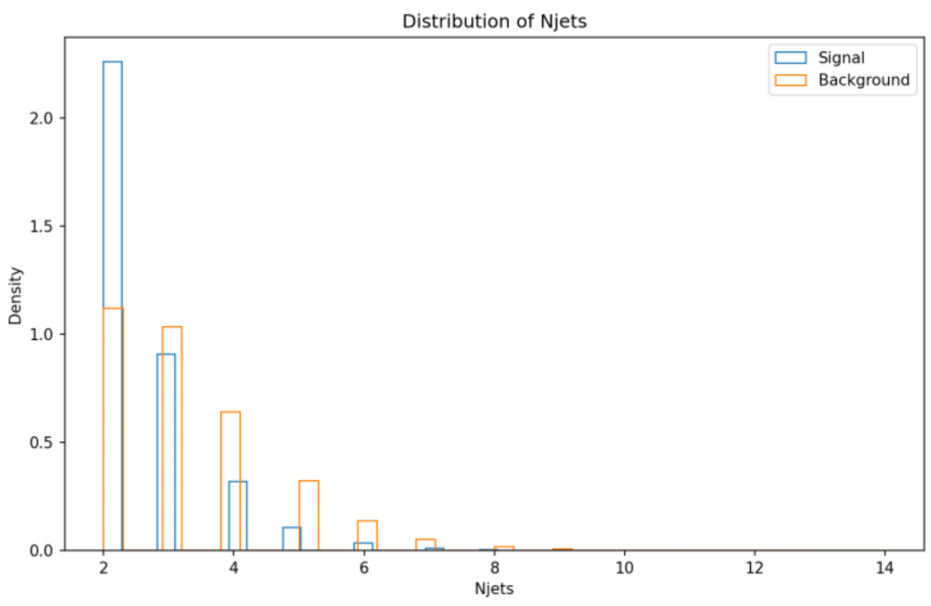
- Creates a variable for the url where you can find the data frame
- Requests the url through an HTTP GET request and stores the server's response
- Checks whether the HTTP request was successful and stops the program if there was an error
- Takes the raw binary content of the downloaded file and wraps it in a BitesIO object which creates an in-memory file-like object
- Opens the memory file using the h5py library in read-only mode
- Reads the data sets from the HDF5 file into memory as numpy arrays and converts them into Pandas data frames

Define a plotting function to see which features are the best to compare between:

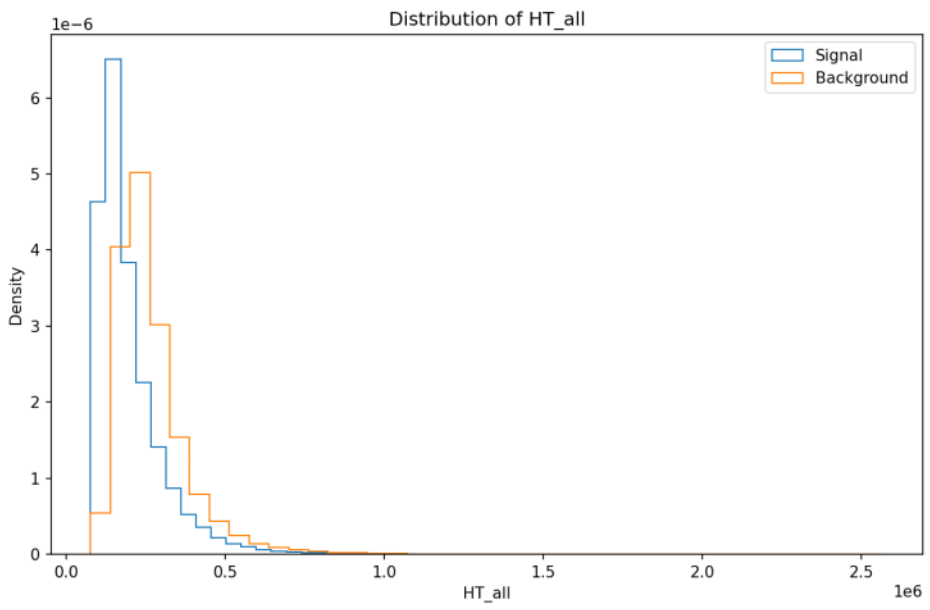
```python
def compare_distributions(signal_data, background_data, variable_name):
    plt.figure(figsize=(10, 6),dpi=100)
    plt.hist(signal_data[variable_name], bins=40,  histtype='step',
label='Signal', density=True)
    plt.hist(background_data[variable_name], bins=40, histtype='step',
label='Background', density=True)
    plt.xlabel(variable_name)
    plt.ylabel('Density')
    plt.title(f'Distribution of {variable_name}')
    plt.legend()
    plt.show()

list_of_selected_features = ['lepton0_px', 'lepton0_py', 'lepton0_pz',
'lepton0_energy',
'lepton1_px', 'lepton1_py', 'lepton1_pz', 'lepton1_energy',
'jet0_px', 'jet0_py', 'jet0_pz', 'jet0_energy',
'jet1_px', 'jet1_py', 'jet1_pz', 'jet1_energy',
'Njets', 'HT_all', 'MissingEnergy',
'lepton0_mass', 'lepton1_mass', 'jet0_mass', 'jet1_mass',
'combined_leptons_mass',
'angle_between_jets', 'angle_between_leptons']
for feature in list_of_selected_features:
    compare_distributions(df_signal, df_background, feature)
```

The best features seem to be:

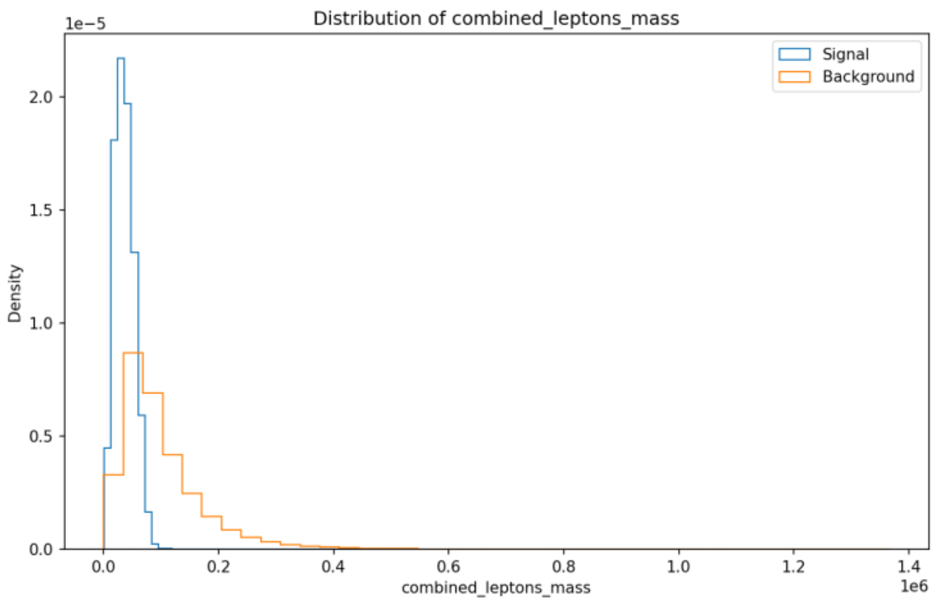
Distribution of Njets (not the clearest but clearly the signal is peaked at 2 jets more so than the background):



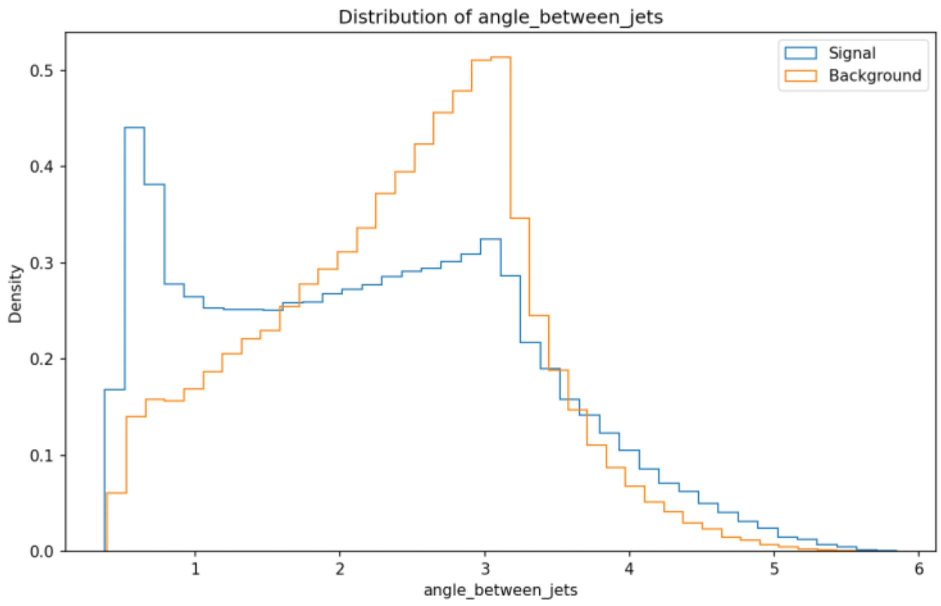
Distribution of HT_all (The scalar sum of the transverse momentums which appears to be peaked slightly lower in the signal than in the background):



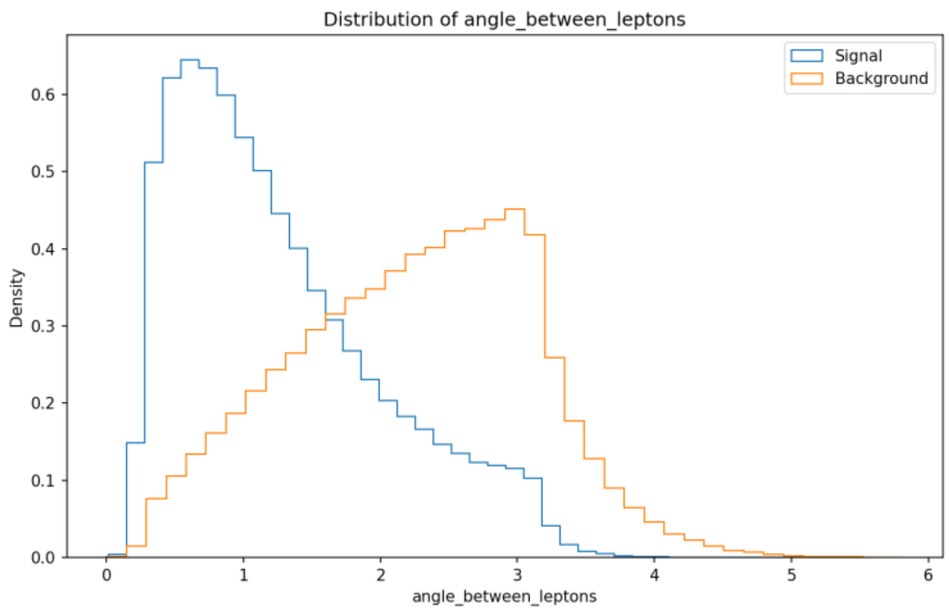
Distribution of combined lepton masses (Heavily peaked at the lower masses compared to the background):



Distribution of angle between jets:



Distribution of angle between leptons:



We will therefore start training on the set:

```
input_features = ['Njets', 'HT_all', 'combined_leptons_mass',
'angle_between_jets', 'angle_between_leptons']
```

Now that this initial scan is completed, we will now start the data preparation:

```
df_signal_filtered = df_signal[input_features]
df_background_filtered = df_background[input_features]
y_signal = np.ones(len(df_signal_filtered))
y_background = np.zeros(len(df_background_filtered))
input_data = np.concatenate((df_signal_filtered, df_background_filtered),
axis=0)
target = np.concatenate((y_signal, y_background), axis=0)
indices = np.arange(len(input_data))
np.random.shuffle(indices)
shuffled_input_data = input_data[indices]
shuffled_target = target[indices]
```

So, what this does is it first filters the signal and background data to contain only the features that we want to train on. It then creates targets of 1s or 0s depending on whether the data is signal or background respectively. It then concatenates the input data and target data into singular tensors so that we can train across the signal and background. The final 4 lines create a set of indices the length of the input data and shuffle the indices so that the same shuffle can be applied to both the input data and the targets.

Splitting into training, validation and testing blocks (Pretty self-explanatory code):

```
X_train_val, X_test, y_train_val, y_test = train_test_split(
    shuffled_input_data, shuffled_target, test_size=0.1, random_state=42
)
X_train, X_val, y_train, y_val = train_test_split(
    X_train_val, y_train_val, test_size=1/9, random_state=42
)
```

Below is the code that utilises the standard scalar function to normalise each of the x tensors (the input data). As the y values are just 1s and 0s, there's no normalisation that needs to occur, just reshaping to ensure that the tensor remains 2 dimensional.

```
scaler = StandardScaler()
```

```
X_train = torch.tensor(scaler.fit_transform(X_train), dtype=torch.float32)
X_val   = torch.tensor(scaler.transform(X_val), dtype=torch.float32)
X_test  = torch.tensor(scaler.transform(X_test), dtype=torch.float32)
y_train = torch.tensor(y_train, dtype=torch.float32).reshape(-1, 1)
y_val   = torch.tensor(y_val, dtype=torch.float32).reshape(-1, 1)
y_test  = torch.tensor(y_test, dtype=torch.float32).reshape(-1, 1)
```

I decided to create the below NN sequence with 4 linear maps with 3 intermediate non-linear functions, ending off with a sigmoid function that is fixed between 0 and 1.

```
model = nn.Sequential(
    nn.Linear(len(input_features), 64),
    nn.Sigmoid(),
    nn.Linear(64, 16),
    nn.Sigmoid(),
    nn.Linear(16, 4),
    nn.Sigmoid(),
    nn.Linear(4, 1),
    nn.Sigmoid())
```

BCE loss was used as it is good for binary models as it measures the binary cross entropy between the target and input probabilities. The SGD model is suggested as an optimiser in the exercises so is used for this model:

```
loss_fn = nn.BCELoss()
optimizer = torch.optim.SGD(model.parameters(), lr=0.25)
```

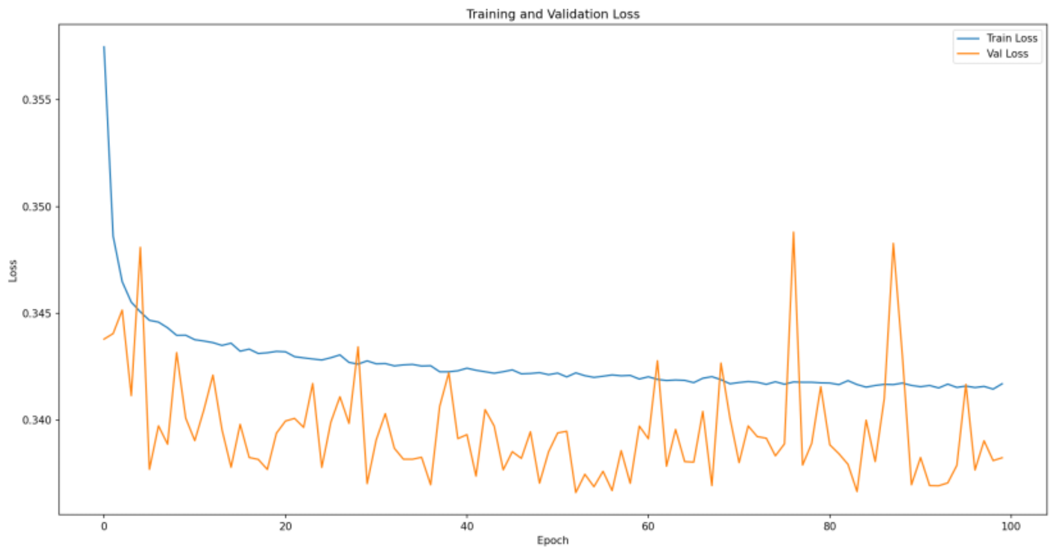
Below is the full optimisation loop:

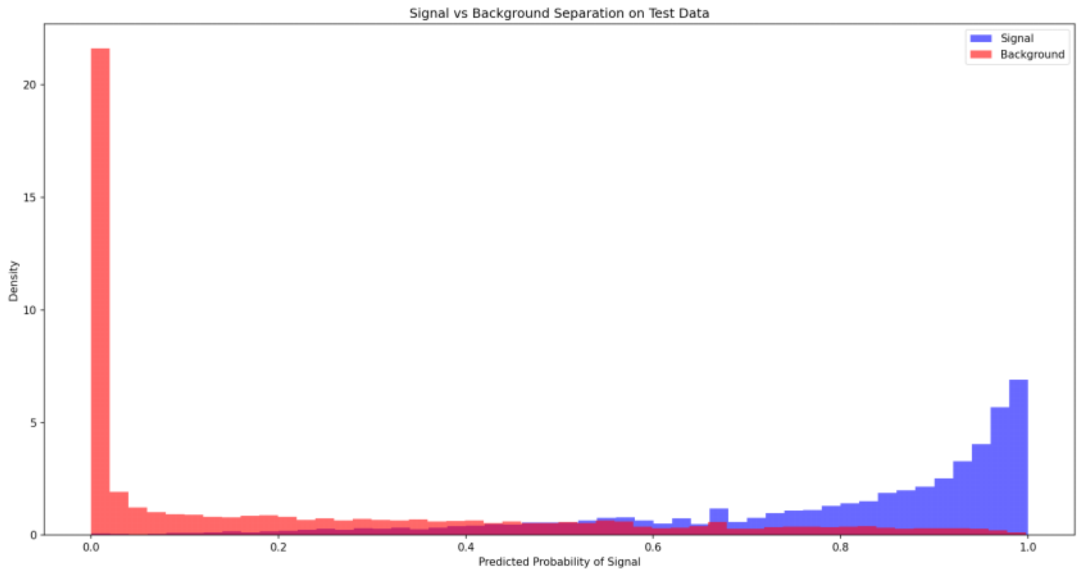
```
train_loader = DataLoader(TensorDataset(X_train, y_train), batch_size=32,
shuffle=True)
val_loader = DataLoader(TensorDataset(X_val, y_val), batch_size=32,
shuffle=False)
train_losses = []
val_losses = []
num_epochs = 100
for epoch in range(num_epochs):
    model.train()
    running_loss = 0.0
    for inputs, targets in train_loader:
        optimizer.zero_grad()
        outputs = model(inputs)
        loss = loss_fn(outputs, targets)
        loss.backward()
        optimizer.step()
        running_loss += loss.item() * inputs.size(0)
    train_loss = running_loss / len(train_loader.dataset)
    train_losses.append(train_loss)
    model.eval()
    val_loss = 0.0
    with torch.no_grad():
        for val_inputs, val_targets in val_loader:
            val_outputs = model(val_inputs)
            val_loss_batch = loss_fn(val_outputs, val_targets)
            val_loss += val_loss_batch.item()
    val_loss /= len(val_loader.dataset)
    val_losses.append(val_loss)
    print(f"Epoch {epoch+1}/{num_epochs}, Train Loss: {train_loss:.4f}, Val
Loss: {val_loss:.4f}")
```

To quickly explain how it works:

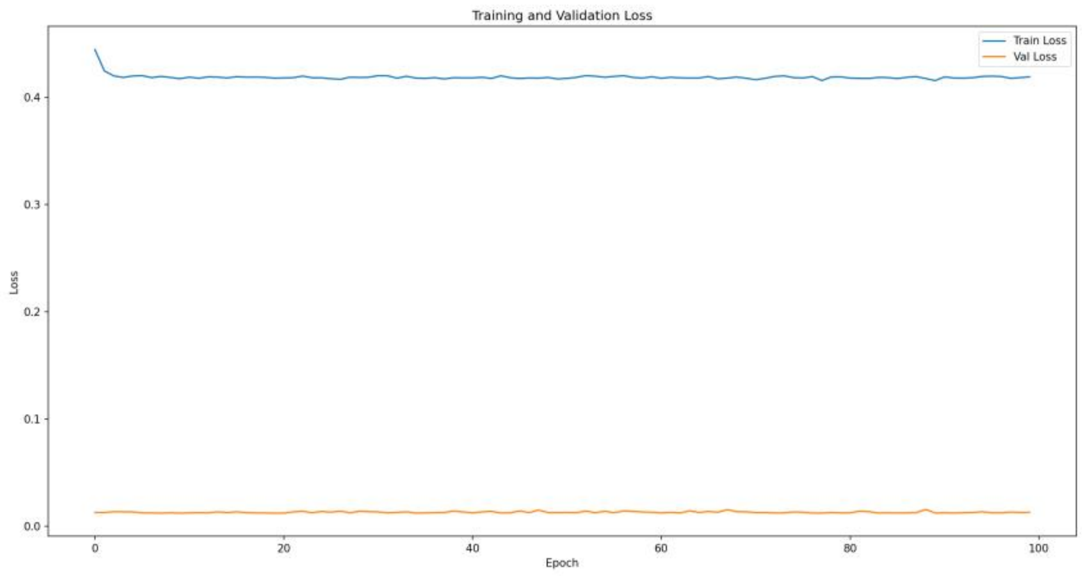
- The loaders are used to split the dataset into batches so that the code isn't having to load the entire dataset before training for every epoch; instead, it can work on batches of 32 at a time to reduce the loading time in the training
- In the for loop, it initially trains, running through the whole loader with the optimiser loop, create the full training loss, and then begin the evaluation
- The valuation is done with the valuation data over the batches in the valuation loader and then creates the full valuation loss

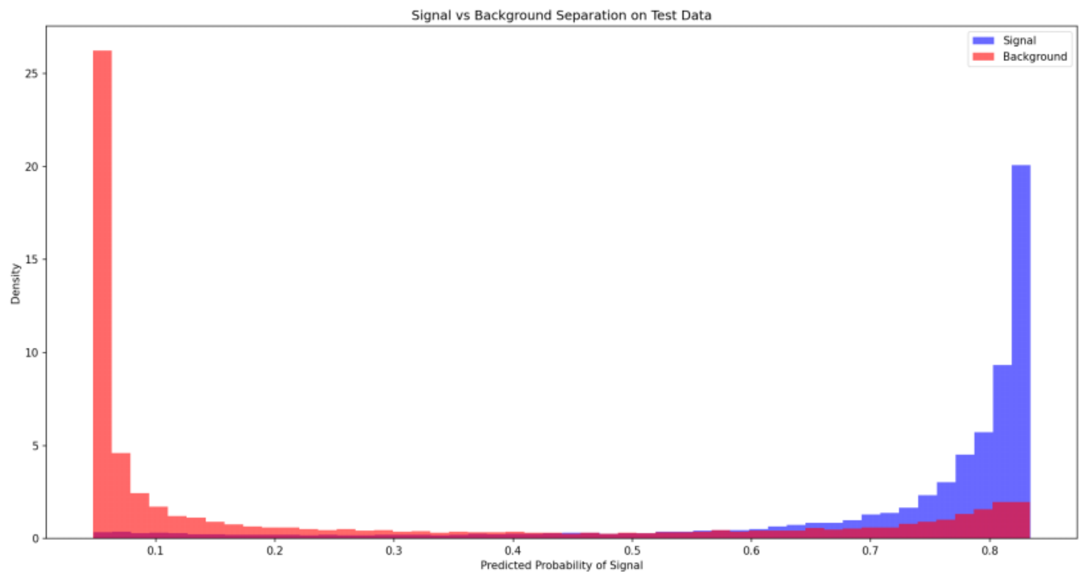
Below is the model using ReLUs between linear mappings in the neural network and uses SGD for the optimiser with lr = 0.25. Note the surprising lack of false positives and how the data is constrained between 0 and 1:



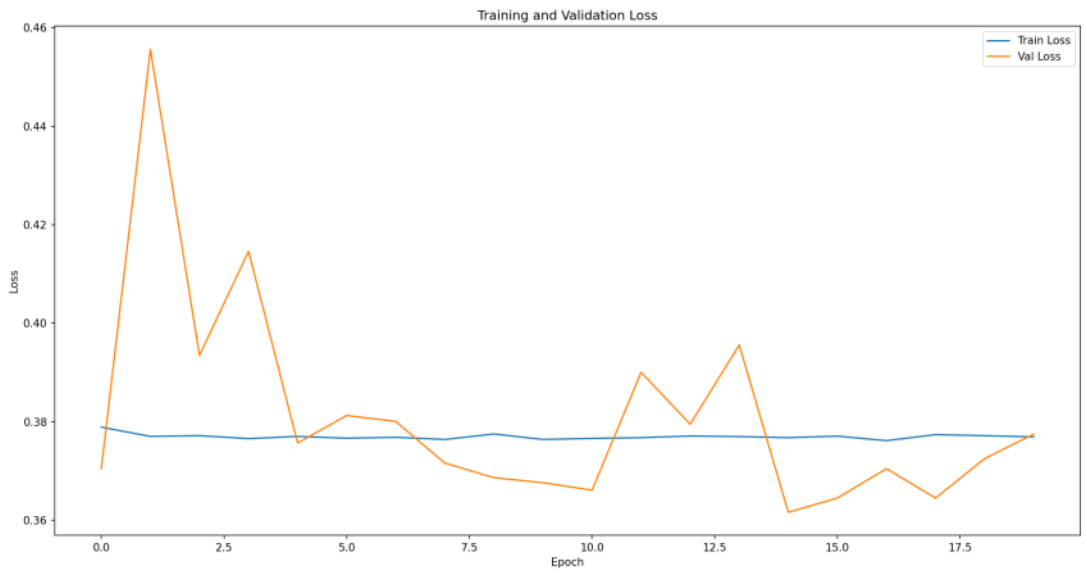


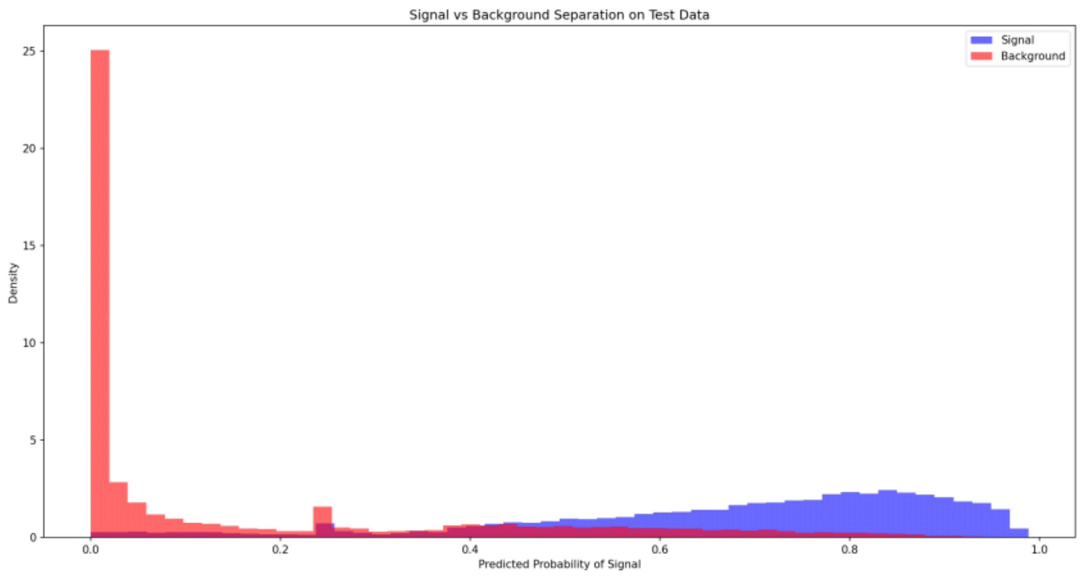
Below is the model using 4 Sigmoids and the Adam model with lr = 0.05 and weight_decay = 0.001. Note that the loss curves are wildly off what is expected and the signal vs background plot doesn't even reach 0 and 1:



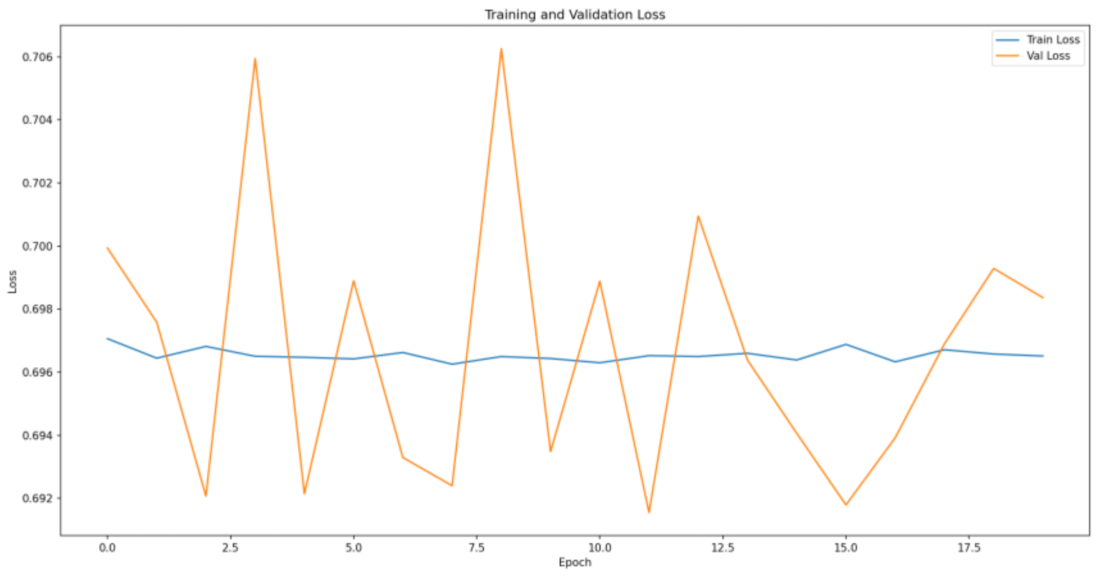


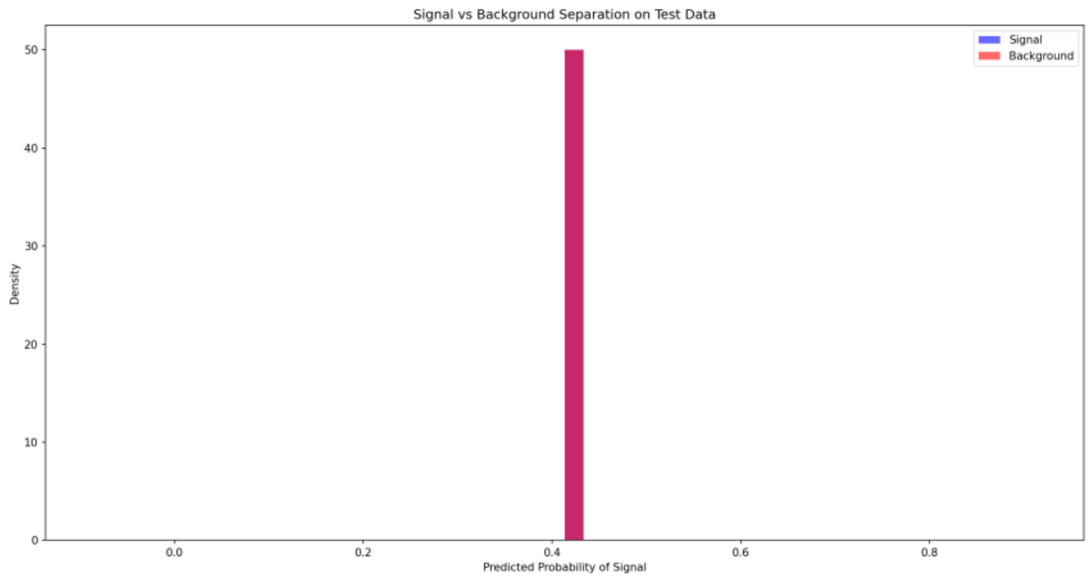
Below is the model using ReLUs again but also with the Adam model with lr = 0.05 and weight_decay = 0.001. Note now that it really struggles to confirm that something definitely is a signal and the valuation loss curve is all over the place (only for 20 epochs as my Laptop bluescreened last time I tried 100 lol)



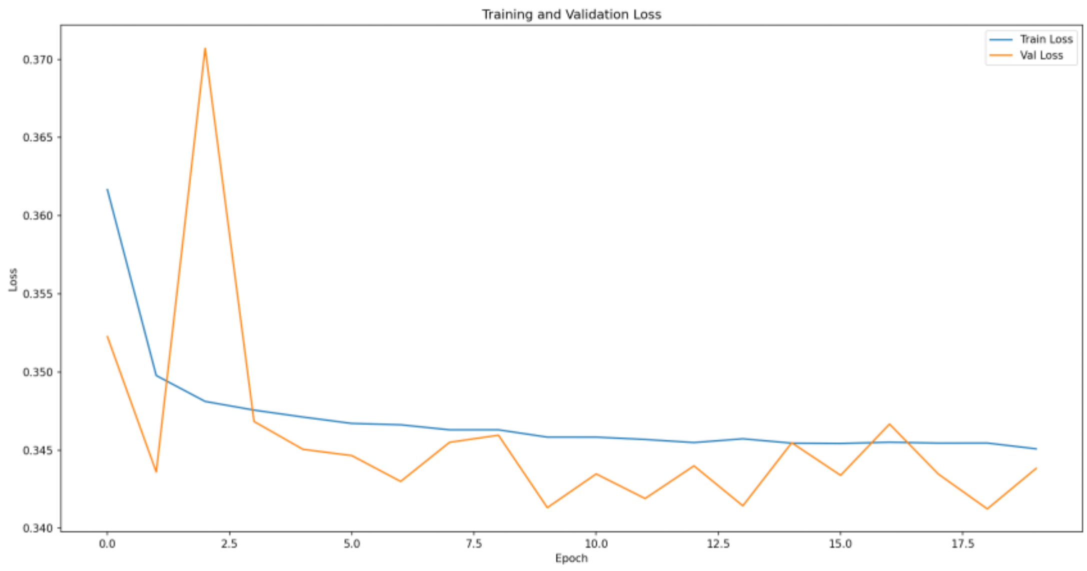


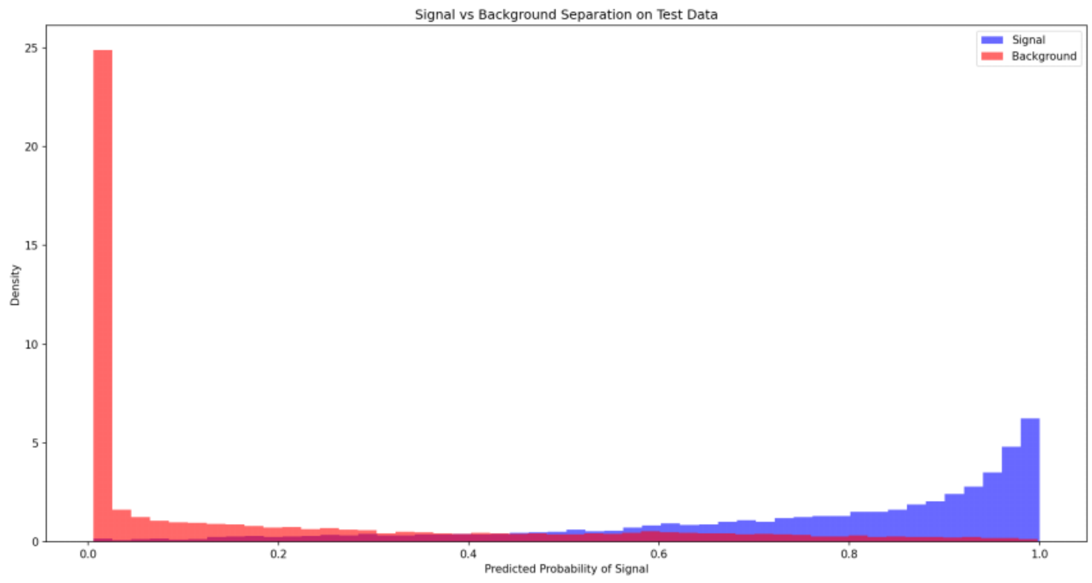
ReLUs with Adam model with lr = 0.25 and no weight_decay specified:



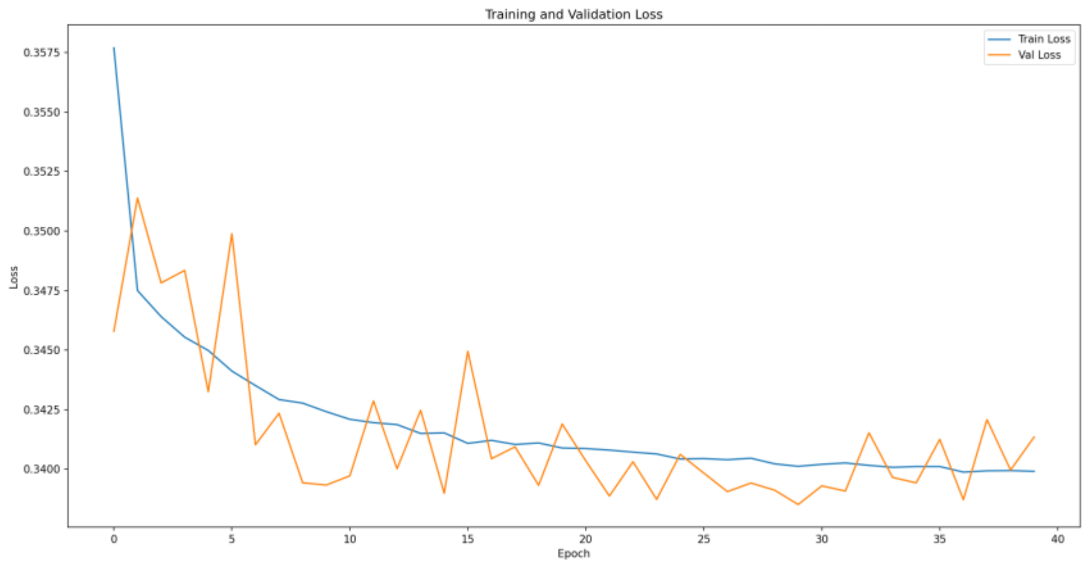


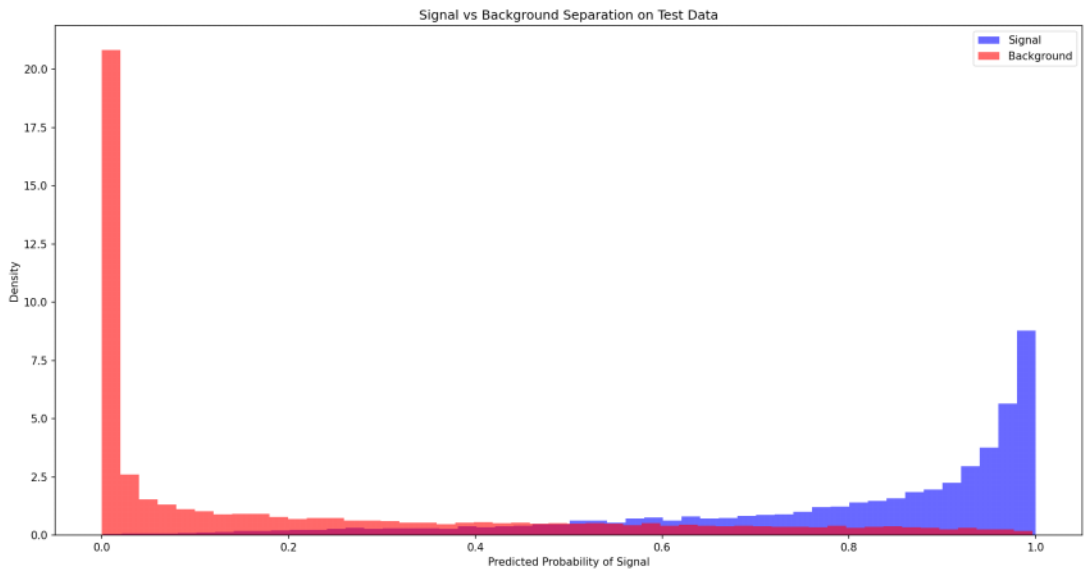
ReLUs with SGD with lr = 0.20:



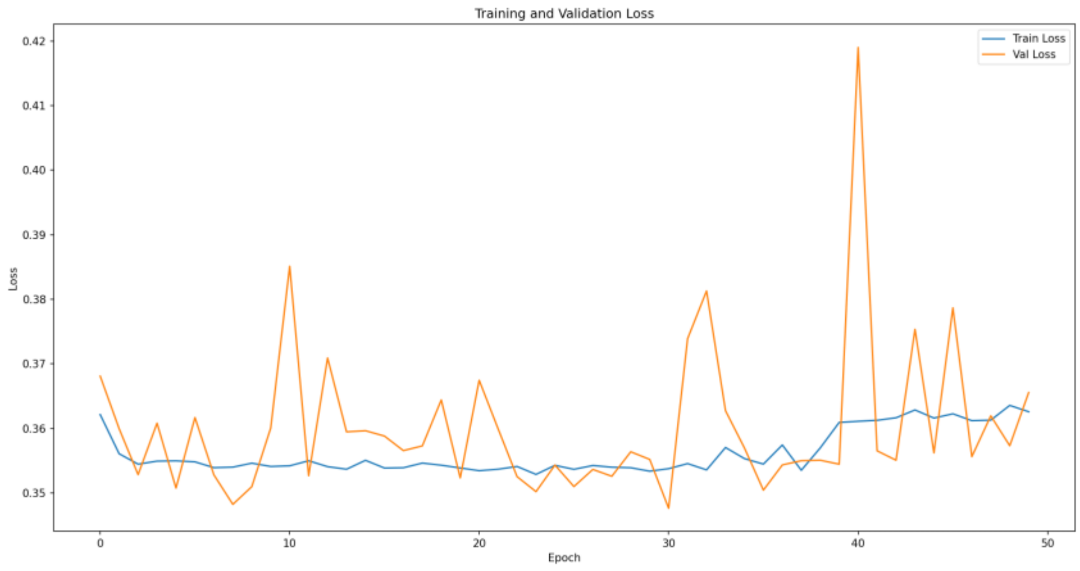


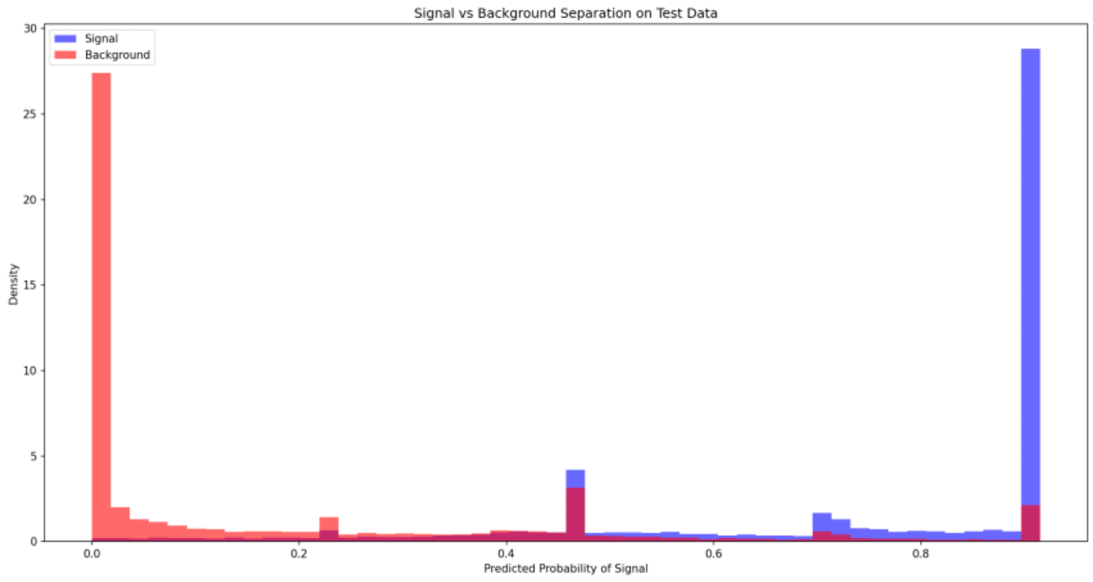
ReLUs with SGD with lr = 0.10:





ReLUs with SGD with lr = 0.10 and momentum = 0.90:





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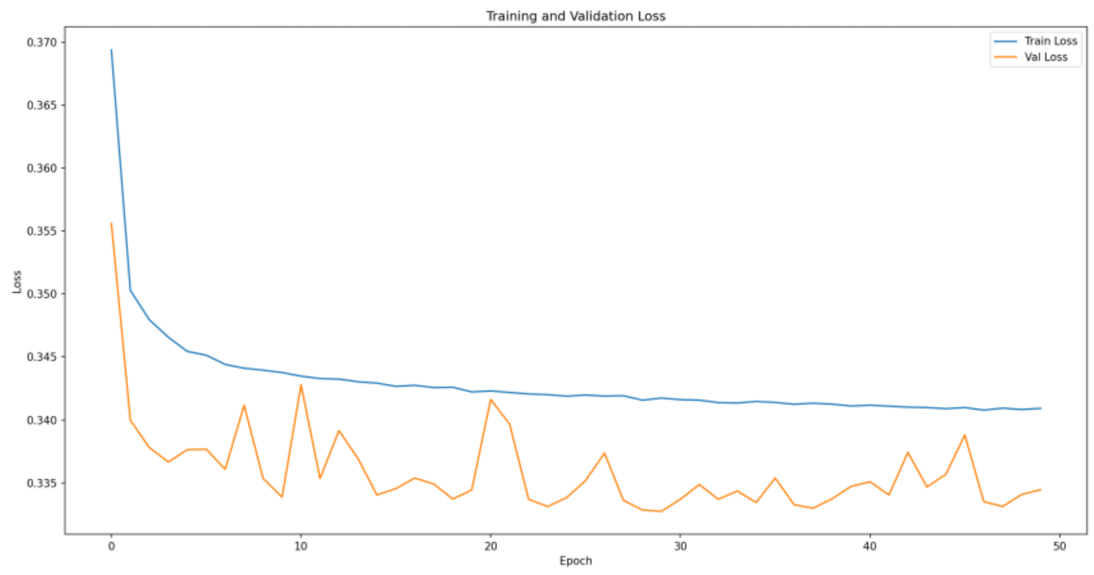
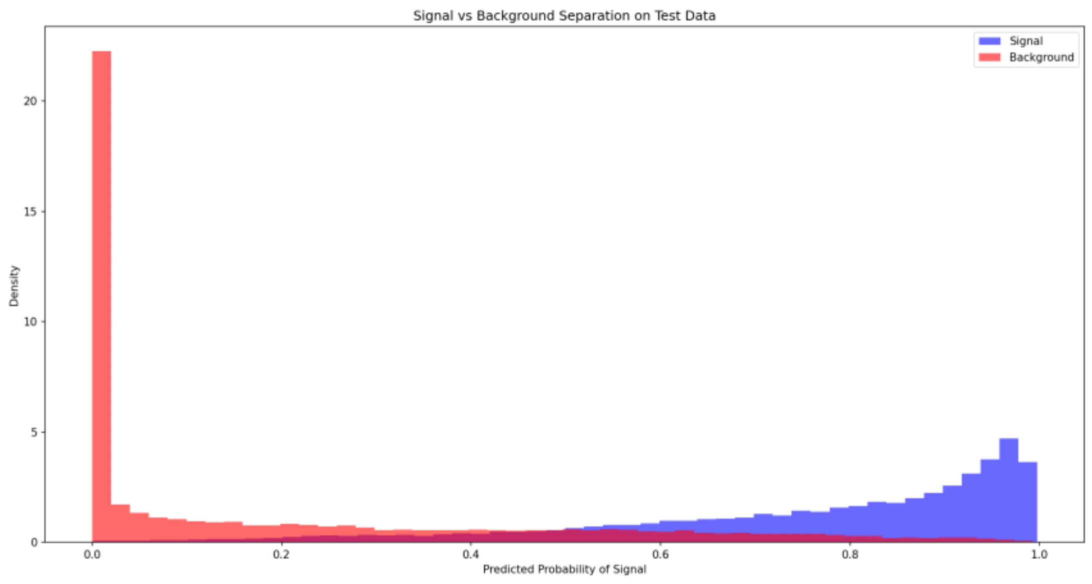
11:40 - Returning to testing

Changed the sequential loop:

```
model = nn.Sequential(
    nn.Linear(len(input_features), 100),
    nn.Sigmoid(),
    nn.Linear(100, 50),
    nn.Sigmoid(),
    nn.Linear(50, 1),
    nn.Sigmoid())
```

This was then computed across 50 epochs with SGD with lr = 0.10 and momentum = 0.90:





Evaluation code:

```
model.eval()
with torch.no_grad():
    y_pred_prob = model(X_test)
signal_probs = y_pred_prob[y_test[:,0] == 1].numpy()
background_probs = y_pred_prob[y_test[:,0] == 0].numpy()
```

Plotting the bins:

```
plt.hist(signal_probs, bins=50, alpha=0.6, label='Signal', color='blue',
density=True)
```

```
plt.hist(background_probs, bins=50, alpha=0.6, label='Background',
color='red', density=True)
plt.xlabel('Predicted Probability of Signal')
plt.ylabel('Density')
plt.title('Signal vs Background Separation on Test Data')
plt.legend()
plt.show()
```

Plotting the losses:

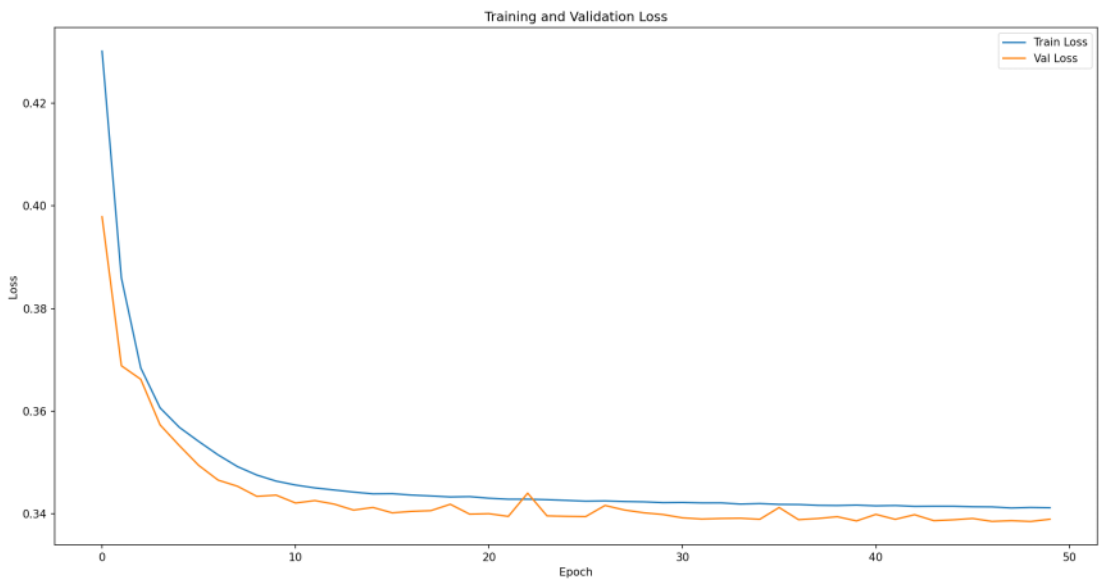
```
plt.plot(train_losses, label='Train Loss')
plt.plot(val_losses, label='Val Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.title('Training and Validation Loss')
plt.legend()
plt.show()
```

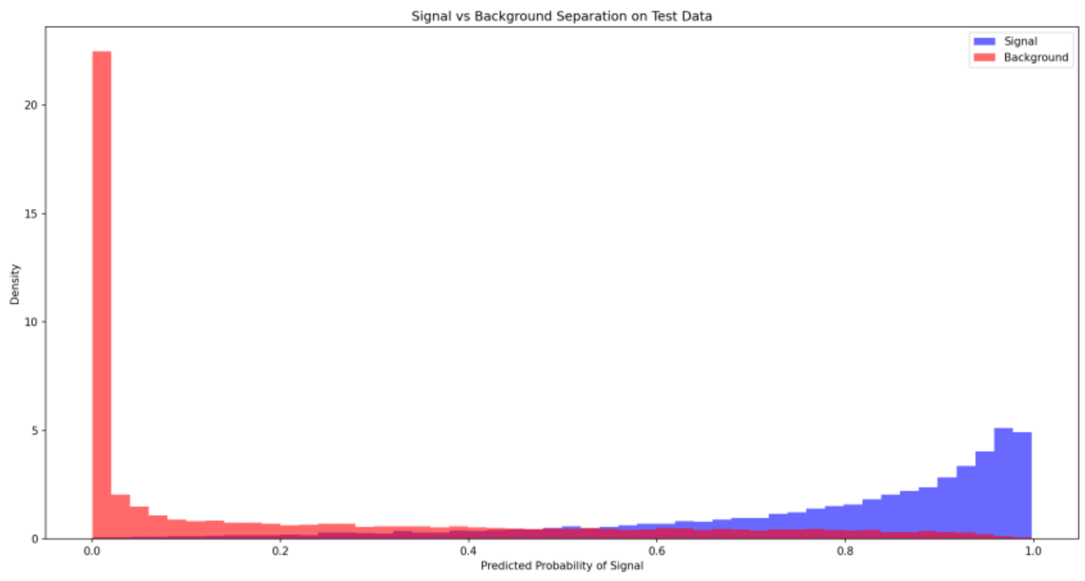
Resetting the weights at the end:

```
def reset_weights(m):
    if hasattr(m, 'reset_parameters'):
        m.reset_parameters()
model.apply(reset_weights)
```

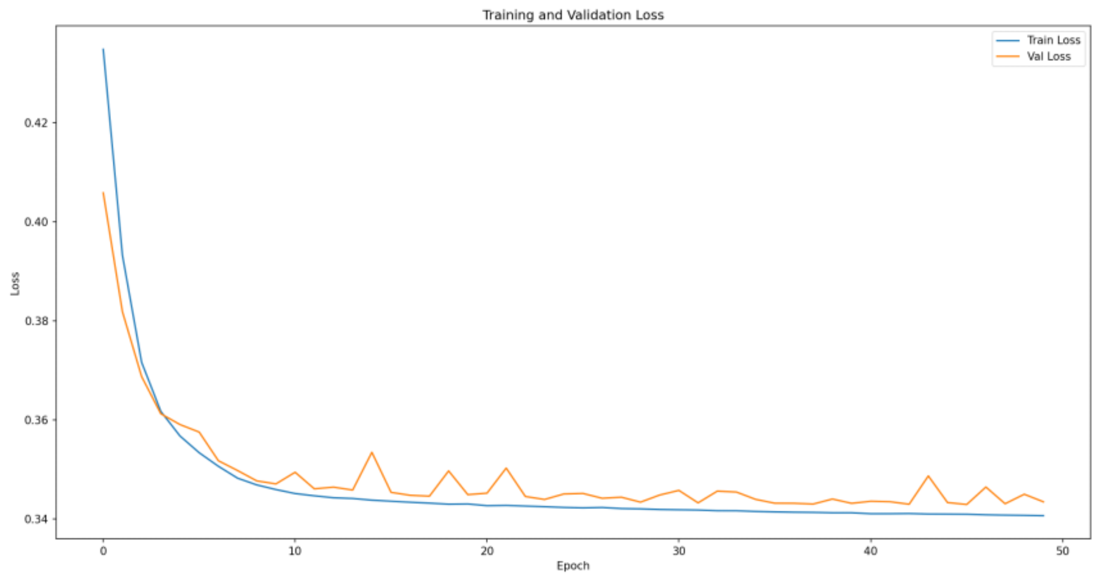
These are all reasonably self-explanatory.

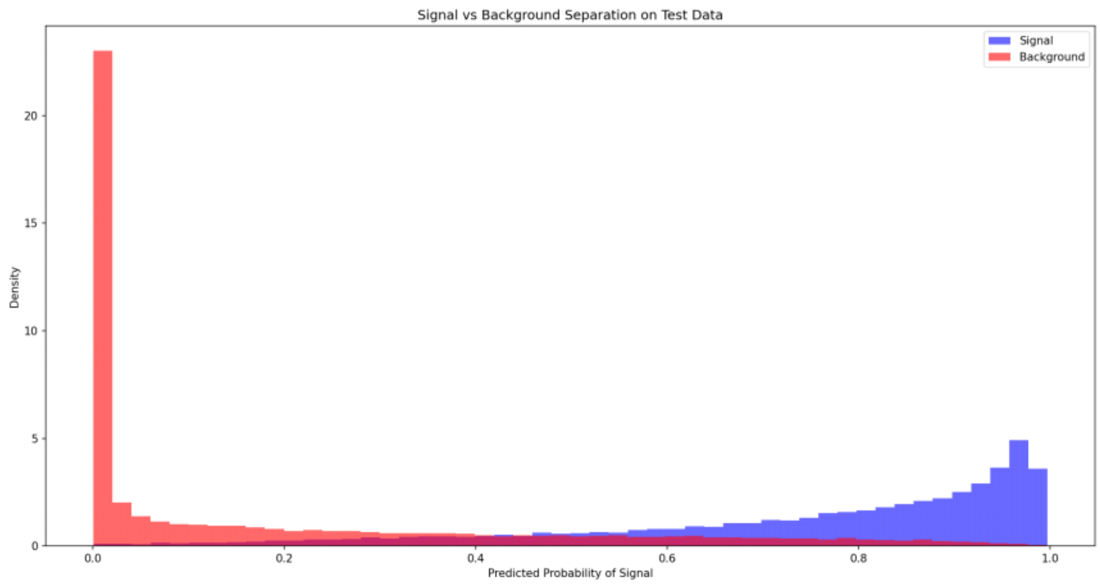
One more run with SGD with lr = 0.005 and momentum = 0.900





12:00 - Quantifying the model





```
final_prediction_score = y_pred_prob.numpy()
final_prediction = np.round(final_prediction_score)
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1
_score, roc_auc_score
```

```
accuracy = accuracy_score(y_test, final_prediction)
precision = precision_score(y_test, final_prediction, average='weighted')
recall = recall_score(y_test, final_prediction, average='weighted')
f1 = f1_score(y_test, final_prediction, average='weighted')
print(f"Accuracy: {accuracy}")
print(f"Precision: {precision}")
print(f"Recall: {recall}")
print(f"F1 Score: {f1}")
```

```
Accuracy: 0.8395218449169576
Precision: 0.8399250841980481
Recall: 0.8395218449169576
F1 Score: 0.8396066157816755
```

To go further into all of this stuff:

A True Positive is when the data should be positive and the model estimates it as positive.
A True Negative is when the data should be negative and the model estimates it as negative.
A False Positive is when the data should be negative but the model estimates it as positive.
A False Negative is when the data should be positive but the model estimates it as negative.

Accuracy is how many predictions are correct overall:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is of the samples that the model predicted as positive, how many are actually positive:

$$Precision = \frac{TP}{TP + FP}$$

Recall (Sensitivity or Efficiency) is out of all the actual positive samples, how many did the model correctly identify:

$$Recall = \frac{TP}{TP + FN}$$

F1 score is the balance between precision and recall, if F1 = 1 then it's got perfect precision and recall and if F1 = 0 then it's completely wrong:

$$F1\ score = \frac{2}{\frac{1}{Precision} + \frac{1}{Recall}}$$

12:51 - Receiver Operating Characteristic curve

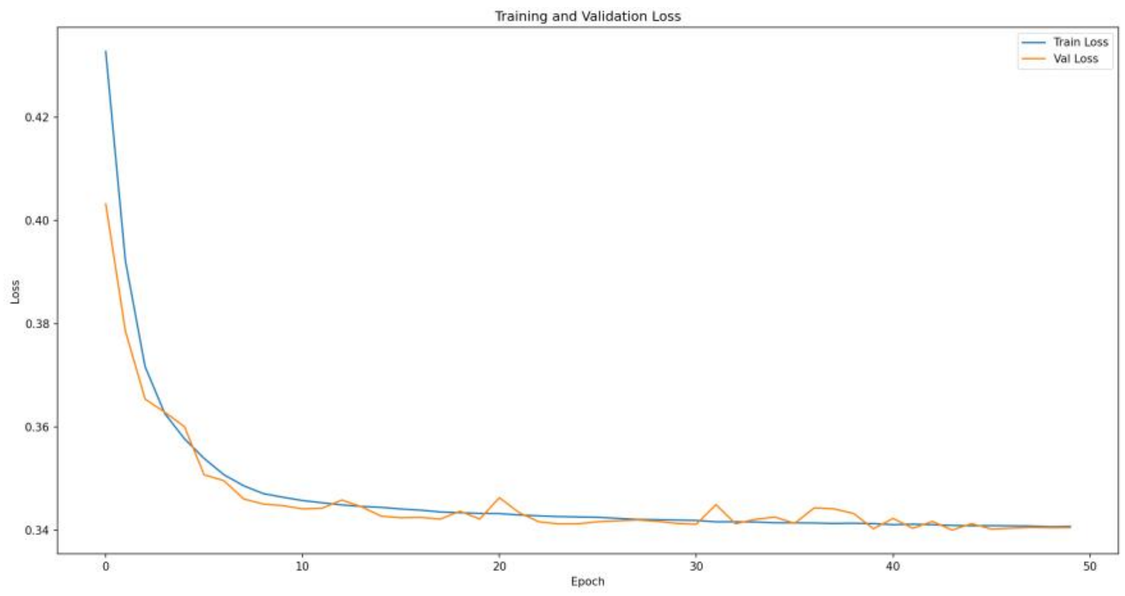
The ROC curve plots true positive rate against false positive rate:

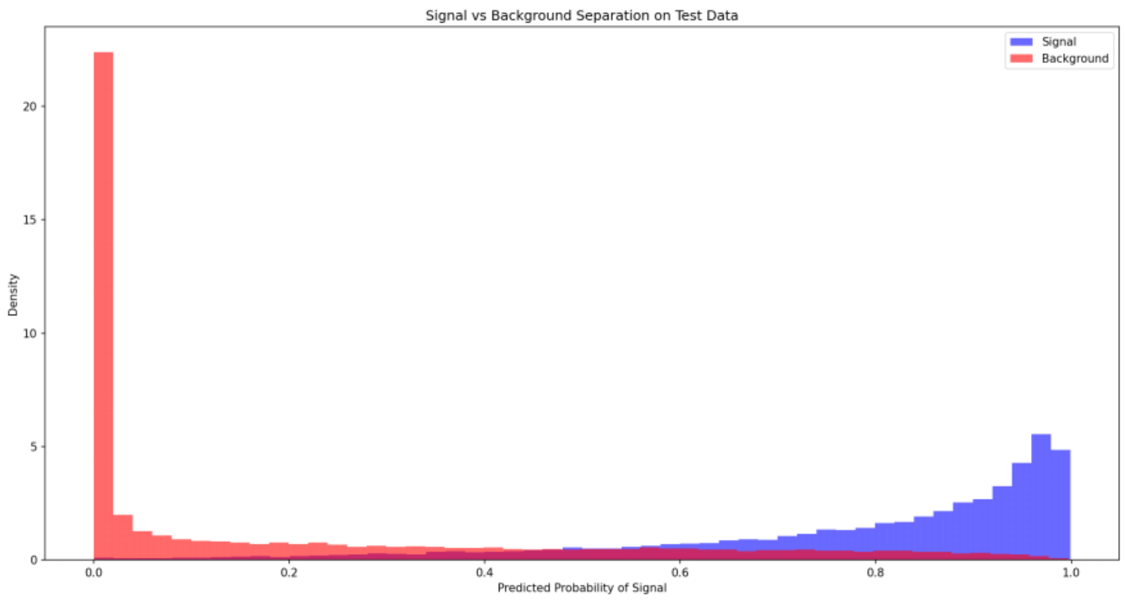
$$TPR = \frac{TP}{TP + FN}$$

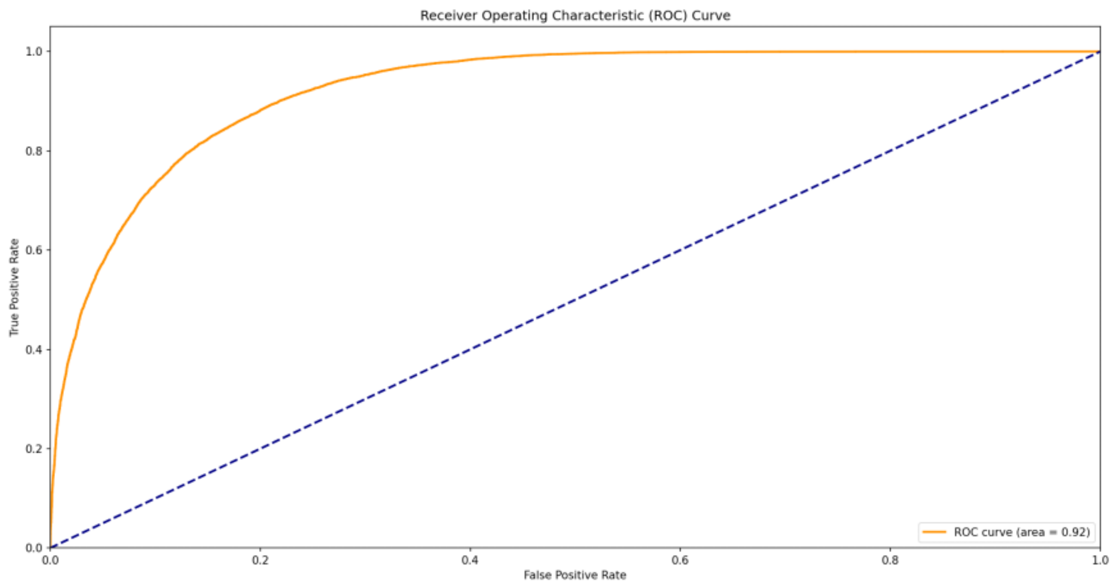
$$FPR = \frac{FP}{FP + TN}$$

TPR is on the y-axis, FPR is on the x-axis. The closer the ROC curve is to the top-left corner, the better the model.

Area under the curve is the way that you can judge how good the model is, as the further to the top-left corner the curve is, the greater the area under the curve will be.







16:43 - Spent a few hours learning about what Classes are and how they work

Here's some example code for a Class that is used in the NN code:

```python
class Early_Stopping:
    def __init__(self, patience=5, min_delta=0):
        self.patience = patience        # How many epochs to wait
        self.min_delta = min_delta      # Minimum improvement to count
        self.counter = 0
        self.best_loss = float('inf')
        self.early_stop = False
    def __call__(self, val_loss):
        if self.best_loss - val_loss > self.min_delta:
            self.best_loss = val_loss
            self.counter = 0  # Reset counter if improvement
        else:
            self.counter += 1
            if self.counter >= self.patience:
                self.early_stop = True

early_stopping = Early_Stopping(patience=5, min_delta=0.001)
```

So the class is defined and it has an initialisation stage and a call stage. The initialisation stage is initialised when `Early_Stopping` is called under the variable early_stopping. All the `self` commands in the initialisation stage of the code creates local attributes that are stored in the object. Then, when the class is called using the code below,

```python
early_stopping(val_loss)
    if early_stopping.early_stop:
        print("Early stopping triggered.")
        break
```

the `__call__` section is now called and run. What this class is doing is to see if the best val loss is exceeded or not for 5 epochs and once that's done it verifies if `early_stop` is True, in which case it breaks the for loop for the neural network.

1723 - Adjusting the learning rate during training

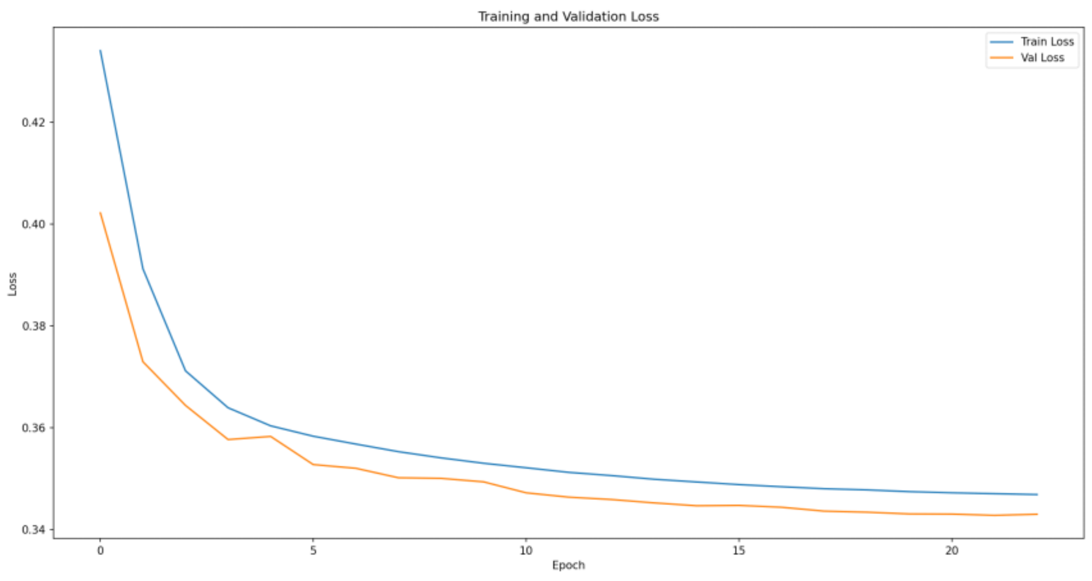
You can use schedulers to adjust the learning rate throughout the training depending on the number of epochs that have already passed or by implementing a dynamic system to reduce the learning rate based on validation measurements. **[3]**

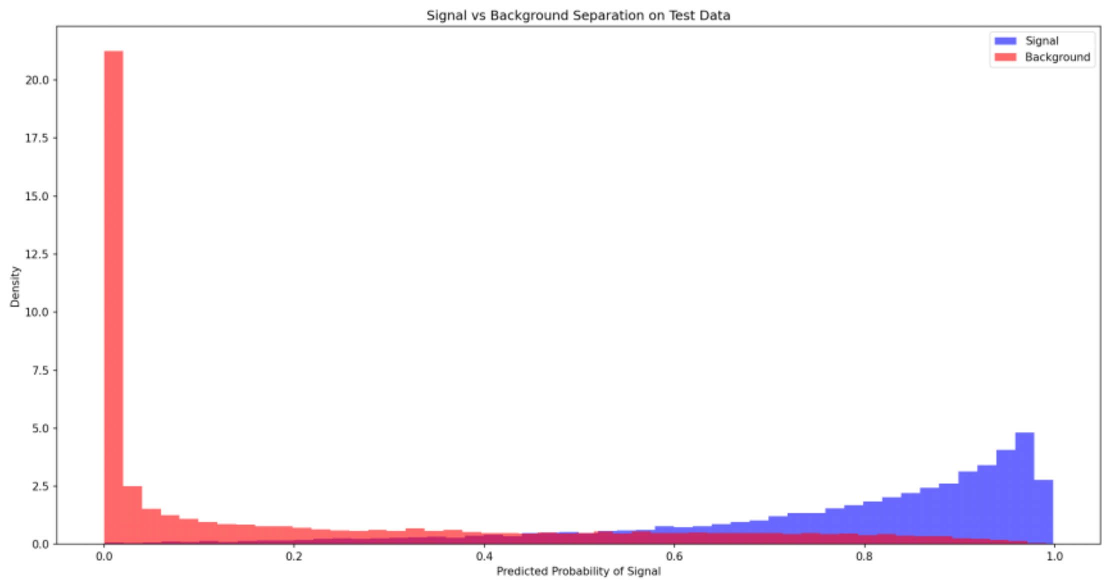
e.g.

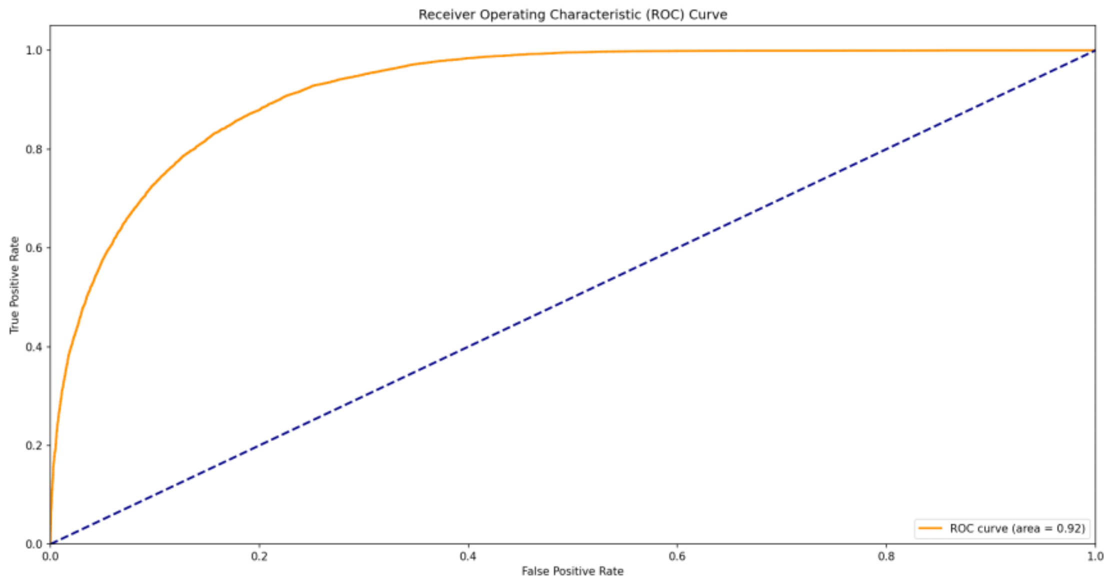
```python
optimizer = optim.SGD(model.parameters(), lr=0.01, momentum=0.9)
scheduler = ExponentialLR(optimizer, gamma=0.9)
for epoch in range(20):
    for input, target in dataset:
        optimizer.zero_grad()
        output = model(input)
        loss = loss_fn(output, target)
        loss.backward()
        optimizer.step()
    scheduler.step()
```

This code uses the SGD optimiser with an initial lr of 0.01 but the scheduler applies a factor of gamma to the learning rate for every epoch as at the end of each for loop in the epoch, it applies `scheduler.step()`.

I will now apply this to our current NN (Initial lr = 0.01, gamma = 0.9):

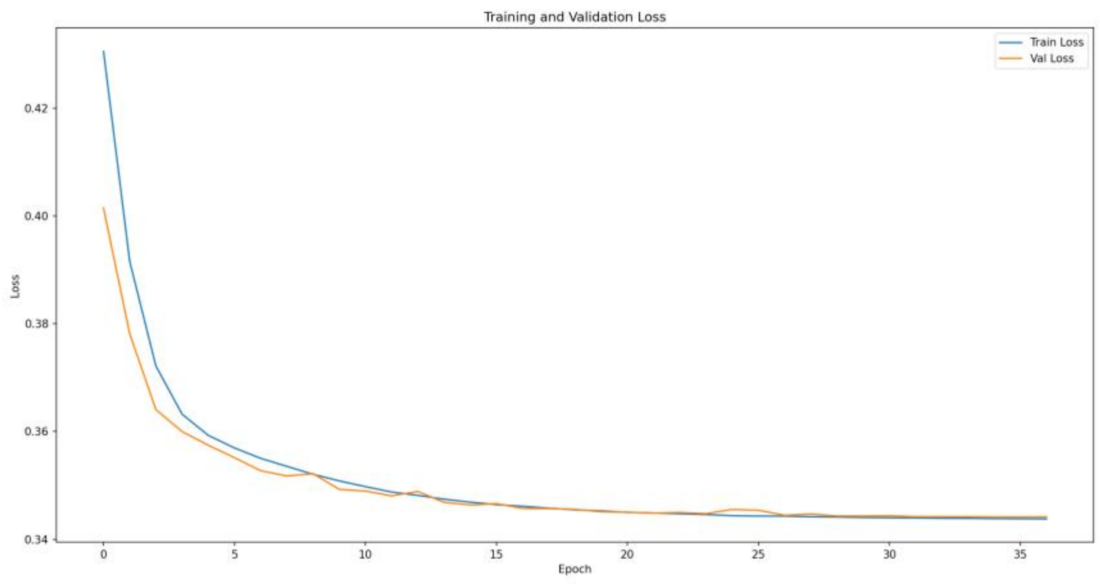


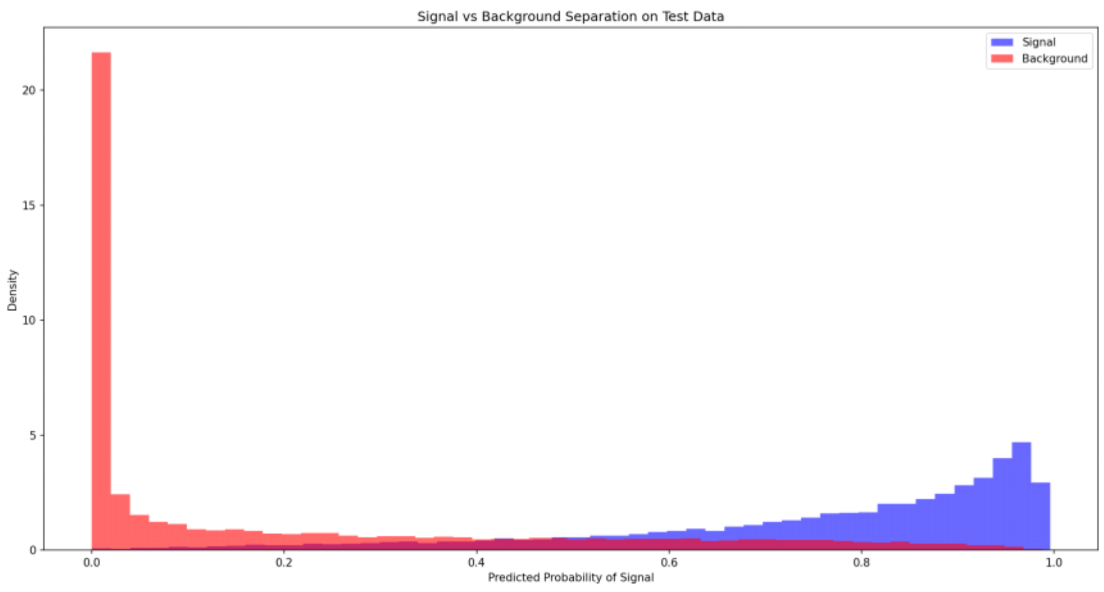


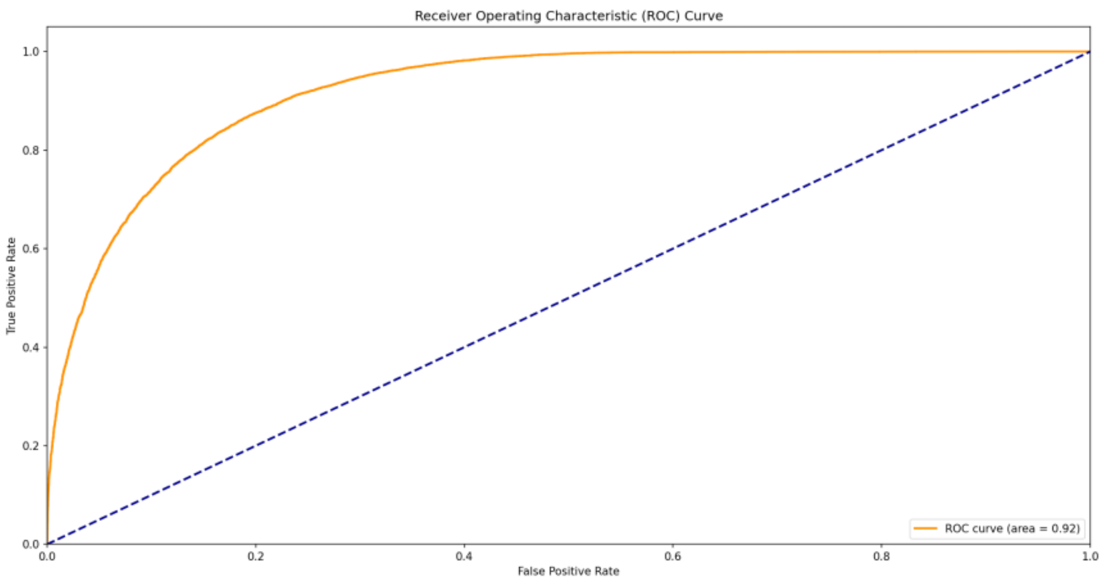


```
Accuracy: 0.8376176875066117
Precision: 0.8415267324256003
Recall: 0.8376176875066117
F1 Score: 0.8377221916855256
ROC AUC Score: 0.9227010034422914
```

These values hardly differ from those without the adapted learning rate, but perhaps if I change my early stopper to need 10 losses without reduction then we may see better results?







Accuracy: 0.8360044430339575

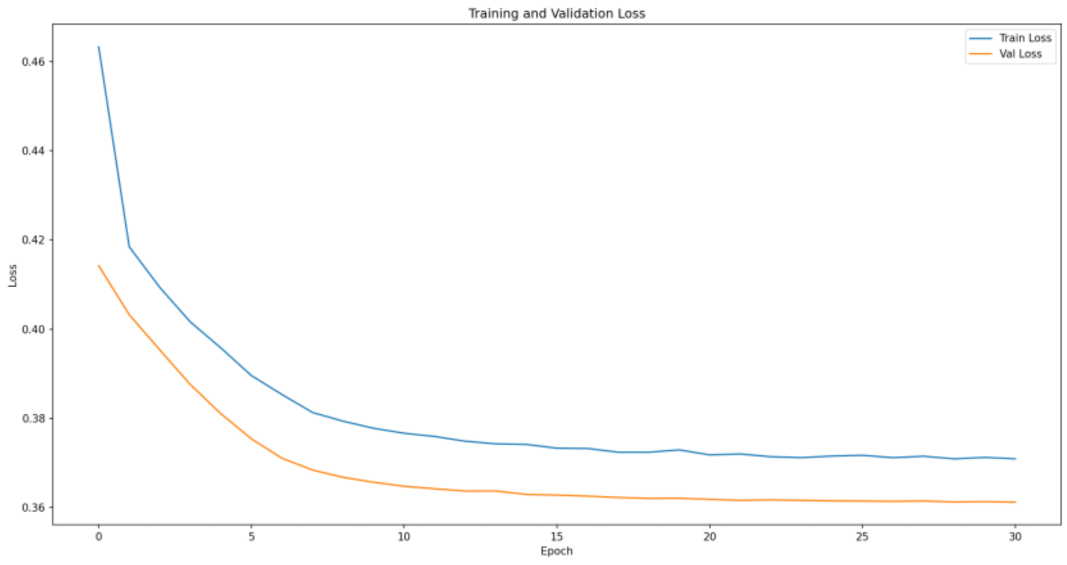
Precision: 0.8381019034814448
Recall: 0.8360044430339575
F1 Score: 0.8361527373803567
ROC AUC Score: 0.9202032934397019

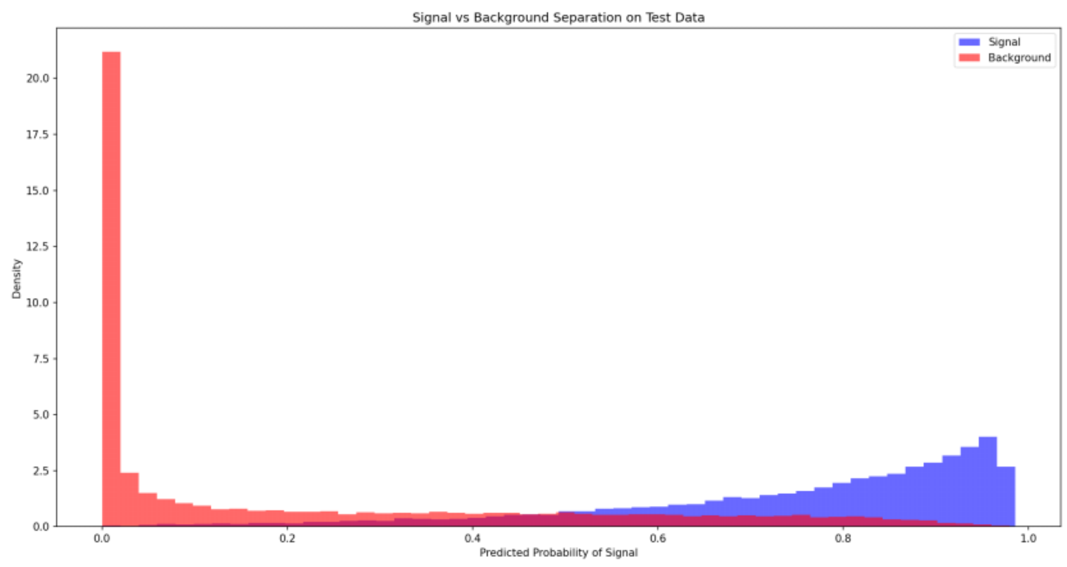
Notice how the values all went down; it's probably overfitting to the valuation data slightly because it's being allowed to fester without loss for too long.

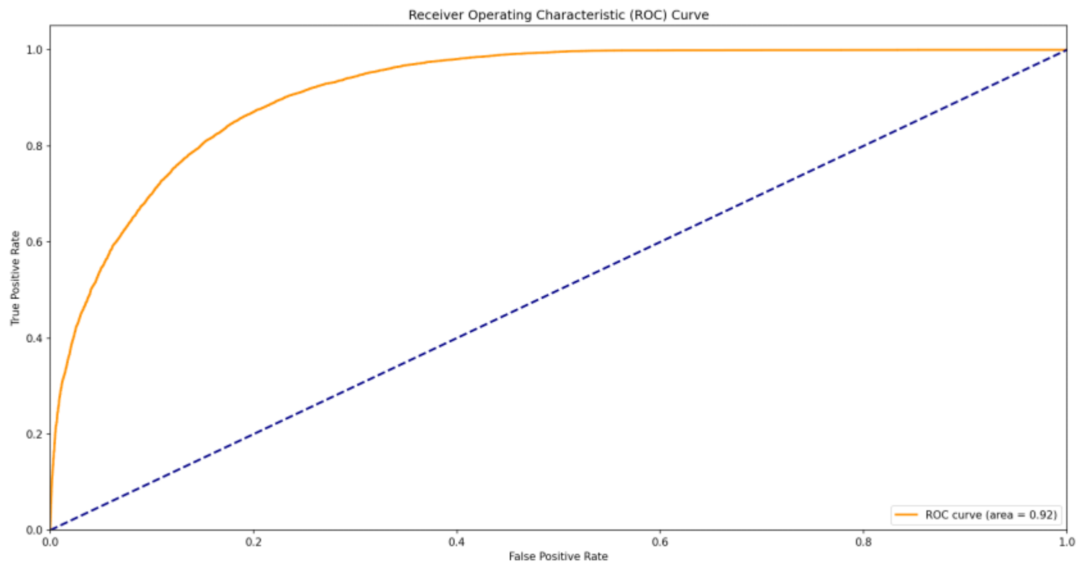
To deal with overfitting you can introduce dropout which randomly turns off parts of the network before a training batch is passed through the network during training which can help to identify any areas that are overfitting. For example, if turning off one bit suddenly increase the valuation loss then you know that this area was responsible for a high degree of fitting to the valuation data and therefore needs to be adjusted. It was taking too much of the load.

This is the model I will now test on:

```
model = nn.Sequential(
    nn.Linear(len(input_features), 100),
    nn.Sigmoid(),
    nn.Dropout(0.2),
    nn.Linear(100, 50),
    nn.Sigmoid(),
    nn.Dropout(0.2),
    nn.Linear(50, 1),
    nn.Sigmoid())
```







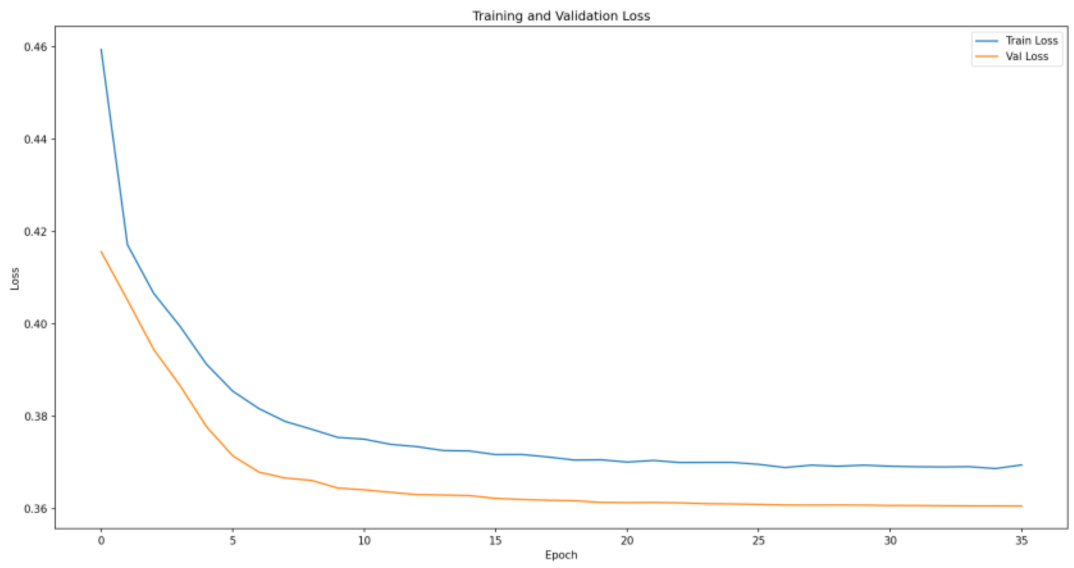
Accuracy: 0.8332804400719348
Precision: 0.8367274494372416
Recall: 0.8332804400719348
F1 Score: 0.8333887353115915
ROC AUC Score: 0.9169914353355983

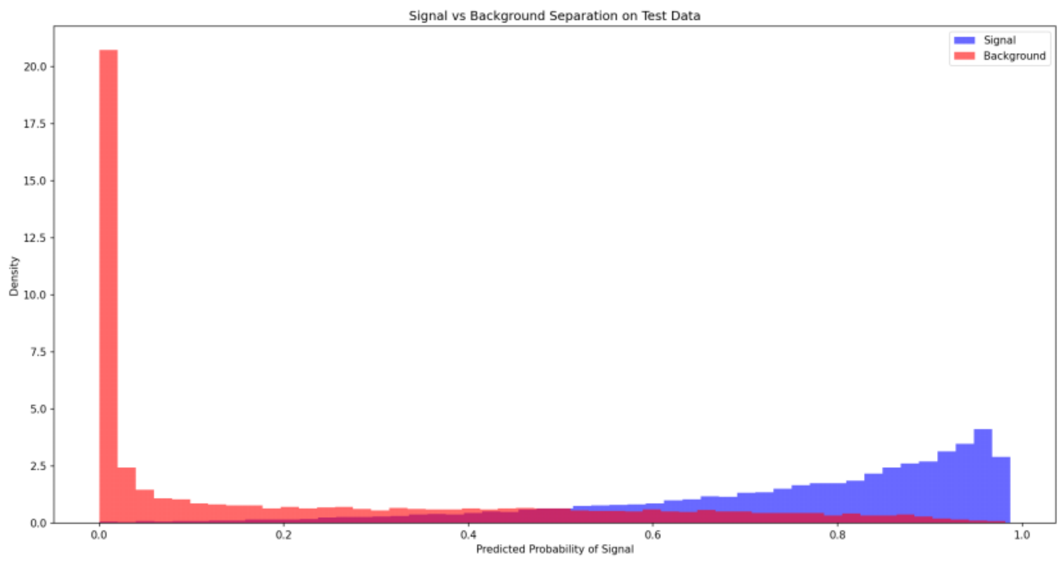
None of the scores have improved from this so it's clear that actually overfitting isn't a big problem for this data set due to its large size and there's therefore something else that is causing the problem.

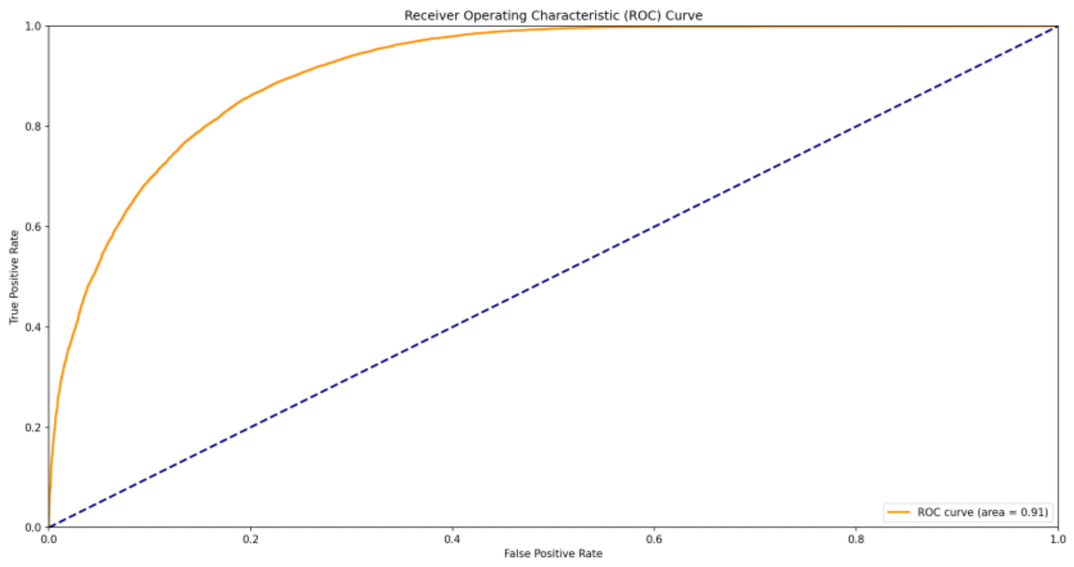
You can study the feature importance of the model by shuffling all the values from one feature in that column and seeing how drastically it changes the losses. If it makes the losses far larger then you know it's a key player in determining classification whereas if the losses are unaffected, you can be pretty sure that it doesn't play an important part in the model. Therefore you can define a new function that shuffles the column in question in the valuation data, and applies the model to the new valuation data. You can then see how much the ROC score changes by and judge which metrics are the most important to the model.

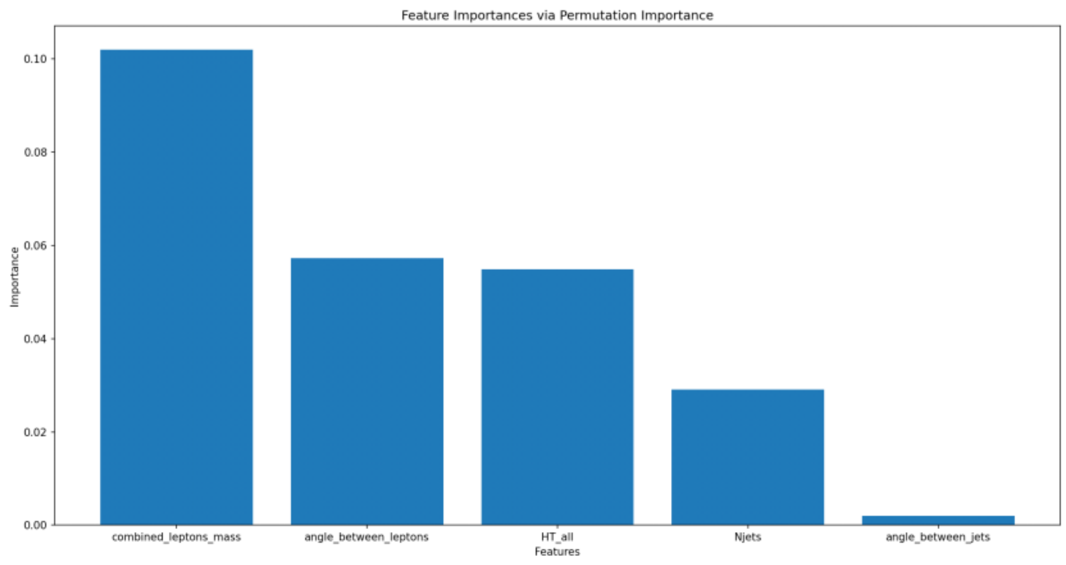
10/10/2025

15:00 - Messing around with feature importance on the train home


Training and Validation Loss
Train Loss
Val Loss
Loss
Epoch
0.46
0.44
0.42
0.40
0.38
0.36
0
5
10
15
20
25
30
35


Signal vs Background Separation on Test Data
Signal
Background
Density
Predicted Probability of Signal
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
0.0
0.2
0.4
0.6
0.8
1.0


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
ROC curve (area = 0.91)
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0



```
Accuracy: 0.8289696392679573
Precision: 0.8320145618700118
Recall: 0.8289696392679573
F1 Score: 0.8290709404313431
ROC AUC Score: 0.9134822392177419
Feature importances (from highest to lowest):
combined_leptons_mass: 0.10491378398392048
HT_all: 0.057204062202475425
angle_between_leptons: 0.05358087379667831
Njets: 0.033851687295038624
angle_between_jets: 0.0019306040410451697
```

Surprisingly angle between jets doesn't seem to play any major role in the model when compared to the likes of the combined lepton mass (over 50x smaller value).

12/10/2025

15:54 - Feature importance curve

The feature importances are based off how much their absence changes the accuracy of the model. Or in other words, when the column of feature data is shuffled, how much does this break the model? If it causes a massive decrease in accuracy then it's very important. Therefore the code for the feature importance must create a shuffled column that the model can be tested on:

```
def permutation_importance(model, X_val, y_val):
    detatch_to_binary = lambda x: np.round(model(x).detach().numpy())
    baseline_preds = detatch_to_binary(X_val)
    baseline_accuracy = accuracy_score(y_val, baseline_preds)
    importances = {}

    for i in range(X_val.shape[1]):
        X_val_permuted = X_val.clone()
        permuted_column = X_val_permuted[:, i]
[torch.randperm(X_val_permuted.size(0))]
        X_val_permuted[:, i] = permuted_column

        permuted_preds = detatch_to_binary(X_val_permuted)
        permuted_accuracy = accuracy_score(y_val, permuted_preds)

        importances[input_features[i]] = baseline_accuracy - permuted_accuracy
    return importances
importances = permutation_importance(model, X_val, y_val)
```

```
sorted_importances = dict(sorted(importances.items(), key=lambda item:
item[1], reverse=True))
print("Feature importances (from highest to lowest):")
for feature, importance in sorted_importances.items():
    print(f"{feature}: {importance}")
plt.figure(figsize=(10, 6))
plt.bar(sorted_importances.keys(), sorted_importances.values())
plt.xlabel('Features')
plt.ylabel('Importance')
plt.title('Feature Importances via Permutation Importance')
plt.show()
```

Now to go through this code one line at a time for future refernce:

- Define the function `permutation_importance` with inputs of the model, and the X and y valuation tensors
- The second line defines a lambda function. For any input x to `detatch_to_binary`, it is acted on by the model, the values detached, the tensor converted to a numpy array and the values rounded (to either 0 or 1 in this case)
- The third line just acts with this function on the inputted X valuation data
- The fourth line is working out the initial accuracy, similar to as is done before in the quantifying section prior
- Then, an importances tuple is created which will be the change in accuracy from each column shuffle
- The for loop is then completed for a range of the horizontal length of the X valuation tensor, which is the number of different features that the model uses
- An internal variable, `X_val_permuted`, is created as a clone of the X valuation tensor, which will become the data that is shuffled
- The permuted column line creates a new permuted tensor, shuffling the ith column through `torch.randperm(X_val_permuted.size(0))`
- This permuted column is then reintroduced into the permuted data tensor
- A new permuted predictions array is made by applying `detatch_to_binary` to the permuted tensor
- The permuted accuracy is then calculated
- Finally, the final line of the for loop creates a new dictionary entry for each of the input features
- This dictionary is then returned
- Using the model and the X and y valuation data, the importances are calculated
- They are then sorted using a dictionary sort in terms of the feature values and printed before then being plotted as a bar chart

End of Week 2

Week 2 aims and objectives achieved?

- **Gained an understanding of applications of neural networks for HEP**
- **Able to classify signal and background effectively**
- **Learnt different testing models, ROC and accuracy information and feature importances**
- **Important information gained about classes and other more advanced python code**

Anything to catch up with next week?

- **Just need to finish off the final bit about nn modules and then get to work on the ROOT data and DNNs from there**

Comments:

I'm feeling much more confident with writing DNN code now, and having got this exercise fully annotated with information about how all the code works, if I were to forget anything now I can always just come back to look at this week and all of the notes that I've written about each of the lines of code. Hopefully this should now make it much easier to make progress in the future as I've got a baseline understanding of how everything works. I'm looking forwards to now going forwards independently in trying to write my own code for DNN regression.

[2] Reference: https://arxiv.org/pdf/1412.6980

[3] Reference: https://docs.pytorch.org/docs/stable/optim.html#how-to-adjust-learning-rate

Week 3 (13/10 - 19/10)

14 October 2025 10:46

14/10/2025

Week 3 aims and objectives:

- **Final quick understanding of nn module**
- **Go through the HEP data preparation exercise to understand how to work with ROOT data**
- **Do a literature review on transformers and attention mechanisms to understand a bit more about how they work**
- **Learn how to use terminals for CSF**
- **Begin work on our own DNN for regressing invariant mass and angles between final state products**

10:49 - Final bit on nn module

```
class SimpleDNN(nn.Module):
    def __init__(self, N_input_features): # You can add more parameters here, 
such that the size of all layers can be
        # defined in the constructor
        """
        In the constructor we instantiate two nn.Linear modules and assign 
them as
        member variables.
        """
        super(SimpleDNN, self).__init__()
        self.linear1 = nn.Linear(N_input_features, 50)
        self.linear2 = nn.Linear(50, 1)
    def forward(self, x):
        """
        In the forward function we accept a Tensor of input data and we must 
return
        a Tensor of output data. We can use Modules defined in the constructor 
as
        well as arbitrary operators on Tensors.
        """
        # Compute the forward pass.
        # The first layer is self.linear1, then we apply the ReLU activation 
function
        x1     = F.relu(self.linear1(x))
        # The second layer is self.linear2, then we apply the sigmoid 
activation function to get our final output
        y_pred = F.sigmoid(self.linear2(x1))
        return y_pred
```

Let's go through this nn module class:

- Initially you define the initialisation phase, where we've instantiated two nn.Linear modules as is explained in the comments
- It also takes in an input features number so it knows how many it is starting from
- Then for the forward pass, you initiate the linear layers one at a time with a non-linear activation function between each of them
- Effectively this just does the nn.Sequential but in a class form

11:32 - Still feeling very ill, not sure I can do much more work today

20:32 - Literature review

An Introduction to Transformers - Richard E. Turner **[4]**

I was unfortunately very ill for the duration of this week and was unable to complete any substantial work. My supervisor and co-supervisor were very understanding of this and I have now made a full recovery at the end of the week.

Week 3 aims and objectives achieved?

- **Understood nn.module**

Anything to catch up with next week?

- **Need to understand fully how to manipulate HEP data**
- **Need to read up fully on transformers**
- **Need to learn how to use CSF**
- **Continue the DNN work that Aathavan has completed in my absence**

Comments:

Unfortunately I was able to achieve little this week but endeavour to make up for it next week. Hopefully we should have the DNN completed by the end of next week and can then start work on transformers.

References

Week 4 (20/10 - 26/10)

21 October 2025 10:46

21/10/2025

Week 4 aims and objectives:

- **Understand CSF**
- **Understand how to manipulate HEP data**
- **Read up on transformers**
- **Continue DNN work that Aathavan has completed in my absence**

09:00 - Start of Week 4 Meeting with Yvonne & Ethan

Discussions included:

- Presentation of slides as to what we've completed so far (not a lot to present on my end as I wasn't able to complete much work throughout last week)
- Asked Ethan about CSF stuff which he explained after the meeting
- Listened in to Jack's meeting which was actually quite interesting as it was about classification of 3 and 4 top quark events with a transformer and showed remarkable distinctiveness to which they were trying to attribute a cause

10:20 - CSF learning

Going to spend the next 30 minutes or so trying to get around using CSF. **[4]**

10:51 - Summary of learning on CSF so far

I have been able to login to the ssh on VSCode using:

ssh n55181ic@csf3.itservices.manchester.ac.uk

I then set up a node using the command:

srun --partition=gpuL --gpus=1 --ntasks=4 --time=1-0 --pty bash

Then it gets more difficult as a batch has to be created and then run. For now I will leave it at this point until I have developed a DNN which I can test it on. It should be noted that I need to remember to save figures and stuff as the terminal will not be able to display normal graphs from a simple plt.show command.

11:10 - DNN Work

Firstly downloaded the file we're working with from the google drive. Can be found in my directory at:

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\tttt_NLO_523243_mc23a_fullsim.root

New python file to be working with:

C:\Users\Ian Standard\Documents\Manchester\Physics\MPhys_Project\MPhys4TopDNN.py

So to begin with you just simply open the downloaded file (from the shared google drive) and set the tree as reco to see what variables we're working with:

```python
import uproot
file_tt = uproot.open("tttt_NLO_523243_mc23a_fullsim.root")
tree = file_tt["reco"]
print(tree.keys())
```

Having had a bit of a play with manipulating the root data this is the resulting code:

```python
import awkward as ak
EventNumber = tree["eventNumber"].array()
LeptonCharge = tree["lepton_charge"].array()
New_array = tree.arrays(["eventNumber", "lepton_charge"])
print(New_array)
New_array_branch_names = {
    "EN": "eventNumber",
    "LC": "lepton_charge"
}
Selected_array = tree.arrays(New_array_branch_names.keys(), aliases =
New_array_branch_names)
print(Selected_array["EN"])
print(Selected_array["LC"])
```

Effectively what we're doing here is creating arrays from each of the trees in reco. Similarly you can take multiple trees to form an array. Then, you can use simpler names for the different branches and apply these keys so that you can print out different arrays easily.

Just to keep a note of all the different keys for future reference and so I don't have to keep printing them out:

['HT_all_NOSYS', 'HT_fjets_NOSYS', 'HT_jets_NOSYS', 'el_DFCommonAddAmbiguity', 'el_DFCommonElectronsDNNLoose_NOSYS', 'el_DFCommonElectronsDNNMedium_NOSYS', 'el_DFCommonElectronsDNNTight_NOSYS', 'el_DFCommonElectronsECIDSResult_NOSYS', 'el_TLV_NOSYS', 'el_TLV_NOSYS/el_TLV_NOSYS.fCoordinates.fPt', 'el_TLV_NOSYS/el_TLV_NOSYS.fCoordinates.fEta', 'el_TLV_NOSYS/el_TLV_NOSYS.fCoordinates.fPhi', 'el_TLV_NOSYS/el_TLV_NOSYS.fCoordinates.fE', 'el_charge', 'el_e_NOSYS', 'el_eta', 'el_firstEgMotherPdgId', 'el_firstEgMotherTruthOrigin', 'el_firstEgMotherTruthType', 'el_passECIDS_NOSYS', 'el_phi', 'el_pt_NOSYS', 'el_select_loose_NOSYS', 'el_select_outputSelect_NOSYS', 'el_select_tight_NOSYS', 'el_truthOrigin', 'el_truthPdgId', 'el_truthTopIndex', 'el_truthType', 'eventNumber', 'jet_GN2v01_Continuous_quantile', 'jet_GN2v01_FixedCutBEff_65_select', 'jet_GN2v01_FixedCutBEff_70_select', 'jet_GN2v01_FixedCutBEff_77_select', 'jet_GN2v01_FixedCutBEff_85_select', 'jet_GN2v01_FixedCutBEff_90_select', 'jet_TLV_NOSYS', 'jet_TLV_NOSYS/jet_TLV_NOSYS.fCoordinates.fPt', 'jet_TLV_NOSYS/jet_TLV_NOSYS.fCoordinates.fEta', 'jet_TLV_NOSYS/jet_TLV_NOSYS.fCoordinates.fPhi', 'jet_TLV_NOSYS/jet_TLV_NOSYS.fCoordinates.fE', 'jet_e_NOSYS', 'jet_eta', 'jet_jvtEfficiency_NOSYS', 'jet_partonid', 'jet_phi', 'jet_pt_NOSYS', 'jet_select_GN2v01_FixedCutBEff_65_NOSYS', 'jet_select_GN2v01_FixedCutBEff_70_NOSYS', 'jet_select_GN2v01_FixedCutBEff_77_NOSYS', 'jet_select_GN2v01_FixedCutBEff_85_NOSYS', 'jet_select_GN2v01_FixedCutBEff_90_NOSYS', 'jet_select_baselineJvt_NOSYS', 'jet_select_outputSelect_NOSYS', 'jet_truthTopIndex', 'jet_truthflav', 'lepton_0_pt_GeV_NOSYS', 'lepton_1_pt_GeV_NOSYS', 'lepton_DFCommonAddAmbiguity', 'lepton_Id', 'lepton_charge', 'lepton_e_NOSYS', 'lepton_eta', 'lepton_phi', 'lepton_pt_NOSYS', 'lepton_truthCat', 'met_met_NOSYS', 'met_phi_NOSYS', 'met_significance_NOSYS', 'met_sumet_NOSYS', 'mu_TLV_NOSYS', 'mu_TLV_NOSYS/mu_TLV_NOSYS.fCoordinates.fPt', 'mu_TLV_NOSYS/mu_TLV_NOSYS.fCoordinates.fEta', 'mu_TLV_NOSYS/mu_TLV_NOSYS.fCoordinates.fPhi', 'mu_TLV_NOSYS/mu_TLV_NOSYS.fCoordinates.fE', 'mu_TTVA_effSF_loose_NOSYS', 'mu_TTVA_effSF_tight_NOSYS', 'mu_charge', 'mu_e_NOSYS', 'mu_eta', 'mu_isol_effSF_tight_NOSYS', 'mu_phi', 'mu_pt_NOSYS', 'mu_reco_effSF_loose_NOSYS', 'mu_reco_effSF_tight_NOSYS', 'mu_select_loose_NOSYS', 'mu_select_outputSelect_NOSYS', 'mu_select_tight_NOSYS', 'mu_truthOrigin', 'mu_truthTopIndex', 'mu_truthType', 'nBjets_GN2v01_65WP', 'nBjets_GN2v01_70WP', 'nBjets_GN2v01_77WP', 'nBjets_GN2v01_85WP', 'nBjets_GN2v01_90WP', 'nElectrons', 'nFJets', 'nJets', 'nLeptons', 'nMuons', 'num_truth_bjets_nocuts', 'num_truth_cjets_nocuts', 'parton_top_eta', 'parton_top_isFromZprime', 'parton_top_isHadronic', 'parton_top_m', 'parton_top_phi', 'parton_top_pt', 'pass_SSee_NOSYS', 'pass_SSee_passCF_NOSYS', 'pass_SSem_NOSYS', 'pass_SSem_passCF_NOSYS', 'pass_SSmm_NOSYS', 'pass_eee_NOSYS', 'pass_eee_ZVeto_NOSYS', 'pass_eem_NOSYS', 'pass_eem_ZVeto_NOSYS', 'pass_emm_NOSYS', 'pass_emm_ZVeto_NOSYS', 'pass_llll_NOSYS', 'pass_llll_ZVeto_NOSYS', 'pass_mmm_NOSYS', 'pass_mmm_ZVeto_NOSYS', 'runNumber', 'weight_ftag_effSF_GN2v01_Continuous_NOSYS', 'weight_jvt_effSF_NOSYS', 'weight_leptonSF_tight_NOSYS', 'weight_mc_NOSYS', 'weight_pileup_NOSYS', 'weight_total_NOSYS', 'weight_total_squared_NOSYS', 'xSection']

References:

[4] https://github.com/els285/MPhys2025/blob/main/CSF_Instructions.md