

# TJ Keras Neural Net

November 21, 2020

## 1 Tommy John Neural Network

```
[200]: import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
```

```
[201]: df_train = pd.read_csv('/Users/timmorales/Desktop/STAT 6341/Tommy John Project/
↳Data/SMOTETRAIN.csv')
df_test = pd.read_csv('/Users/timmorales/Desktop/STAT 6341/Tommy John Project/
↳Data/testset.csv')

df_test = df_test.drop(df_test.columns[0], axis=1)
df_train = df_train.drop(df_train.columns[0], axis=1)
```

```
[202]: from copy import deepcopy
df_train = deepcopy(df_train)
df_test = deepcopy(df_test)
```

```
[203]: df_train.head()
```

```
[203]:
```

	player_age	p_game	xba	xslg	xwoba	xobp	xiso	\
0	0.449343	0.271899	-0.236873	-0.433236	-0.346471	-0.221791	-0.481580	
1	-0.366322	-1.198887	2.683901	2.403073	2.954865	3.126211	1.774630	
2	-0.366322	-1.151442	1.147790	0.499249	1.177223	1.071755	-0.010346	
3	2.624452	-1.056553	1.364144	2.558488	2.555803	2.498461	2.859896	
4	1.536897	-0.961663	0.282376	-0.180688	-0.001826	0.025505	-0.453021	

	exit_velocity_avg	launch_angle_avg	barrel_batted_rate	...	bats_L	\
0	-0.455052	-0.622586	-0.331504	...	0	
1	0.644949	0.078895	1.192009	...	0	
2	1.103283	-2.676924	-0.625515	...	0	
3	-0.363385	1.565368	-0.090950	...	0	
4	0.599116	0.245915	-0.625515	...	1	

	bats_R	throws_L	throws_R	throws_S	TJ_Yes	made_postseason_X0	\
0	1	0	1	0	0	0	
1	1	0	1	0	0	1	

2	1	0	1	0	0	1
3	1	0	1	0	0	1
4	0	1	0	0	0	1

	made_postseason_X1	warm_birch_place_X0	warm_birch_place_X1
0	1	1	0
1	0	1	0
2	0	1	0
3	0	0	1
4	0	0	1

[5 rows x 337 columns]

```
[204]: #setting up my targets
y_train = df_train['TJ_Yes'].values.astype(np.int)
y_test = df_test['TJ_Yes'].values.astype(np.int)
```

## 1.1 Model Work

With the data successfully and properly loaded, I bring in keras and tensorflow.

```
[205]: from sklearn import metrics as mt
from tensorflow import keras
from tensorflow.keras.layers import Dense, Activation, Input
from tensorflow.keras.layers import Embedding, Flatten, Concatenate
from tensorflow.keras.models import Model
```

```
[206]: # combine the features into a single large matrix
X_train = df_train.drop(["TJ_Yes"],axis=1).to_numpy()
X_test = df_test.drop(["TJ_Yes"],axis=1).to_numpy()
```

Input size will always be the same. I start off with the most basic model possible.

```
[207]: #id number of features
num_features = X_train.shape[1]
#set up input
input_tensor = Input(shape=(num_features,))
```

```
[208]: from keras.models import Sequential
from keras.layers import Dropout
from keras.layers import Dense
import tensorflow as tf
from sklearn import metrics as mt
```

Start out extremely simple with no relu, dropout or penalization to see how it fits.

```
[209]: model = Sequential()
model.add(Dense(10, input_dim=num_features, activation='sigmoid'))
model.add(Dense(5, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid'))
```

Im using adam to hopefully find the minima quickly without bouncing around too much and using recall as our metric of choice. Binary Cross is a pretty standard use for this case. 50 epochs and small validation set to start.

```
[210]: recall = tf.keras.metrics.Recall()

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit([X_train],
                    y_train,
                    epochs=50,
                    batch_size=16,
                    verbose=1,
                    validation_split = .2)

model.summary()
```

```
Epoch 1/50
157/157 [=====] - 0s 2ms/step - loss: 0.5376 -
accuracy: 0.8401 - val_loss: 1.1647 - val_accuracy: 0.0000e+00
Epoch 2/50
157/157 [=====] - 0s 1ms/step - loss: 0.3559 -
accuracy: 0.9512 - val_loss: 1.5097 - val_accuracy: 0.0000e+00
Epoch 3/50
157/157 [=====] - 0s 1ms/step - loss: 0.2817 -
accuracy: 0.9512 - val_loss: 1.8093 - val_accuracy: 0.0000e+00
Epoch 4/50
157/157 [=====] - 0s 2ms/step - loss: 0.2426 -
accuracy: 0.9512 - val_loss: 2.0613 - val_accuracy: 0.0000e+00
Epoch 5/50
157/157 [=====] - 0s 2ms/step - loss: 0.2210 -
accuracy: 0.9512 - val_loss: 2.2817 - val_accuracy: 0.0000e+00
Epoch 6/50
157/157 [=====] - 0s 2ms/step - loss: 0.2087 -
accuracy: 0.9512 - val_loss: 2.4593 - val_accuracy: 0.0000e+00
Epoch 7/50
157/157 [=====] - 0s 1ms/step - loss: 0.2018 -
accuracy: 0.9512 - val_loss: 2.5880 - val_accuracy: 0.0000e+00
Epoch 8/50
157/157 [=====] - 0s 998us/step - loss: 0.1925 -
```

```

accuracy: 0.9512 - val_loss: 2.4821 - val_accuracy: 0.0000e+00
Epoch 9/50
157/157 [=====] - 0s 1ms/step - loss: 0.1744 -
accuracy: 0.9512 - val_loss: 2.3900 - val_accuracy: 0.0000e+00
Epoch 10/50
157/157 [=====] - 0s 1000us/step - loss: 0.1626 -
accuracy: 0.9512 - val_loss: 2.3797 - val_accuracy: 0.0000e+00
Epoch 11/50
157/157 [=====] - 0s 1ms/step - loss: 0.1540 -
accuracy: 0.9512 - val_loss: 2.2849 - val_accuracy: 0.0000e+00
Epoch 12/50
157/157 [=====] - 0s 1ms/step - loss: 0.1474 -
accuracy: 0.9512 - val_loss: 2.1753 - val_accuracy: 0.0000e+00
Epoch 13/50
157/157 [=====] - 0s 1ms/step - loss: 0.1420 -
accuracy: 0.9512 - val_loss: 2.1722 - val_accuracy: 0.0000e+00
Epoch 14/50
157/157 [=====] - 0s 1ms/step - loss: 0.1374 -
accuracy: 0.9512 - val_loss: 2.1077 - val_accuracy: 0.0000e+00
Epoch 15/50
157/157 [=====] - 0s 1ms/step - loss: 0.1332 -
accuracy: 0.9512 - val_loss: 2.2367 - val_accuracy: 0.0000e+00
Epoch 16/50
157/157 [=====] - 0s 1ms/step - loss: 0.1299 -
accuracy: 0.9516 - val_loss: 1.8244 - val_accuracy: 0.0016
Epoch 17/50
157/157 [=====] - 0s 1ms/step - loss: 0.1259 -
accuracy: 0.9636 - val_loss: 2.0664 - val_accuracy: 0.0447
Epoch 18/50
157/157 [=====] - 0s 1ms/step - loss: 0.1224 -
accuracy: 0.9716 - val_loss: 2.0699 - val_accuracy: 0.0942
Epoch 19/50
157/157 [=====] - 0s 1ms/step - loss: 0.1185 -
accuracy: 0.9732 - val_loss: 2.0512 - val_accuracy: 0.1581
Epoch 20/50
157/157 [=====] - 0s 1ms/step - loss: 0.1158 -
accuracy: 0.9736 - val_loss: 1.9033 - val_accuracy: 0.2396
Epoch 21/50
157/157 [=====] - 0s 1ms/step - loss: 0.1133 -
accuracy: 0.9736 - val_loss: 1.7463 - val_accuracy: 0.3227
Epoch 22/50
157/157 [=====] - 0s 1ms/step - loss: 0.1103 -
accuracy: 0.9740 - val_loss: 1.6785 - val_accuracy: 0.3578
Epoch 23/50
157/157 [=====] - 0s 2ms/step - loss: 0.1081 -
accuracy: 0.9756 - val_loss: 1.7344 - val_accuracy: 0.3482
Epoch 24/50
157/157 [=====] - 0s 1ms/step - loss: 0.1050 -

```

accuracy: 0.9752 - val\_loss: 1.7404 - val\_accuracy: 0.3466  
 Epoch 25/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.1028 -  
 accuracy: 0.9760 - val\_loss: 1.7064 - val\_accuracy: 0.3690  
 Epoch 26/50  
 157/157 [=====] - 0s 2ms/step - loss: 0.1001 -  
 accuracy: 0.9768 - val\_loss: 1.6879 - val\_accuracy: 0.3882  
 Epoch 27/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0977 -  
 accuracy: 0.9764 - val\_loss: 1.5690 - val\_accuracy: 0.4345  
 Epoch 28/50  
 157/157 [=====] - 0s 2ms/step - loss: 0.0954 -  
 accuracy: 0.9772 - val\_loss: 1.5714 - val\_accuracy: 0.4361  
 Epoch 29/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0927 -  
 accuracy: 0.9776 - val\_loss: 1.6742 - val\_accuracy: 0.4121  
 Epoch 30/50  
 157/157 [=====] - 0s 2ms/step - loss: 0.0908 -  
 accuracy: 0.9780 - val\_loss: 1.6720 - val\_accuracy: 0.4121  
 Epoch 31/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0883 -  
 accuracy: 0.9792 - val\_loss: 1.7514 - val\_accuracy: 0.3898  
 Epoch 32/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0869 -  
 accuracy: 0.9796 - val\_loss: 1.6834 - val\_accuracy: 0.4185  
 Epoch 33/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0846 -  
 accuracy: 0.9816 - val\_loss: 1.5704 - val\_accuracy: 0.4489  
 Epoch 34/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0825 -  
 accuracy: 0.9824 - val\_loss: 1.6768 - val\_accuracy: 0.4201  
 Epoch 35/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0806 -  
 accuracy: 0.9824 - val\_loss: 1.6613 - val\_accuracy: 0.4265  
 Epoch 36/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0784 -  
 accuracy: 0.9832 - val\_loss: 1.6674 - val\_accuracy: 0.4409  
 Epoch 37/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0770 -  
 accuracy: 0.9832 - val\_loss: 1.7335 - val\_accuracy: 0.4105  
 Epoch 38/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0746 -  
 accuracy: 0.9844 - val\_loss: 1.6795 - val\_accuracy: 0.4377  
 Epoch 39/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0728 -  
 accuracy: 0.9836 - val\_loss: 1.7563 - val\_accuracy: 0.4105  
 Epoch 40/50  
 157/157 [=====] - 0s 1ms/step - loss: 0.0705 -

```

accuracy: 0.9852 - val_loss: 1.8054 - val_accuracy: 0.4026
Epoch 41/50
157/157 [=====] - 0s 1ms/step - loss: 0.0688 -
accuracy: 0.9852 - val_loss: 1.7502 - val_accuracy: 0.4201
Epoch 42/50
157/157 [=====] - 0s 1ms/step - loss: 0.0668 -
accuracy: 0.9856 - val_loss: 1.7394 - val_accuracy: 0.4345
Epoch 43/50
157/157 [=====] - 0s 2ms/step - loss: 0.0655 -
accuracy: 0.9864 - val_loss: 1.7809 - val_accuracy: 0.4217
Epoch 44/50
157/157 [=====] - 0s 2ms/step - loss: 0.0637 -
accuracy: 0.9868 - val_loss: 1.7009 - val_accuracy: 0.4505
Epoch 45/50
157/157 [=====] - 0s 2ms/step - loss: 0.0619 -
accuracy: 0.9880 - val_loss: 1.6950 - val_accuracy: 0.4569
Epoch 46/50
157/157 [=====] - 0s 1ms/step - loss: 0.0601 -
accuracy: 0.9868 - val_loss: 1.7160 - val_accuracy: 0.4585
Epoch 47/50
157/157 [=====] - 0s 1ms/step - loss: 0.0584 -
accuracy: 0.9876 - val_loss: 1.7516 - val_accuracy: 0.4441
Epoch 48/50
157/157 [=====] - 0s 1ms/step - loss: 0.0563 -
accuracy: 0.9880 - val_loss: 1.6174 - val_accuracy: 0.4856
Epoch 49/50
157/157 [=====] - 0s 1ms/step - loss: 0.0545 -
accuracy: 0.9888 - val_loss: 1.7046 - val_accuracy: 0.4585
Epoch 50/50
157/157 [=====] - 0s 1ms/step - loss: 0.0536 -
accuracy: 0.9884 - val_loss: 1.8209 - val_accuracy: 0.4249
Model: "sequential_36"

```

Layer (type)	Output Shape	Param #
dense_105 (Dense)	(None, 10)	3370
dense_106 (Dense)	(None, 5)	55
dense_107 (Dense)	(None, 1)	6

```

Total params: 3,431
Trainable params: 3,431
Non-trainable params: 0

```

```
[211]: # now lets see how well the model performed
yhat_proba = model.predict(X_test)
yhat = np.where(yhat_proba > 0.5, 1, 0)
print(mt.confusion_matrix(y_test,yhat))
print(mt.classification_report(y_test,yhat))
```

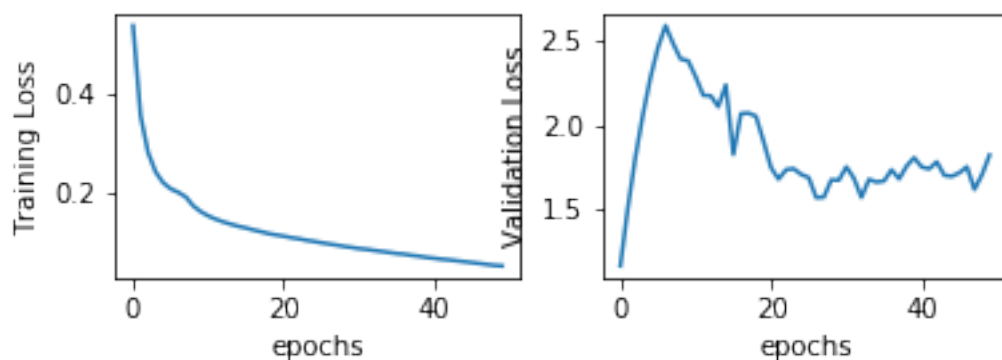
```
[[1042  22]
 [ 28   1]]
```

	precision	recall	f1-score	support
0	0.97	0.98	0.98	1064
1	0.04	0.03	0.04	29
accuracy			0.95	1093
macro avg	0.51	0.51	0.51	1093
weighted avg	0.95	0.95	0.95	1093

```
[212]: plt.subplot(2,2,3)
plt.plot(history.history['loss'])
plt.ylabel('Training Loss')
plt.xlabel('epochs')

plt.subplot(2,2,4)
plt.plot(history.history['val_loss'])
plt.ylabel('Validation Loss')
plt.xlabel('epochs')
```

```
[212]: Text(0.5, 0, 'epochs')
```



Model doesnt seem to converge fully, will add more epochs, but looks like we may be starting to overfit.

```
[213]: model.compile(optimizer='adam',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])

history = model.fit([X_train],
                    y_train,
                    epochs=25,
                    batch_size=16,
                    verbose=0,
                    validation_split = .2)

model.summary()
```

Model: "sequential\_36"

Layer (type)	Output Shape	Param #
dense_105 (Dense)	(None, 10)	3370
dense_106 (Dense)	(None, 5)	55
dense_107 (Dense)	(None, 1)	6

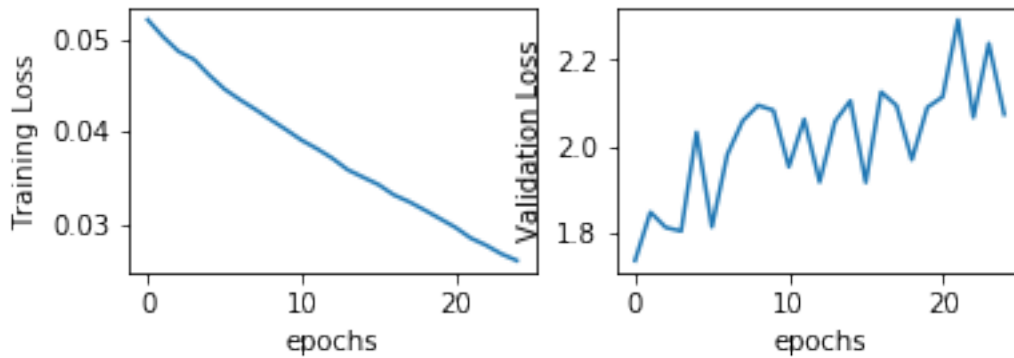
Total params: 3,431  
 Trainable params: 3,431  
 Non-trainable params: 0

```
[214]: plt.subplot(2,2,3)
plt.plot(history.history['loss'])
plt.ylabel('Training Loss')
plt.xlabel('epochs')

plt.subplot(2,2,4)
plt.plot(history.history['val_loss'])
plt.ylabel('Validation Loss')
plt.xlabel('epochs')
```

```
[214]: Text(0.5, 0, 'epochs')
```





Looks like adding the 25 actually resulted in some overfitting when comparing validation and training loss. We therefore will fit for 70 total epochs, but include some drop out. I also include some regularization on the hidden layer to aid in the overfitting.

Since I see no issue with the model training I don't change activation function.

```
[215]: model = Sequential()
model.add(Dense(10, input_dim=num_features, activation='sigmoid'))
model.add(Dropout(0.25))
model.add(Dense(5, activation='sigmoid', kernel_regularizer=tf.keras.
    ↳regularizers.l2(1e-4)))
model.add(Dropout(0.1))
model.add(Dense(1, activation='sigmoid'))
```

```
[216]: model.compile(optimizer='adam',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])

history = model.fit([X_train],
                    y_train,
                    epochs=70,
                    batch_size=16,
                    verbose=1,
                    validation_split = .2)

model.summary()
```

Epoch 1/70

157/157 [=====] - 0s 2ms/step - loss: 0.3087 - accuracy: 0.9464 - val\_loss: 2.1051 - val\_accuracy: 0.0000e+00

Epoch 2/70

157/157 [=====] - 0s 1ms/step - loss: 0.2250 - accuracy: 0.9508 - val\_loss: 2.5909 - val\_accuracy: 0.0000e+00

Epoch 3/70  
157/157 [=====] - 0s 1ms/step - loss: 0.2008 -  
accuracy: 0.9512 - val\_loss: 2.6669 - val\_accuracy: 0.0000e+00

Epoch 4/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1891 -  
accuracy: 0.9512 - val\_loss: 2.6470 - val\_accuracy: 0.0000e+00

Epoch 5/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1734 -  
accuracy: 0.9512 - val\_loss: 2.5104 - val\_accuracy: 0.0000e+00

Epoch 6/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1676 -  
accuracy: 0.9512 - val\_loss: 2.5101 - val\_accuracy: 0.0000e+00

Epoch 7/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1613 -  
accuracy: 0.9512 - val\_loss: 2.3670 - val\_accuracy: 0.0000e+00

Epoch 8/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1560 -  
accuracy: 0.9512 - val\_loss: 2.3374 - val\_accuracy: 0.0000e+00

Epoch 9/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1528 -  
accuracy: 0.9512 - val\_loss: 2.2518 - val\_accuracy: 0.0000e+00

Epoch 10/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1426 -  
accuracy: 0.9516 - val\_loss: 2.0788 - val\_accuracy: 0.0000e+00

Epoch 11/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1419 -  
accuracy: 0.9564 - val\_loss: 2.2219 - val\_accuracy: 0.0000e+00

Epoch 12/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1403 -  
accuracy: 0.9584 - val\_loss: 2.1352 - val\_accuracy: 0.0000e+00

Epoch 13/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1373 -  
accuracy: 0.9604 - val\_loss: 2.0941 - val\_accuracy: 0.0000e+00

Epoch 14/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1378 -  
accuracy: 0.9592 - val\_loss: 1.9955 - val\_accuracy: 0.0048

Epoch 15/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1307 -  
accuracy: 0.9612 - val\_loss: 1.9488 - val\_accuracy: 0.0224

Epoch 16/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1348 -  
accuracy: 0.9632 - val\_loss: 1.8590 - val\_accuracy: 0.0719

Epoch 17/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1255 -  
accuracy: 0.9668 - val\_loss: 1.9578 - val\_accuracy: 0.1006

Epoch 18/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1317 -  
accuracy: 0.9656 - val\_loss: 1.8788 - val\_accuracy: 0.1454

Epoch 19/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1305 -  
accuracy: 0.9668 - val\_loss: 1.8386 - val\_accuracy: 0.1725

Epoch 20/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1231 -  
accuracy: 0.9688 - val\_loss: 1.7317 - val\_accuracy: 0.2524

Epoch 21/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1227 -  
accuracy: 0.9696 - val\_loss: 1.8374 - val\_accuracy: 0.2300

Epoch 22/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1175 -  
accuracy: 0.9688 - val\_loss: 1.8807 - val\_accuracy: 0.2300

Epoch 23/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1180 -  
accuracy: 0.9708 - val\_loss: 1.8948 - val\_accuracy: 0.2428

Epoch 24/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1176 -  
accuracy: 0.9680 - val\_loss: 1.9699 - val\_accuracy: 0.2380

Epoch 25/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1095 -  
accuracy: 0.9712 - val\_loss: 1.8254 - val\_accuracy: 0.3003

Epoch 26/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1135 -  
accuracy: 0.9680 - val\_loss: 1.7853 - val\_accuracy: 0.3163

Epoch 27/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1094 -  
accuracy: 0.9716 - val\_loss: 1.7864 - val\_accuracy: 0.3307

Epoch 28/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1105 -  
accuracy: 0.9744 - val\_loss: 1.8322 - val\_accuracy: 0.3259

Epoch 29/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1144 -  
accuracy: 0.9684 - val\_loss: 1.7290 - val\_accuracy: 0.3674

Epoch 30/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1126 -  
accuracy: 0.9744 - val\_loss: 1.7534 - val\_accuracy: 0.3610

Epoch 31/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1113 -  
accuracy: 0.9724 - val\_loss: 1.8818 - val\_accuracy: 0.3243

Epoch 32/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1069 -  
accuracy: 0.9732 - val\_loss: 1.7270 - val\_accuracy: 0.3770

Epoch 33/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1043 -  
accuracy: 0.9732 - val\_loss: 1.7665 - val\_accuracy: 0.3674

Epoch 34/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1075 -  
accuracy: 0.9744 - val\_loss: 1.8006 - val\_accuracy: 0.3626

Epoch 35/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1087 -  
accuracy: 0.9724 - val\_loss: 1.7185 - val\_accuracy: 0.3962

Epoch 36/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1046 -  
accuracy: 0.9752 - val\_loss: 1.7690 - val\_accuracy: 0.3914

Epoch 37/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1046 -  
accuracy: 0.9744 - val\_loss: 1.7832 - val\_accuracy: 0.3866

Epoch 38/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1028 -  
accuracy: 0.9772 - val\_loss: 1.7297 - val\_accuracy: 0.4089

Epoch 39/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1031 -  
accuracy: 0.9760 - val\_loss: 1.6698 - val\_accuracy: 0.4361

Epoch 40/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1048 -  
accuracy: 0.9760 - val\_loss: 1.6268 - val\_accuracy: 0.4473

Epoch 41/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1013 -  
accuracy: 0.9744 - val\_loss: 1.7136 - val\_accuracy: 0.4217

Epoch 42/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1006 -  
accuracy: 0.9788 - val\_loss: 1.5470 - val\_accuracy: 0.4808

Epoch 43/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1002 -  
accuracy: 0.9752 - val\_loss: 1.8153 - val\_accuracy: 0.3978

Epoch 44/70  
157/157 [=====] - 0s 1ms/step - loss: 0.1004 -  
accuracy: 0.9756 - val\_loss: 1.7643 - val\_accuracy: 0.4121

Epoch 45/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0954 -  
accuracy: 0.9780 - val\_loss: 1.8138 - val\_accuracy: 0.4058

Epoch 46/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0969 -  
accuracy: 0.9760 - val\_loss: 1.5965 - val\_accuracy: 0.4744

Epoch 47/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0998 -  
accuracy: 0.9760 - val\_loss: 1.6546 - val\_accuracy: 0.4633

Epoch 48/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0977 -  
accuracy: 0.9764 - val\_loss: 1.7214 - val\_accuracy: 0.4329

Epoch 49/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0930 -  
accuracy: 0.9768 - val\_loss: 1.6842 - val\_accuracy: 0.4489

Epoch 50/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0919 -  
accuracy: 0.9736 - val\_loss: 1.7338 - val\_accuracy: 0.4329

Epoch 51/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0968 -  
accuracy: 0.9756 - val\_loss: 1.7959 - val\_accuracy: 0.4073  
Epoch 52/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0924 -  
accuracy: 0.9792 - val\_loss: 1.7483 - val\_accuracy: 0.4217  
Epoch 53/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0936 -  
accuracy: 0.9788 - val\_loss: 1.6698 - val\_accuracy: 0.4505  
Epoch 54/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0942 -  
accuracy: 0.9776 - val\_loss: 1.7485 - val\_accuracy: 0.4297  
Epoch 55/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0939 -  
accuracy: 0.9764 - val\_loss: 1.7138 - val\_accuracy: 0.4409  
Epoch 56/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0985 -  
accuracy: 0.9744 - val\_loss: 1.7578 - val\_accuracy: 0.4217  
Epoch 57/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0914 -  
accuracy: 0.9776 - val\_loss: 1.6458 - val\_accuracy: 0.4728  
Epoch 58/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0866 -  
accuracy: 0.9792 - val\_loss: 1.7283 - val\_accuracy: 0.4441  
Epoch 59/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0905 -  
accuracy: 0.9768 - val\_loss: 1.7801 - val\_accuracy: 0.4249  
Epoch 60/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0918 -  
accuracy: 0.9748 - val\_loss: 1.5805 - val\_accuracy: 0.5032  
Epoch 61/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0890 -  
accuracy: 0.9780 - val\_loss: 1.6761 - val\_accuracy: 0.4649  
Epoch 62/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0889 -  
accuracy: 0.9788 - val\_loss: 1.7070 - val\_accuracy: 0.4617  
Epoch 63/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0868 -  
accuracy: 0.9792 - val\_loss: 1.6066 - val\_accuracy: 0.5032  
Epoch 64/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0833 -  
accuracy: 0.9788 - val\_loss: 1.7748 - val\_accuracy: 0.4457  
Epoch 65/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0885 -  
accuracy: 0.9776 - val\_loss: 1.5944 - val\_accuracy: 0.4968  
Epoch 66/70  
157/157 [=====] - 0s 1ms/step - loss: 0.0942 -  
accuracy: 0.9760 - val\_loss: 1.5903 - val\_accuracy: 0.5080

```
Epoch 67/70
157/157 [=====] - 0s 1ms/step - loss: 0.0845 -
accuracy: 0.9812 - val_loss: 1.7004 - val_accuracy: 0.4792
Epoch 68/70
157/157 [=====] - 0s 1ms/step - loss: 0.0840 -
accuracy: 0.9804 - val_loss: 1.6196 - val_accuracy: 0.5064
Epoch 69/70
157/157 [=====] - 0s 1ms/step - loss: 0.0805 -
accuracy: 0.9820 - val_loss: 1.6595 - val_accuracy: 0.4936
Epoch 70/70
157/157 [=====] - 0s 1ms/step - loss: 0.0819 -
accuracy: 0.9792 - val_loss: 1.6255 - val_accuracy: 0.5112
Model: "sequential_37"
```

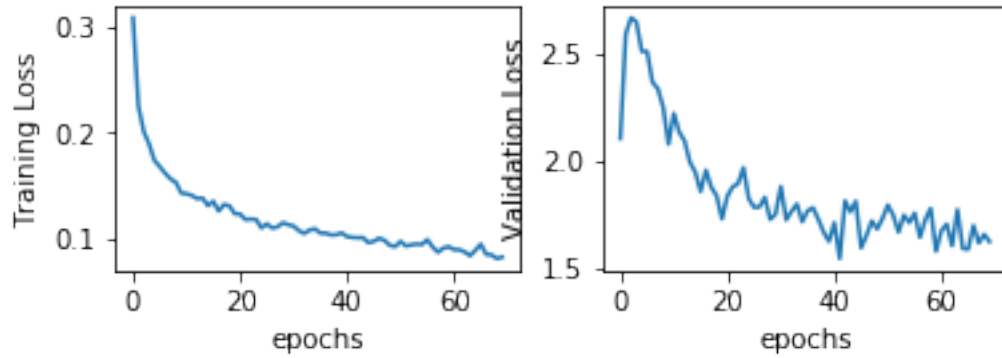
Layer (type)	Output Shape	Param #
dense_108 (Dense)	(None, 10)	3370
dropout_63 (Dropout)	(None, 10)	0
dense_109 (Dense)	(None, 5)	55
dropout_64 (Dropout)	(None, 5)	0
dense_110 (Dense)	(None, 1)	6

Total params: 3,431  
 Trainable params: 3,431  
 Non-trainable params: 0

```
[217]: plt.subplot(2,2,3)
plt.plot(history.history['loss'])
plt.ylabel('Training Loss')
plt.xlabel('epochs')

plt.subplot(2,2,4)
plt.plot(history.history['val_loss'])
plt.ylabel('Validation Loss')
plt.xlabel('epochs')
```

```
[217]: Text(0.5, 0, 'epochs')
```



```
[218]: # now lets see how well the model performed
yhat_proba = model.predict(X_test)
yhat = np.where(yhat_proba > 0.5, 1, 0)
print(mt.confusion_matrix(y_test,yhat))
print(mt.classification_report(y_test,yhat))
```

```
[[1041   23]
 [  28    1]]
```

	precision	recall	f1-score	support
0	0.97	0.98	0.98	1064
1	0.04	0.03	0.04	29
accuracy			0.95	1093
macro avg	0.51	0.51	0.51	1093
weighted avg	0.95	0.95	0.95	1093

No improvement in the results. Since it did not seem to be training very well after a few epochs, I will use relu instead of sigmoid to address gradient issue potentially.

```
[219]: model = Sequential()
model.add(Dense(10, input_dim=num_features, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(5, activation='relu',kernel_regularizer=tf.keras.regularizers.
↪l2(1e-4)))
model.add(Dropout(0.1))
model.add(Dense(1, activation='relu'))
```

```
[220]: model.compile(optimizer='adam',
                    loss='binary_crossentropy',
                    metrics=['accuracy'])
```

```
history = model.fit([X_train],
                    y_train,
                    epochs=70,
                    batch_size=16,
                    verbose=1,
                    validation_split = .2)

model.summary()
```

Epoch 1/70

157/157 [=====] - 0s 2ms/step - loss: 0.7605 -  
accuracy: 0.9504 - val\_loss: 15.4255 - val\_accuracy: 0.0000e+00

Epoch 2/70

157/157 [=====] - 0s 1ms/step - loss: 0.7527 -  
accuracy: 0.9512 - val\_loss: 15.4254 - val\_accuracy: 0.0000e+00

Epoch 3/70

157/157 [=====] - 0s 1ms/step - loss: 0.7531 -  
accuracy: 0.9508 - val\_loss: 15.4253 - val\_accuracy: 0.0000e+00

Epoch 4/70

157/157 [=====] - 0s 1ms/step - loss: 0.7525 -  
accuracy: 0.9512 - val\_loss: 15.4253 - val\_accuracy: 0.0000e+00

Epoch 5/70

157/157 [=====] - 0s 1ms/step - loss: 0.7526 -  
accuracy: 0.9512 - val\_loss: 15.4252 - val\_accuracy: 0.0000e+00

Epoch 6/70

157/157 [=====] - 0s 1ms/step - loss: 0.7524 -  
accuracy: 0.9512 - val\_loss: 15.4252 - val\_accuracy: 0.0000e+00

Epoch 7/70

157/157 [=====] - 0s 1ms/step - loss: 0.7524 -  
accuracy: 0.9512 - val\_loss: 15.4252 - val\_accuracy: 0.0000e+00

Epoch 8/70

157/157 [=====] - 0s 1ms/step - loss: 0.7525 -  
accuracy: 0.9512 - val\_loss: 15.4252 - val\_accuracy: 0.0000e+00

Epoch 9/70

157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4252 - val\_accuracy: 0.0000e+00

Epoch 10/70

157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00

Epoch 11/70

157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00

Epoch 12/70

157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00

Epoch 13/70

157/157 [=====] - 0s 1ms/step - loss: 0.7523 -



accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00  
Epoch 14/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00  
Epoch 15/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00  
Epoch 16/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00  
Epoch 17/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00  
Epoch 18/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00  
Epoch 19/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4251 - val\_accuracy: 0.0000e+00  
Epoch 20/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 21/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 22/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 23/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 24/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 25/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 26/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 27/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 28/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 29/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -

accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 30/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 31/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 32/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 33/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 34/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 35/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 36/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 37/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 38/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 39/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 40/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 41/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7523 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 42/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 43/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 44/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 45/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -

accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 46/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 47/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 48/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 49/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7522 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 50/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 51/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 52/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 53/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 54/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 55/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 56/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 57/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 58/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 59/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 60/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -  
accuracy: 0.9512 - val\_loss: 15.4250 - val\_accuracy: 0.0000e+00  
Epoch 61/70  
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -

```

accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 62/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 63/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 64/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 65/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 66/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 67/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 68/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 69/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Epoch 70/70
157/157 [=====] - 0s 1ms/step - loss: 0.7521 -
accuracy: 0.9512 - val_loss: 15.4250 - val_accuracy: 0.0000e+00
Model: "sequential_38"

```

Layer (type)	Output Shape	Param #
dense_111 (Dense)	(None, 10)	3370
dropout_65 (Dropout)	(None, 10)	0
dense_112 (Dense)	(None, 5)	55
dropout_66 (Dropout)	(None, 5)	0
dense_113 (Dense)	(None, 1)	6

```

Total params: 3,431
Trainable params: 3,431
Non-trainable params: 0

```

```
[221]: %matplotlib inline

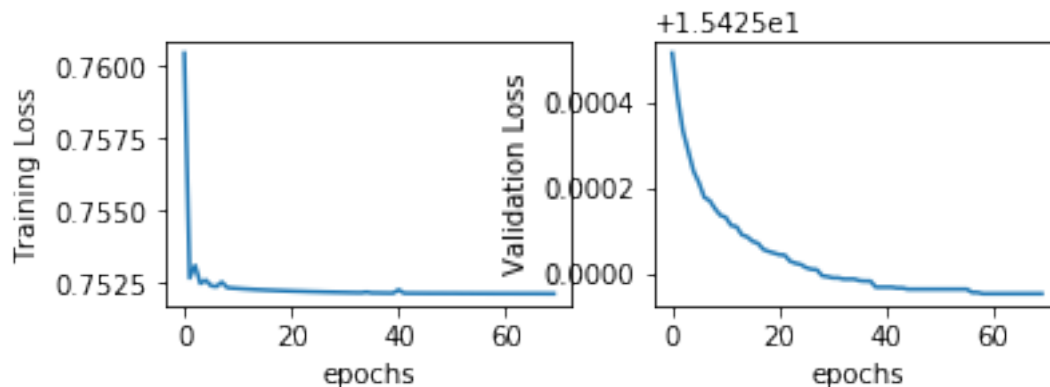
# plt.figure(figsize=(10,4))
# plt.subplot(2,2,1)
# plt.plot(history.history['recall'])

# plt.ylabel('Accuracy %')
# plt.title('Training')
# plt.subplot(2,2,2)
# plt.plot(history.history['val_accuracy'])
# plt.title('Validation')

plt.subplot(2,2,3)
plt.plot(history.history['loss'])
plt.ylabel('Training Loss')
plt.xlabel('epochs')

plt.subplot(2,2,4)
plt.plot(history.history['val_loss'])
plt.ylabel('Validation Loss')
plt.xlabel('epochs')
```

```
[221]: Text(0.5, 0, 'epochs')
```



Looks to be overfitting again, but now at around 40 epochs. The relu has helped to train much faster.

```
[222]: model = Sequential()
model.add(Dense(10, input_dim=num_features, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(5, activation='relu', kernel_regularizer=tf.keras.regularizers.
    ↳l2(1e-4)))
model.add(Dropout(0.1))
```

```

model.add(Dense(1, activation='relu'))

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit([X_train],
                    y_train,
                    epochs=40,
                    batch_size=16,
                    verbose=1,
                    validation_split = .2)

model.summary()

```

```

Epoch 1/40
157/157 [=====] - 0s 2ms/step - loss: 0.6971 -
accuracy: 0.9452 - val_loss: 14.1004 - val_accuracy: 0.0000e+00
Epoch 2/40
157/157 [=====] - 0s 1ms/step - loss: 0.6089 -
accuracy: 0.9552 - val_loss: 13.1706 - val_accuracy: 0.0016
Epoch 3/40
157/157 [=====] - 0s 1ms/step - loss: 0.5847 -
accuracy: 0.9588 - val_loss: 11.8667 - val_accuracy: 0.0304
Epoch 4/40
157/157 [=====] - 0s 1ms/step - loss: 0.5404 -
accuracy: 0.9616 - val_loss: 13.0796 - val_accuracy: 0.0048
Epoch 5/40
157/157 [=====] - 0s 1ms/step - loss: 0.5528 -
accuracy: 0.9636 - val_loss: 13.2361 - val_accuracy: 0.0064
Epoch 6/40
157/157 [=====] - 0s 1ms/step - loss: 0.5506 -
accuracy: 0.9628 - val_loss: 13.2077 - val_accuracy: 0.0096
Epoch 7/40
157/157 [=====] - 0s 1ms/step - loss: 0.5108 -
accuracy: 0.9656 - val_loss: 12.2625 - val_accuracy: 0.0256
Epoch 8/40
157/157 [=====] - 0s 1ms/step - loss: 0.5652 -
accuracy: 0.9620 - val_loss: 13.6683 - val_accuracy: 0.0080
Epoch 9/40
157/157 [=====] - 0s 1ms/step - loss: 0.5318 -
accuracy: 0.9656 - val_loss: 12.6389 - val_accuracy: 0.0240
Epoch 10/40
157/157 [=====] - 0s 1ms/step - loss: 0.5139 -
accuracy: 0.9660 - val_loss: 13.2466 - val_accuracy: 0.0112
Epoch 11/40

```

```

157/157 [=====] - 0s 1ms/step - loss: 0.5627 -
accuracy: 0.9632 - val_loss: 13.5850 - val_accuracy: 0.0128
Epoch 12/40
157/157 [=====] - 0s 1ms/step - loss: 0.5377 -
accuracy: 0.9648 - val_loss: 12.7645 - val_accuracy: 0.0272
Epoch 13/40
157/157 [=====] - 0s 1ms/step - loss: 0.5191 -
accuracy: 0.9660 - val_loss: 13.0016 - val_accuracy: 0.0256
Epoch 14/40
157/157 [=====] - 0s 1ms/step - loss: 0.5126 -
accuracy: 0.9668 - val_loss: 13.0074 - val_accuracy: 0.0256
Epoch 15/40
157/157 [=====] - 0s 1ms/step - loss: 0.5313 -
accuracy: 0.9656 - val_loss: 13.2750 - val_accuracy: 0.0160
Epoch 16/40
157/157 [=====] - 0s 1ms/step - loss: 0.5633 -
accuracy: 0.9632 - val_loss: 13.2336 - val_accuracy: 0.0128
Epoch 17/40
157/157 [=====] - 0s 1ms/step - loss: 0.5372 -
accuracy: 0.9648 - val_loss: 13.4930 - val_accuracy: 0.0128
Epoch 18/40
157/157 [=====] - 0s 1ms/step - loss: 0.5494 -
accuracy: 0.9644 - val_loss: 13.3100 - val_accuracy: 0.0192
Epoch 19/40
157/157 [=====] - 0s 1ms/step - loss: 0.5309 -
accuracy: 0.9656 - val_loss: 13.3550 - val_accuracy: 0.0256
Epoch 20/40
157/157 [=====] - 0s 1ms/step - loss: 0.5369 -
accuracy: 0.9652 - val_loss: 13.7001 - val_accuracy: 0.0160
Epoch 21/40
157/157 [=====] - 0s 1ms/step - loss: 0.5497 -
accuracy: 0.9632 - val_loss: 12.3731 - val_accuracy: 0.0511
Epoch 22/40
157/157 [=====] - 0s 1ms/step - loss: 0.4430 -
accuracy: 0.9660 - val_loss: 4.7972 - val_accuracy: 0.1438
Epoch 23/40
157/157 [=====] - 0s 1ms/step - loss: 0.3935 -
accuracy: 0.9648 - val_loss: 8.7303 - val_accuracy: 0.1166
Epoch 24/40
157/157 [=====] - 0s 1ms/step - loss: 0.4077 -
accuracy: 0.9636 - val_loss: 8.7951 - val_accuracy: 0.0687
Epoch 25/40
157/157 [=====] - 0s 1ms/step - loss: 0.3664 -
accuracy: 0.9664 - val_loss: 7.9730 - val_accuracy: 0.1118
Epoch 26/40
157/157 [=====] - 0s 1ms/step - loss: 0.3658 -
accuracy: 0.9640 - val_loss: 6.0295 - val_accuracy: 0.1725
Epoch 27/40

```

```

157/157 [=====] - 0s 1ms/step - loss: 0.3449 -
accuracy: 0.9656 - val_loss: 6.4255 - val_accuracy: 0.1422
Epoch 28/40
157/157 [=====] - 0s 1ms/step - loss: 0.3644 -
accuracy: 0.9656 - val_loss: 7.5874 - val_accuracy: 0.1278
Epoch 29/40
157/157 [=====] - 0s 1ms/step - loss: 0.3439 -
accuracy: 0.9636 - val_loss: 7.1197 - val_accuracy: 0.1342
Epoch 30/40
157/157 [=====] - 0s 1ms/step - loss: 0.3464 -
accuracy: 0.9680 - val_loss: 7.5189 - val_accuracy: 0.1486
Epoch 31/40
157/157 [=====] - 0s 1ms/step - loss: 0.3427 -
accuracy: 0.9676 - val_loss: 7.6842 - val_accuracy: 0.1278
Epoch 32/40
157/157 [=====] - 0s 1ms/step - loss: 0.3793 -
accuracy: 0.9680 - val_loss: 8.8887 - val_accuracy: 0.1246
Epoch 33/40
157/157 [=====] - 0s 1ms/step - loss: 0.3527 -
accuracy: 0.9688 - val_loss: 9.2948 - val_accuracy: 0.1150
Epoch 34/40
157/157 [=====] - 0s 1ms/step - loss: 0.3691 -
accuracy: 0.9668 - val_loss: 8.4674 - val_accuracy: 0.1502
Epoch 35/40
157/157 [=====] - 0s 1ms/step - loss: 0.3548 -
accuracy: 0.9664 - val_loss: 8.8380 - val_accuracy: 0.1374
Epoch 36/40
157/157 [=====] - 0s 1ms/step - loss: 0.3366 -
accuracy: 0.9708 - val_loss: 8.0470 - val_accuracy: 0.1310
Epoch 37/40
157/157 [=====] - 0s 1ms/step - loss: 0.3511 -
accuracy: 0.9672 - val_loss: 9.0637 - val_accuracy: 0.1150
Epoch 38/40
157/157 [=====] - 0s 1ms/step - loss: 0.3461 -
accuracy: 0.9692 - val_loss: 9.1729 - val_accuracy: 0.1246
Epoch 39/40
157/157 [=====] - 0s 1ms/step - loss: 0.3382 -
accuracy: 0.9680 - val_loss: 6.6909 - val_accuracy: 0.1326
Epoch 40/40
157/157 [=====] - 0s 1ms/step - loss: 0.2840 -
accuracy: 0.9656 - val_loss: 7.8233 - val_accuracy: 0.1182
Model: "sequential_39"

```

Layer (type)	Output Shape	Param #
dense_114 (Dense)	(None, 10)	3370
dropout_67 (Dropout)	(None, 10)	0



```

-----
dense_115 (Dense)                (None, 5)                55
-----
dropout_68 (Dropout)             (None, 5)                0
-----
dense_116 (Dense)                (None, 1)                6
=====
Total params: 3,431
Trainable params: 3,431
Non-trainable params: 0
-----

```

```

[223]: plt.subplot(2,2,3)
plt.plot(history.history['loss'])
plt.ylabel('Training Loss')
plt.xlabel('epochs')

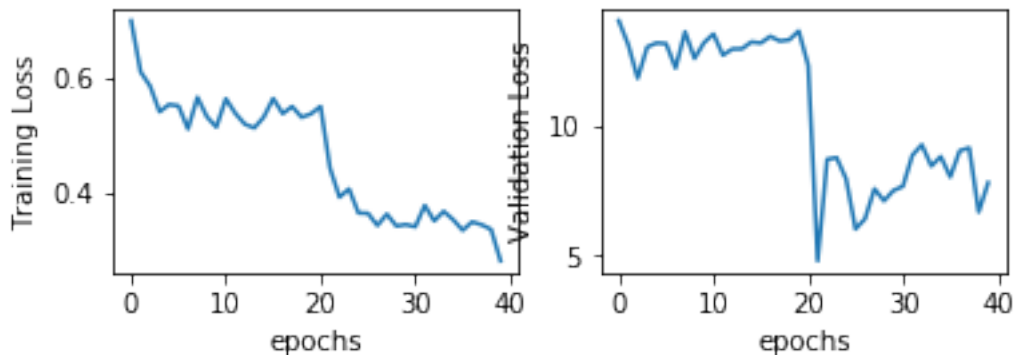
plt.subplot(2,2,4)
plt.plot(history.history['val_loss'])
plt.ylabel('Validation Loss')
plt.xlabel('epochs')

```

```

[223]: Text(0.5, 0, 'epochs')

```



```

[224]: # now lets see how well the model performed
yhat_proba = model.predict(X_test)
yhat = np.where(yhat_proba > 0.5, 1, 0)
print(mt.confusion_matrix(y_test,yhat))
print(mt.classification_report(y_test,yhat))

```

```

[[1061   3]
 [  28   1]]
      precision    recall  f1-score   support


```

0	0.97	1.00	0.99	1064
1	0.25	0.03	0.06	29
accuracy			0.97	1093
macro avg	0.61	0.52	0.52	1093
weighted avg	0.96	0.97	0.96	1093

It does look like the model really struggles to find the global minima and that is to be expected with small data. Last thing I will try is to increase the batch size. I keep in scale of 2.

```
[225]: model = Sequential()
model.add(Dense(10, input_dim=num_features, activation='relu'))
model.add(Dropout(0.25))
model.add(Dense(5, activation='relu', kernel_regularizer=tf.keras.regularizers.
    ↪l2(1e-4)))
model.add(Dropout(0.1))
model.add(Dense(1, activation='relu'))

model.compile(optimizer='adam',
              loss='binary_crossentropy',
              metrics=['accuracy'])

history = model.fit([X_train],
                    y_train,
                    epochs=40,
                    batch_size=24,
                    verbose=1,
                    validation_split = .2)

model.summary()
```

```
Epoch 1/40
105/105 [=====] - 0s 2ms/step - loss: 0.7482 -
accuracy: 0.9496 - val_loss: 15.4039 - val_accuracy: 0.0000e+00
Epoch 2/40
105/105 [=====] - 0s 1ms/step - loss: 0.7608 -
accuracy: 0.9504 - val_loss: 15.4059 - val_accuracy: 0.0000e+00
Epoch 3/40
105/105 [=====] - 0s 1ms/step - loss: 0.7443 -
accuracy: 0.9508 - val_loss: 15.4258 - val_accuracy: 0.0000e+00
Epoch 4/40
105/105 [=====] - 0s 1ms/step - loss: 0.7442 -
accuracy: 0.9512 - val_loss: 15.4258 - val_accuracy: 0.0000e+00
Epoch 5/40
105/105 [=====] - 0s 1ms/step - loss: 0.7440 -
accuracy: 0.9512 - val_loss: 15.4258 - val_accuracy: 0.0000e+00
```

Epoch 6/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7277 -  
accuracy: 0.9508 - val\_loss: 15.4258 - val\_accuracy: 0.0000e+00  
Epoch 7/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7066 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 8/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7073 -  
accuracy: 0.9508 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 9/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7218 -  
accuracy: 0.9508 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 10/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7197 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 11/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7246 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 12/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6690 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 13/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7305 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 14/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7079 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 15/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7081 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 16/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7290 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 17/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7184 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 18/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7391 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 19/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7078 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 20/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6986 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 21/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6930 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00

Epoch 22/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7024 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 23/40  
105/105 [=====] - 0s 2ms/step - loss: 0.7331 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 24/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7121 -  
accuracy: 0.9512 - val\_loss: 15.4257 - val\_accuracy: 0.0000e+00  
Epoch 25/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7128 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 26/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6756 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 27/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6817 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 28/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6868 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 29/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6753 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 30/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6847 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 31/40  
105/105 [=====] - 0s 1ms/step - loss: 0.7002 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 32/40  
105/105 [=====] - 0s 2ms/step - loss: 0.6334 -  
accuracy: 0.9512 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 33/40  
105/105 [=====] - 0s 2ms/step - loss: 0.6548 -  
accuracy: 0.9520 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 34/40  
105/105 [=====] - 0s 2ms/step - loss: 0.6666 -  
accuracy: 0.9516 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 35/40  
105/105 [=====] - 0s 2ms/step - loss: 0.6679 -  
accuracy: 0.9508 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 36/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6853 -  
accuracy: 0.9532 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00  
Epoch 37/40  
105/105 [=====] - 0s 1ms/step - loss: 0.6880 -  
accuracy: 0.9528 - val\_loss: 15.4256 - val\_accuracy: 0.0000e+00

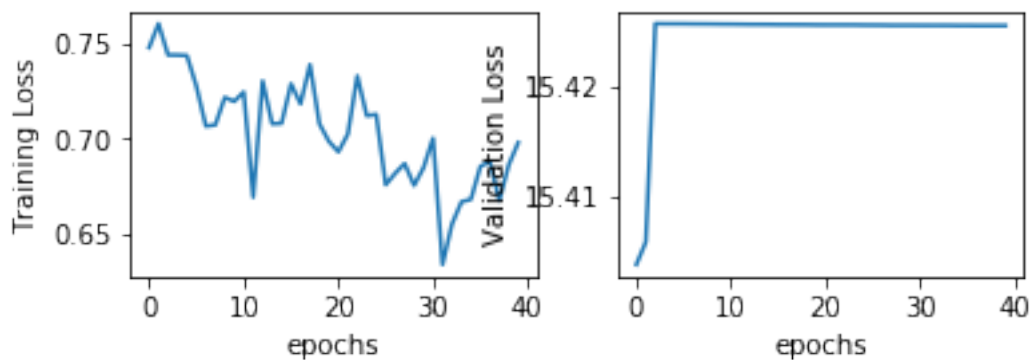
```
Epoch 38/40
105/105 [=====] - 0s 1ms/step - loss: 0.6672 -
accuracy: 0.9532 - val_loss: 15.4256 - val_accuracy: 0.0000e+00
Epoch 39/40
105/105 [=====] - 0s 1ms/step - loss: 0.6862 -
accuracy: 0.9528 - val_loss: 15.4256 - val_accuracy: 0.0000e+00
Epoch 40/40
105/105 [=====] - 0s 2ms/step - loss: 0.6979 -
accuracy: 0.9520 - val_loss: 15.4256 - val_accuracy: 0.0000e+00
Model: "sequential_40"
```

Layer (type)	Output Shape	Param #
dense_117 (Dense)	(None, 10)	3370
dropout_69 (Dropout)	(None, 10)	0
dense_118 (Dense)	(None, 5)	55
dropout_70 (Dropout)	(None, 5)	0
dense_119 (Dense)	(None, 1)	6
Total params: 3,431		
Trainable params: 3,431		
Non-trainable params: 0		

```
[226]: plt.subplot(2,2,3)
plt.plot(history.history['loss'])
plt.ylabel('Training Loss')
plt.xlabel('epochs')

plt.subplot(2,2,4)
plt.plot(history.history['val_loss'])
plt.ylabel('Validation Loss')
plt.xlabel('epochs')
```

```
[226]: Text(0.5, 0, 'epochs')
```



[227]: *# now lets see how well the model performed*

```
yhat_proba = model.predict(X_test)
yhat = np.where(yhat_proba > 0.5, 1, 0)
print(mt.confusion_matrix(y_test,yhat))
print(mt.classification_report(y_test,yhat))
```

```
[[1064    0]
 [   29    0]]
```

	precision	recall	f1-score	support
0	0.97	1.00	0.99	1064
1	0.00	0.00	0.00	29
accuracy			0.97	1093
macro avg	0.49	0.50	0.49	1093
weighted avg	0.95	0.97	0.96	1093

The model just predicts 0 for the entire dataset with larger batch size.

## 2 Conclusion

There does not seem to be anything really here in the data. It is tough to avoid phacking by continuing on and modifying and I do not really see any noticable improvement on a random guess. More data would most likely be helpful.