Binary_Classification_Report (1)

April 11, 2021

0.1 Task 1 Relevance Modelling: Predict the relevance of documents given search interaction features.

Class: CS987

Group: AE

- Andrea Oteo: 202059017
- Ane Etxeandia Erauskin: 202077594
- Crawford Middleton: 202082754
- Daragh McCarthy: 202075755
- Elijah Reid: 202093659

1 Overview and Abstract

Briefly describe what you did

- We began by exploring the data to see what values seemed likely to have an effect on whether the document was classified as relevant or not. Following this, we dropped the variables that we deemed as irrelevant and then used one-hot encoding to transform the categorical variables into numerical ones so they could be better understood by our algorithms. After this we split the data into training, validation and test sets using sci-learn train_test_split before scaling the data to give it a mean of 0 and standard deviation of 1.
- We fed this into a standard machine learning model (random forest classifier) but due the highly skewed nature of the data (relevant documents make up only ~6% of the entire dataset) the performance was not great.
- To alleviate this we created a three-layer neural network as a baseline and experimented with various techniques to overcome the imbalance. This included oversampling, undersampling, ensemble methods, SMOTE, setting the initial bias and class weights to see which would deliver the best performance.
- We also performed data augmentation on the cpvs column to both increase the number of features and rows. We exploded the list to increase length, and then shortened the code to the first two numbers to represent 'division' before one-hot encoding it.
- In the end, the method that gave the best performance was adjusting the class weights to better fit the data, so we decided to move forward using the class weights of the three layer model for our next two models.

- We created a neural network with several more layers than the initial baseline to see if a deeper network would perform better than a shallow one. This turned out to be true although the performance was only mildly better.
- Finally we created a wide and deep network, splitting the inputs into a relevant and irrelevant training set so the network could better learn how to distinguish between the two and hopefuly improve it's classification performance. Ultimately the model's performance was unsatisfactory as it quickly overfit the training data and ended up predicting every document as being irrelevant.

2 Method

2.0.1 Import Modules

```
[ ]: # Include your packages/imports here.
!pip install -q pyyaml h5py

from google.colab import drive

import tensorflow as tf
from tensorflow import keras

import os
import tempfile

import matplotlib as mpl
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure
import numpy as np
import pandas as pd
import seaborn as sns
import math

import sklearn
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score,␣
 ↪precision_score, recall_score, roc_curve,roc_auc_score, classification_report
from sklearn.model_selection import train_test_split, StratifiedKFold,␣
 ↪GridSearchCV, RandomizedSearchCV, cross_val_score, cross_validate
from sklearn.preprocessing import StandardScaler, MinMaxScaler, LabelEncoder

from keras.models import Sequential
from keras.layers import Dense, Flatten, Activation, Dropout
from keras.callbacks import Callback
from keras.utils import normalize, to_categorical
from keras.wrappers.scikit_learn import KerasClassifier
```

```python
from ast import literal_eval
from functools import partial

mpl.rcParams['figure.figsize'] = (12, 10)
colors = plt.rcParams['axes.prop_cycle'].by_key()['color']
```

2.1 Describe the data processing, feature extraction, etc. performed (and why it was performed)

After the data was loaded in, we began by dropping columns that contained too many unique values. This was because our approach was to one-hot encode categorical variables and if we had encoded these variables the model would have ended up overfitting on the training set due to the large number of variables.

While we initially considered dropping the CPVs column for the above reasons, we instead shortened the code to it's first two digits (this refers to the code's division category) to reduce the number of unique variations in the dataset and then encoded this column as well.

2.2 Describe the baseline model to be used (and why it was selected)

The standard machine learning base line algorithm we have selected is the random forest model. Random forest algorithm is an emsemble of decision trees, which is trained using the technique of bagging.

During training the model is focused on selecting the best features instead of instances. The algorithm selects the best features from a random subset of features.

The model is appropriate for several reasons: - the algortihm has high bias/low variance. This is ideal for the dataset as it has a large number of observations compared to the number of features. - it allows us to analyse feature importance by describing the most applicable features to impact a user assessing a document as relevant or not.

2.3 Describe each neural model configuration / setup that will be used.

The model's we have decided to include are the following: - Three Layer MLP model - Dense Deep Model (ultimately 6 layers were selected) - A Wide and Deep Model as we believed this may have helped to reduce the effect of the bias towards irrelevant documents featured in the data (more on this below)

Other models were trialled, including a Deep Belief Network and a Natural Language Model but ultimately, they performed worse both in terms of their f1 score and the time needed to train them.

2.4 Describe the training schedule and approach that you undertook.

While training we used several methods to improve the models performance and limit it from overfitting.

We created a custom dense layer to use, which made use of: - the ELU activation function (This is slower to compute than the standard RELU function, but it makes up for it by tending to converge faster during training) - the He initialiser (this initialisation method is optimised for

ReLU variations) - l2 regularisation (this helps constrain the neural network's connection weights and limits overfitting)

When creating our models, we added both batch normalisation and drop out layers: - Batch normalisation works with the He initialiser and ELU to ensure that the vanishing/exploding gradient problem does not occur by normalising and zero-centring each input and then scaling and shifting the result based on this. - The drop out layer works by giving each neuron a random chance to be dropped out at each training step, helping to prevent overreliance on specific connections and decreasing the error rate in validation.

We decided to use the Nadam optimiser because it is an adaptive optimiser- it combines the Adam optimiser (which is already able to keep track of an exponentially decaying average of past gradient like momentum optimisation, and can keep track of past squared gradients like RMSProp) with the Nesterov trick, allowing it to run slightly faster than the standard Adam optimiser.

Finally, the Learning Rate Scheduler we used was 1cycle scheduling. Unlike most other approaches it increases the learning rate linearly up to halfway through training and then decreases it in the second half, dropping down several orders of magnitude in the last few epochs. We selected it as it has been shown to produce similar validation accuracy results to other methods, but in a far shorter time span.

2.5 Define the functions that will help you to perform the training schedule

[ ]:

```
# Create Dense layer with built in selu function and appropriate regularisation
RegularizedDense = partial(keras.layers.Dense,
                           activation="elu",
                           kernel_initializer="he_normal",
                           kernel_regularizer=keras.regularizers.l1_l2(0.01))

WDRegularizedDense = partial(keras.layers.Dense,
                           activation="selu",
                           kernel_initializer="lecun_normal",
                           kernel_regularizer=keras.regularizers.l1_l2(0.01))

# Sets up all the metrics that allow for the f1_score to be calculated
METRICS = [
      keras.metrics.TruePositives(name='tp'),
      keras.metrics.FalsePositives(name='fp'),
      keras.metrics.TrueNegatives(name='tn'),
      keras.metrics.FalseNegatives(name='fn'),
      keras.metrics.BinaryAccuracy(name='accuracy'),
      keras.metrics.Precision(name='precision'),
      keras.metrics.Recall(name='recall'),
      keras.metrics.AUC(name='auc'),
]

# Implement early stopping to help limit overfitting
early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_precision',
```

```
    verbose=1,
    patience=10,
    mode='max',
    restore_best_weights=True)

# Custom One Cycle Learning Scheduler for use with models
class OneCycleScheduler(keras.callbacks.Callback):
    def __init__(self, iterations, max_rate, start_rate=None,
                 last_iterations=None, last_rate=None):
        self.iterations = iterations
        self.max_rate = max_rate
        self.start_rate = start_rate or max_rate / 10
        self.last_iterations = last_iterations or iterations // 10 + 1
        self.half_iteration = (iterations - self.last_iterations) // 2
        self.last_rate = last_rate or self.start_rate / 1000
        self.iteration = 0
    def _interpolate(self, iter1, iter2, rate1, rate2):
        return ((rate2 - rate1) * (self.iteration - iter1)
                / (iter2 - iter1) + rate1)
    def on_batch_begin(self, batch, logs):
        if self.iteration < self.half_iteration:
            rate = self._interpolate(0, self.half_iteration, self.start_rate,␣
 ↪self.max_rate)
        elif self.iteration < 2 * self.half_iteration:
            rate = self._interpolate(self.half_iteration, 2 * self.
 ↪half_iteration,
                                     self.max_rate, self.start_rate)
        else:
            rate = self._interpolate(2 * self.half_iteration, self.iterations,
                                     self.start_rate, self.last_rate)
        self.iteration += 1
        K.set_value(self.model.optimizer.lr, rate)
```

2.6 Describe any other things that you did or tried in order to improve performance

As the dataset was heavily skewed towards results that were irrelevant (there were only 1962 values for 1 out of 33000 total records - only 5.95% of the total)

To try and alleviate this we used several methods and compared their performance. These are as follows: - We adjusted the biases of the model to try and prevent the model from overfitting on the irrelevant documents (0) and to focus more on the relevant documents (1) to compensate for the vastly different amounts of each. This only applies to the output step however which is less than ideal.

- This did have some effect on the number of false positives, however it led to more false negatives, so we instead decided to adjust the class weights directly. This causes the model to “pay more attention” to examples from an under-represented class” during the training process.

- As a final option we used SMOTE to resample the dataset and oversample the minority class. This means that no adjustments need to be made to the actual model and should improve its ability to recognise what a relevant document looks like.

After trying all 3 methods with our three-layer neural network, both the re-weighted and resampled models performed significantly better than with the models trained on the original data so we continued to use these methods for the dense deep network.

2.6.1 Set-up functions

[ ]:
```
# Add your functions for training here

# one hot encodes categorical variables to allow them to be used in neural␣
 ↪network training
def encode_and_bind(original_dataframe, feature_to_encode):
    dummies = pd.get_dummies(original_dataframe[feature_to_encode])
    res = pd.concat([original_dataframe, dummies], axis=1)
    res = res.drop([feature_to_encode], axis=1)
    return(res)

# Function to display mean and standard deviation of scores for standard␣
 ↪machine learning model
def display_scores(scores):
    print("\nScores:",scores)
    print("\nMean:",scores.mean())
    print("\nStandard Deviation:",scores.std())

# Function to create confusion matrices with various statistics and scores
def plot_cm(labels, predictions, p=0.5):
  cm = confusion_matrix(labels, predictions > p)
  plt.figure(figsize=(5,5))
  sns.heatmap(cm, annot=True, fmt="d")
  plt.title('Confusion matrix @{:.2f}'.format(p))
  plt.ylabel('Actual label')
  plt.xlabel('Predicted label')
  print('f1 Score', (cm[1][1]/(cm[1][1] + (0.5*(cm[0][1] + cm[1][0])))))
  print()

  print('Irrelevant Documents Detected (True Negatives): ', cm[0][0])
  print('Irrelevant Documents Incorrectly Detected (False Positives): ',␣
 ↪cm[0][1])
  print('Relevant Documents Missed (False Negatives): ', cm[1][0])
  print('Relevant Documents Detected (True Positives): ', cm[1][1])
  print('Total Relevant Documents: ', np.sum(cm[1]))

# Function to compare loss performance of two models
```

```python
def plot_loss(history, label, n):
  # Use a log scale on y-axis to show the wide range of values.
  plt.semilogy(history.epoch, history.history['loss'],
               color=colors[n], label='Train ' + label)
  plt.semilogy(history.epoch, history.history['val_loss'],
               color=colors[n], label='Val ' + label,
               linestyle="--")
  plt.xlabel('Epoch')
  plt.ylabel('Loss')

# Function to produce plots of metrics for model training
def plot_metrics(history):
  metrics = ['loss', 'auc', 'precision', 'recall']
  for n, metric in enumerate(metrics):
    name = metric.replace("_"," ").capitalize()
    plt.subplot(2,2,n+1)
    plt.plot(history.epoch, history.history[metric], color=colors[0],␣
 ↪label='Train')
    plt.plot(history.epoch, history.history['val_'+metric],
             color=colors[0], linestyle="--", label='Val')
    plt.xlabel('Epoch')
    plt.ylabel(name)
    if metric == 'loss':
      plt.ylim([0, plt.ylim()[1]])
    elif metric == 'auc':
      plt.ylim([0,1])
    else:
      plt.ylim([0,1])

    plt.legend()

# Function for producing an ROC plot to determine precision and recall of model
def plot_roc(name, labels, predictions, **kwargs):
  fp, tp, _ = sklearn.metrics.roc_curve(labels, predictions)

  plt.plot(100*fp, 100*tp, label=name, linewidth=2, **kwargs)
  plt.xlabel('False positives [%]')
  plt.ylabel('True positives [%]')
  plt.xlim([-0.5,100])
  plt.ylim([0,100.5])
  plt.grid(True)
  ax = plt.gca()
  ax.set_aspect('equal')
```

2.6.2 Models

Final Random Forest Model (Baseline) https://colab.research.google.com/drive/1boa4ZFjmB7C0jcKh6fugi xTP#scrollTo=5hh8XlLyN36C&line=7&uniqifier=1

Three Layer Model Function https://colab.research.google.com/drive/1boa4ZFjmB7C0jcKh6fugi14CXfhQ-xTP#scrollTo=A88mkimt0IDN&line=11&uniqifier=1

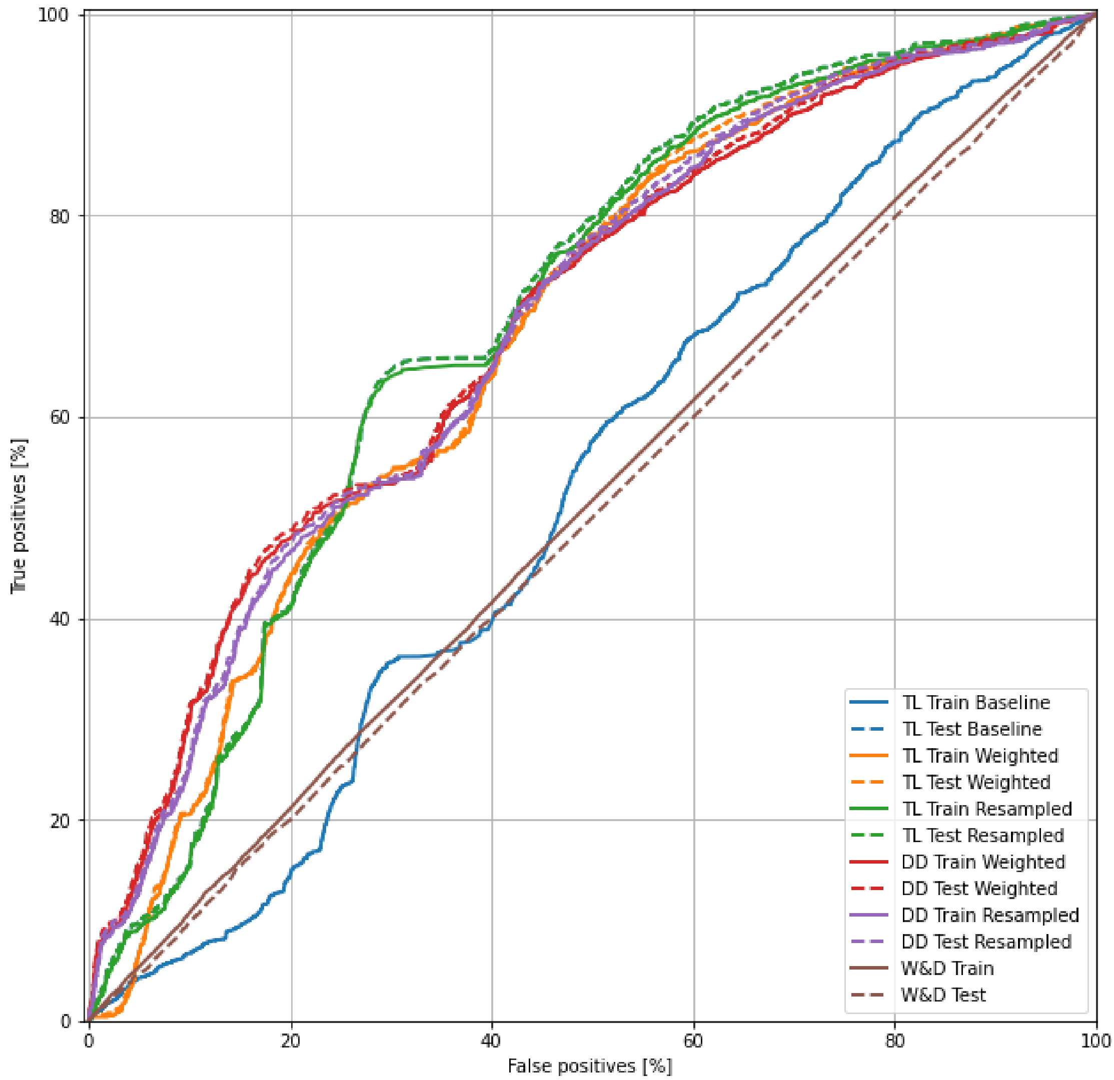
Dense Deep Model Function https://colab.research.google.com/drive/1boa4ZFjmB7C0jcKh6fugi14CXfhQ-xTP#scrollTo=__yMzpAIBxXHB&line=6&uniqifier=1

Wide and Deep Model Class https://colab.research.google.com/drive/1boa4ZFjmB7C0jcKh6fugi14CXfhQ-xTP#scrollTo=Nky1aIvoWBwt&line=6&uniqifier=1

3 Results and Discussion

Model Scores on validation data, loss has been set to 0 for random forests due to the difference of their architectures

The Wide and Deep Model also score highly but this is due to it's f1 score only reflecting it's ability to predict if a document is irrelevant, which it predicted every document as



Graph of each model's train and test performance, comparing percentage of true positives to percentage of false positivies

	Model	Neurons per Layer	Number of Layers	Kernel Initializer	Activation Function	Normalization	Regularisation	Optimizer	Learning Rate Schedule
0	Three Layer Model	30	3	He Initialization	ELU	Batch Normalisation	l1 and l2 regularisation with Dropout if needed	Nadam	1cycle
1	Dense Deep Model	30	5	He Initialization	ELU	Batch Normalisation	l1 and l2 regularisation with Dropout if needed	Nadam	1cycle
2	Wide and Deep Model	30	5 (2 inputs, 2 dense and output)	LeCun Initialization	SELU	None (Self-Normalisation)	l1 and l2 regularisation	Nadam	1cycle

The model that performed the best was the resampled dense deep network, with an f1 score on the test set of (0.10633). However this is only mildly better than the three layer models trained with adjusted class weights and resampled data which score (0.09920) and (0.09267) respectively.

Contrary to our expectations the wide and deep model actually performed the worst as even with a limited epoch run it would very quickly overfit the data and predict all documents as being irrelevant, which scored very well on the skewed training set but poorly on the test set as a result.

Unfortunately even with the methods we've used to try and improve the model's ability to recognise relevant documents, even our best performing model was only able to achieve an F1 score of (0.10633).

	Model	Loss	Accuracy	Precision	Recall	F1 Score
0	Unweighted Random Forest	0.000000	0.929103	1.000000	0.000738	0.001475
1	Weighted Random Forest	0.000000	0.692394	0.174355	0.892949	0.291745
2	Adjusted Bias Three Layer Model	8.002959	0.929050	0.000000	0.000000	0.000000
3	Adjusted Weights Three Layer Model	6.251603	0.921429	0.277863	0.067183	0.108205
4	Resampled Three Layer Model	4.618025	0.555890	0.108872	0.732004	0.189552
5	Dense Deep Model	14.210053	0.095988	0.071944	0.986711	0.134109
6	Resampled Dense Deep Layer Model	6.606988	0.473888	0.100317	0.805094	0.178405
7	Wide and Deep Model	0.257029	0.929050	0.929050	0.929050	0.929050

4 Summary and Recommendations

Based off our results we would recommend that the company should go with our three layer model, as it was the most able to generalise and predict accurately on the test data. The deep dense network also shows promise, and with more in-depth tuning it seems likely that it would be able to outperform the three layer model.

However it still has a lacklustre performance compared to models used for skewed datasets (for instance in credit card fraud detection) and so we would recommend that the company should gather more data points for relevant documents and use these for training their model. Using an embedding layer to include more of the categorical data, and the associations between them would also probably yield better performances.

Alternatively they could train a Generative Adverserial network on the dataset, which would allow them to generate new datapoints and massively improve the performance on the dataset. A Natural Language Model might also be able to perform better on the dataset by reading in the data in text form and converting the cvps codes into their text descriptions.

5 References

- Aurélien Géron (September 2019) *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition edn.*, US: O'Reilly Media, Inc.
- TensorFlow (2020) *Classification on imbalanced data*, Available at: https://www.tensorflow.org/tutorials/structured_data/imbalanced_data

- Andrej Karpathy (2019) *A Recipe for Training Neural Networks*, Available at: http://karpathy.github.io/2019/04/25/recipe/#2-set-up-the-end-to-end-trainingevaluation-skeleton–get-dumb-baselines
- Leslie N. Smith (2018) A disciplined approach to neural network hyper-parameters: Part 1 – learning rate, batch size, momentum, and weight decay
- Nitish Srivastava et al (2014) ‘Dropout: A Simple Way to Prevent Neural Networks from Overfitting’, Journal of Machine Learning Research, 15(), pp. 1929-1958.

6 Code

6.1 Feature Processing

6.1.1 Load in dataset from Github

[ ]:
```
train_url = "https://raw.githubusercontent.com/Wizzzzzzard/Wizzzzzzard/main/
↪CS987/Binary%20Data/train.csv"
test_url = "https://raw.githubusercontent.com/Wizzzzzzard/Wizzzzzzard/main/
↪CS987/Binary%20Data/test.csv"
```

[ ]:
```
train = pd.read_csv(train_url)
test = pd.read_csv(test_url)
```

```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell.py:2718:
DtypeWarning: Columns (16) have mixed types.Specify dtype option on import or
set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

6.1.2 Data processing and exploration

[ ]:
```
train.head()
```

[ ]:
```
         user  … #cpv45
0     8438057  …      1
1     8438876  …      2
2   922102585  …      2
3  2105483652  …      2
4     8438876  …      1

[5 rows x 19 columns]
```

[ ]:
```
test.head()
```

[ ]:
```
         user                           session  … #cpv45  Id
0  2096178939  3C5FDDE0DBC2E5E812A8DFFAB3491DAA  …      1   0
1  2096178939  B9D21C26929EF384ABBB6B544FB38858  …      1   1
2  2096178939  B9D21C26929EF384ABBB6B544FB38858  …      1   2
3  2096178939  B9D21C26929EF384ABBB6B544FB38858  …      2   3
4  2096178939  71182AF6B9BCB557CFA9402F6CD97361  …      1   4
```

```
[5 rows x 19 columns]
```

```
[ ]: # Examine the class label imbalance

neg, pos = np.bincount(train['psrel'])
total = neg + pos
print('Examples:\n    Total: {}\n    Ones: {} ({:.2f}% of total)\n'.format(
    total, pos, 100 * pos / total))
```

```
Examples:
    Total: 33000
    Ones: 1962 (5.95% of total)
```

6.1.3 Clean, split and normalize the data

The raw data has a few issues. First the Time columns as well as the `user`, `session` and `query` columns are too variable to use directly. Drop the Time and other columns (since it's not clear how they would relate to the relevancy in this context) and drop the #`cpvs45` column to remove the colinearity between it and `cpvs`

```
[ ]: cleaned_df = train.copy()

# drop variables
cleaned_df = cleaned_df.drop(["user","session","query", "timestamp", "#cpv45",␣
 ↪"day", "hour","month"], axis=1)
test = test.drop(["user","session","query", "timestamp", "#cpv45", "day",␣
 ↪"hour","month","Id"], axis=1)
```

```
[ ]: # augment cpvs - train - lengthened and widened
cleaned_df['cpvs'] = cleaned_df['cpvs'].apply(literal_eval) #convert to list␣
 ↪type

# explode cpvs list to lengthen dataset
cleaned_df = cleaned_df.explode('cpvs')

# shorten cpvs column to first two numbers which represent division category
cleaned_df['division'] = cleaned_df['cpvs'].astype(str).str[:2]
cleaned_df = cleaned_df.drop("cpvs", axis=1) #drop new column

# augment cpvs - test - only widened - keep 5000 rows
test['cpvs'] = test['cpvs'].apply(literal_eval) #convert to list type
test["cpv_new"] = test["cpvs"].str[0] #copy first entry from each list
test = test.drop("cpvs", axis=1) #drop original column

test["division"] = test['cpv_new'].astype(str).str[:2]
test = test.drop("cpv_new", axis=1) #drop new column column
```

```
[ ]: # One-hot encode the categorical variables that seem like they may have an␣
     ↪effect on the relevancy of the document found

     features_to_encode = ['search', 'source', 'type', 'nature', 'division']

     for feature in features_to_encode:
         cleaned_df = encode_and_bind(cleaned_df, feature)

     for feature in features_to_encode:
         test = encode_and_bind(test, feature)
```

6.2 Training and Validating etc.

- Show your working here – where you report all your training and validation, etc. that you performed in order to get the results.
- Note that it is important that you results can be replicated. All code to reproduce the final predictions must be included, along with any code that justifies your choices.

Split the dataset into train, validation, and test sets.

- The validation set is used during the model fitting to evaluate the loss and any metrics, however the model is not fit with this data.
- The test set is completely unused during the training phase and is only used at the end to evaluate how well the model generalizes to new data.

This is especially important in our case due to the imbalanced dataset as overfitting is a significant concern from the lack of training data.

```
[ ]: # Use sklearn train_test_split to split and shuffle our dataset.
     train_df, test_df = train_test_split(cleaned_df, test_size=0.2)
     train_df, val_df = train_test_split(train_df, test_size=0.2)

     train_wide_and_deep_df, test_wide_and_deep_df = train_test_split(cleaned_df,␣
     ↪test_size=0.2)
     train_wide_and_deep_df, val_wide_and_deep_df =␣
     ↪train_test_split(train_wide_and_deep_df, test_size=0.2)

     # Form np arrays of labels and features.
     train_labels = np.array(train_df.pop('psrel'))
     bool_train_labels = train_labels != 0
     val_labels = np.array(val_df.pop('psrel'))
     test_labels = np.array(test_df.pop('psrel'))

     train_features = np.array(train_df)
     val_features = np.array(val_df)
     test_features = np.array(test_df)
```

[ ]:

```
# wide and deep model feature selection
# ----------------------------------------

## Train
# search
print("advanced: ", train_wide_and_deep_df.columns.get_loc("advanced"))
print("saved: ", train_wide_and_deep_df.columns.get_loc("saved"))
print("dropdown: ", train_wide_and_deep_df.columns.get_loc("dropdown"))
print("quick: ", train_wide_and_deep_df.columns.get_loc("quick"))
# source
print("Contracts Finder: ", train_wide_and_deep_df.columns.get_loc("Contracts␣
↪Finder"))
print("Contrax Weekly: ", train_wide_and_deep_df.columns.get_loc("Contrax␣
↪Weekly"))
print("Defence Contracts International: ", train_wide_and_deep_df.columns.
↪get_loc("Defence Contracts International"))
print("EBS: ", train_wide_and_deep_df.columns.get_loc("EBS"))
print("Exporting Opportunity: ", train_wide_and_deep_df.columns.
↪get_loc("Exporting Opportunity"))
print("FedCon: ", train_wide_and_deep_df.columns.get_loc("FedCon"))
print("Glenigan: ", train_wide_and_deep_df.columns.get_loc("Glenigan"))
print("Intercon: ", train_wide_and_deep_df.columns.get_loc("Intercon"))
print("MoD Contracts Bulletin: ", train_wide_and_deep_df.columns.get_loc("MoD␣
↪Contracts Bulletin"))
print("PCS: ", train_wide_and_deep_df.columns.get_loc("PCS"))
print("Project: ", train_wide_and_deep_df.columns.get_loc("Project"))
print("Tracker: ", train_wide_and_deep_df.columns.get_loc("Tracker"))

# type
print("notice: ", train_wide_and_deep_df.columns.get_loc("notice"))
print("award: ", train_wide_and_deep_df.columns.get_loc("award"))
print("adden: ", train_wide_and_deep_df.columns.get_loc("adden"))
print("tenis: ", train_wide_and_deep_df.columns.get_loc("tenis"))

# nature
print("services: ", train_wide_and_deep_df.columns.get_loc("services"))
print("supplies: ", train_wide_and_deep_df.columns.get_loc("supplies"))
print("works: ", train_wide_and_deep_df.columns.get_loc("works"))

# psrel
print("psrel: ", train_wide_and_deep_df.columns.get_loc("psrel"))


## Test
# search
print("advanced: ", test.columns.get_loc("advanced"))
print("saved: ", test.columns.get_loc("saved"))
```

```
print("dropdown: ", test.columns.get_loc("dropdown"))
print("quick: ", test.columns.get_loc("quick"))
# source
print("Contracts Finder: ", test.columns.get_loc("Contracts Finder"))
print("Contrax Weekly: ", test.columns.get_loc("Contrax Weekly"))
print("Defence Contracts International: ", test.columns.get_loc("Defence␣
↪Contracts International"))
print("EBS: ", test.columns.get_loc("EBS"))
print("Exporting Opportunity: ", test.columns.get_loc("Exporting Opportunity"))
print("FedCon: ", test.columns.get_loc("FedCon"))
print("Glenigan: ", test.columns.get_loc("Glenigan"))
print("Intercon: ", test.columns.get_loc("Intercon"))
print("MoD Contracts Bulletin: ", test.columns.get_loc("MoD Contracts␣
↪Bulletin"))
print("PCS: ", test.columns.get_loc("PCS"))
print("Project: ", test.columns.get_loc("Project"))
print("Tracker: ", test.columns.get_loc("Tracker"))

# type
print("notice: ", test.columns.get_loc("notice"))
print("award: ", test.columns.get_loc("award"))
print("adden: ", test.columns.get_loc("adden"))
print("tenis: ", test.columns.get_loc("tenis"))

# nature
print("services: ", test.columns.get_loc("services"))
print("supplies: ", test.columns.get_loc("supplies"))
print("works: ", test.columns.get_loc("works"))
```

```
advanced:  6
saved:  9
dropdown:  7
quick:  8
Contracts Finder:  10
Contrax Weekly:  11
Defence Contracts International:  12
EBS:  13
Exporting Opportunity:  14
FedCon:  15
Glenigan:  16
Intercon:  17
MoD Contracts Bulletin:  18
PCS:  19
Project:  20
Tracker:  21
notice:  24
award:  23
```

```
adden:  22
tenis:  25
services:  26
supplies:  27
works:  28
psrel:  5
advanced:  5
saved:  8
dropdown:  6
quick:  7
Contracts Finder:  9
Contrax Weekly:  10
Defence Contracts International:  11
EBS:  12
Exporting Opportunity:  13
FedCon:  14
Glenigan:  15
Intercon:  16
MoD Contracts Bulletin:  17
PCS:  18
Project:  19
Tracker:  20
notice:  23
award:  22
adden:  21
tenis:  24
services:  25
supplies:  26
works:  27
```

[ ]:
```
wide_train_df = train_wide_and_deep_df.iloc[:,
 ↪[5,6,9,7,8,10,11,12,13,14,15,16,17,18,19,20,21,24,23,22,25,26,27,28]]
deep_train_df = train_wide_and_deep_df

wide_val_df = val_wide_and_deep_df.iloc[:,
 ↪[5,6,9,7,8,10,11,12,13,14,15,16,17,18,19,20,21,24,23,22,25,26,27,28]]
deep_val_df = val_wide_and_deep_df

wide_test_df = test_wide_and_deep_df.iloc[:,
 ↪[5,6,9,7,8,10,11,12,13,14,15,16,17,18,19,20,21,24,23,22,25,26,27,28]]
deep_test_df = test_wide_and_deep_df

wide_test = test.iloc[:,
 ↪[5,8,6,7,9,10,11,12,13,14,15,16,17,18,19,20,23,22,21,24,26,26,27]]
deep_test = test
```

```
[ ]: # Form np arrays of labels and features.
wide_train_labels = np.array(wide_train_df.pop('psrel'))
wide_bool_train_labels = wide_train_labels != 0
wide_val_labels = np.array(wide_val_df.pop('psrel'))
wide_test_labels = np.array(wide_test_df.pop('psrel'))

wide_train_features = np.array(wide_train_df)
wide_val_features = np.array(wide_val_df)
wide_test_features = np.array(wide_test_df)

#wide_test = np.array(wide_test)
```

```
[ ]: # Form np arrays of labels and features.
deep_train_labels = np.array(deep_train_df.pop('psrel'))
deep_bool_train_labels = deep_train_labels != 0
deep_val_labels = np.array(deep_val_df.pop('psrel'))
deep_test_labels = np.array(deep_test_df.pop('psrel'))

deep_train_features = np.array(deep_train_df)
deep_val_features = np.array(deep_val_df)
deep_test_features = np.array(deep_test_df)

#deep_test = np.array(deep_test)
```

Normalize the input features using the sklearn StandardScaler - this will set the mean to 0 and standard deviation to 1.

Only the `StandardScaler` is fit using the `train_features` to ensure the model is not gaining any information about the validation or test sets.

```
[ ]: scaler = StandardScaler()

train_df, test_df = train_test_split(cleaned_df, test_size=0.2)

X = cleaned_df.drop(labels="psrel", axis=1)
y = cleaned_df['psrel']

X_train, X_test, y_train, y_test = train_test_split(X, y)

train_features = scaler.fit_transform(train_features)

val_features = scaler.transform(val_features)
test_features = scaler.transform(test_features) # This is to be used to compare␣
 ↪the predictions after training has occurred
test = scaler.transform(test) # this is the originally imported test that will␣
 ↪be used for final predictions

train_features = np.clip(train_features, -5, 5)
```

```
val_features = np.clip(val_features, -5, 5)
test_features = np.clip(test_features, -5, 5)
test = np.clip(test, -5, 5)


print('Training labels shape:', train_labels.shape)
print('Validation labels shape:', val_labels.shape)
print('Test labels shape:', test_labels.shape)

print('Training features shape:', train_features.shape)
print('Validation features shape:', val_features.shape)
print('Test features shape:', test_features.shape)

print('Test shape', test.shape)
```

```
Training labels shape: (122179,)
Validation labels shape: (30545,)
Test labels shape: (38182,)
Training features shape: (122179, 74)
Validation features shape: (30545, 74)
Test features shape: (38182, 74)
Test shape (5000, 74)
```

[ ]:
```
wide_test.shape
```

[ ]: (5000, 23)

[ ]:
```
wide_train_features = scaler.fit_transform(wide_train_features)

wide_val_features = scaler.transform(wide_val_features)
wide_test_features = scaler.transform(wide_test_features) # This is to be used␣
↪to compare the predictions after training has occurred
wide_test = scaler.transform(wide_test) # this is the originally imported test␣
↪that will be used for final predictions

wide_train_features = np.clip(wide_train_features, -5, 5)
wide_val_features = np.clip(wide_val_features, -5, 5)
wide_test_features = np.clip(wide_test_features, -5, 5)
wide_test = np.clip(wide_test, -5, 5)

print('Wide Training labels shape:', wide_train_labels.shape)
print('Wide Validation labels shape:', wide_val_labels.shape)
print('Wide Test labels shape:', wide_test_labels.shape)

print('Wide Training features shape:', wide_train_features.shape)
print('Wide Validation features shape:', wide_val_features.shape)
print('Wide Test features shape:', wide_test_features.shape)
```

```
print('Wide Test shape', wide_test.shape)
```

```
Wide Training labels shape: (122179,)
Wide Validation labels shape: (30545,)
Wide Test labels shape: (38182,)
Wide Training features shape: (122179, 23)
Wide Validation features shape: (30545, 23)
Wide Test features shape: (38182, 23)
Wide Test shape (5000, 23)
```

[ ]:
```
deep_train_features = scaler.fit_transform(deep_train_features)

deep_val_features = scaler.transform(deep_val_features)
deep_test_features = scaler.transform(deep_test_features) # This is to be used␣
↪to compare the predictions after training has occurred
deep_test = scaler.transform(deep_test) # this is the originally imported test␣
↪that will be used for final predictions


deep_train_features = np.clip(deep_train_features, -5, 5)
deep_val_features = np.clip(deep_val_features, -5, 5)
deep_test_features = np.clip(deep_test_features, -5, 5)
deep_test = np.clip(deep_test, -5, 5)


print('Deep Training labels shape:', deep_train_labels.shape)
print('Deep Validation labels shape:', deep_val_labels.shape)
print('Deep Test labels shape:', deep_test_labels.shape)

print('Deep Training features shape:', deep_train_features.shape)
print('Deep Validation features shape:', deep_val_features.shape)
print('Deep Test features shape:', deep_test_features.shape)

print('Deep Test shape', deep_test.shape)
```

```
Deep Training labels shape: (122179,)
Deep Validation labels shape: (30545,)
Deep Test labels shape: (38182,)
Deep Training features shape: (122179, 74)
Deep Validation features shape: (30545, 74)
Deep Test features shape: (38182, 74)
Deep Test shape (5000, 74)
```

###Standard Machine Learning Model Baseline - Random Forest (Decision Tree Ensemble)

[ ]:
```
# perform a grid search to determine optimal hyperparameters for this model
```

```python
"""param_grid = {
    'criterion': ["gini", "entropy"],
    'max_features': ["auto", "sqrt", "log2"],
    'max_leaf_nodes': [1, 10, 100],
    'min_samples_leaf': [1, 10, 100],
    'n_estimators': [200, 250, 300]
}

rnd_clf = RandomForestClassifier()

grid_search = GridSearchCV(estimator = rnd_clf, param_grid = param_grid,
                          cv = 5, n_jobs = -1)
grid_search.fit(train_features, train_labels)
grid_search.best_params_"""
```

[ ]:

```
'param_grid = {\n    \'criterion\': ["gini", "entropy"],\n    \'max_features\':
["auto", "sqrt", "log2"],\n    \'max_leaf_nodes\': [1, 10, 100],\n
\'min_samples_leaf\': [1, 10, 100],\n    \'n_estimators\': [200, 250,
300]\n}\n\nrnd_clf = RandomForestClassifier()\n\ngrid_search =
GridSearchCV(estimator = rnd_clf, param_grid = param_grid, \n
cv = 5, n_jobs = -1)\ngrid_search.fit(train_features,
train_labels)\ngrid_search.best_params_'
```

[ ]:

```python
# Standard Machine Learning Model
rnd_clf = RandomForestClassifier(criterion = "gini",
                                 n_estimators=200,
                                 max_leaf_nodes=100,
                                 min_samples_leaf=1,
                                 max_features="sqrt",
                                 n_jobs=-1)
```

[ ]:

```python
rnd_clf.fit(train_features, train_labels)

pred_labels = rnd_clf.predict(test_features)

scores = cross_validate(rnd_clf, train_features, train_labels,
                        scoring=('accuracy'),cv=10)

unwt_rnd = {'Model': 'Unweighted Random Forest',
                'Loss': 0,
                'Accuracy': accuracy_score(test_labels, pred_labels),
                'Precision': precision_score(test_labels, pred_labels),
                'Recall': recall_score(test_labels, pred_labels),
                'F1 Score': f1_score(test_labels, pred_labels)}
```

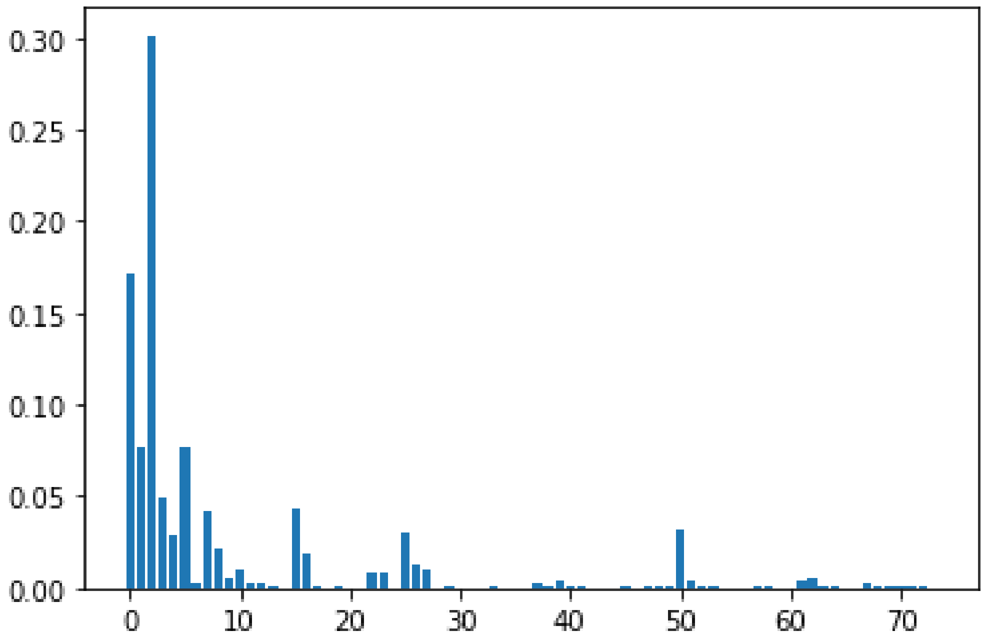
```
unwt_rnd
```

[ ]:
```
{'Accuracy': 0.9302550940233618,
 'F1 Score': 0.010405053883314752,
 'Loss': 0,
 'Model': 'Unweighted Random Forest',
 'Precision': 1.0,
 'Recall': 0.005229734777736272}
```

[ ]:
```
# get importance
importance = rnd_clf.feature_importances_
# summarize feature importance
for i,v in enumerate(importance):
        print('Feature: %0d, Score: %.5f' % (i,v))
# plot feature importance
plt.bar([x for x in range(len(importance))], importance)
plt.show()
```

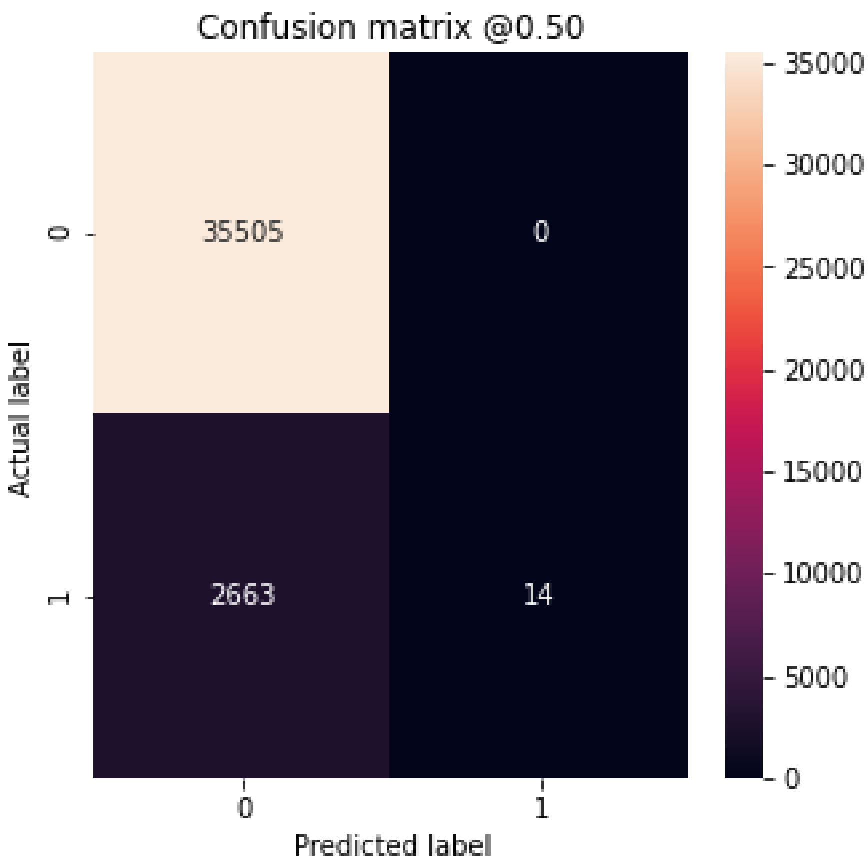
```
Feature: 0, Score: 0.17117
Feature: 1, Score: 0.07676
Feature: 2, Score: 0.30138
Feature: 3, Score: 0.04864
Feature: 4, Score: 0.02851
Feature: 5, Score: 0.07690
Feature: 6, Score: 0.00197
Feature: 7, Score: 0.04160
Feature: 8, Score: 0.02170
Feature: 9, Score: 0.00553
Feature: 10, Score: 0.01000
Feature: 11, Score: 0.00256
Feature: 12, Score: 0.00219
Feature: 13, Score: 0.00050
Feature: 14, Score: 0.00001
Feature: 15, Score: 0.04345
Feature: 16, Score: 0.01836
Feature: 17, Score: 0.00073
Feature: 18, Score: 0.00042
Feature: 19, Score: 0.00110
Feature: 20, Score: 0.00007
Feature: 21, Score: 0.00039
Feature: 22, Score: 0.00807
Feature: 23, Score: 0.00812
Feature: 24, Score: 0.00024
Feature: 25, Score: 0.03018
Feature: 26, Score: 0.01237
Feature: 27, Score: 0.00975
Feature: 28, Score: 0.00007
Feature: 29, Score: 0.00080
```

```
Feature: 30, Score: 0.00014
Feature: 31, Score: 0.00033
Feature: 32, Score: 0.00005
Feature: 33, Score: 0.00125
Feature: 34, Score: 0.00005
Feature: 35, Score: 0.00038
Feature: 36, Score: 0.00006
Feature: 37, Score: 0.00310
Feature: 38, Score: 0.00072
Feature: 39, Score: 0.00448
Feature: 40, Score: 0.00052
Feature: 41, Score: 0.00086
Feature: 42, Score: 0.00025
Feature: 43, Score: 0.00017
Feature: 44, Score: 0.00021
Feature: 45, Score: 0.00057
Feature: 46, Score: 0.00018
Feature: 47, Score: 0.00047
Feature: 48, Score: 0.00075
Feature: 49, Score: 0.00119
Feature: 50, Score: 0.03232
Feature: 51, Score: 0.00368
Feature: 52, Score: 0.00110
Feature: 53, Score: 0.00070
Feature: 54, Score: 0.00042
Feature: 55, Score: 0.00015
Feature: 56, Score: 0.00020
Feature: 57, Score: 0.00099
Feature: 58, Score: 0.00061
Feature: 59, Score: 0.00023
Feature: 60, Score: 0.00044
Feature: 61, Score: 0.00447
Feature: 62, Score: 0.00549
Feature: 63, Score: 0.00099
Feature: 64, Score: 0.00063
Feature: 65, Score: 0.00013
Feature: 66, Score: 0.00036
Feature: 67, Score: 0.00307
Feature: 68, Score: 0.00085
Feature: 69, Score: 0.00090
Feature: 70, Score: 0.00173
Feature: 71, Score: 0.00062
Feature: 72, Score: 0.00047
Feature: 73, Score: 0.00021
```



[ ]:
```
train_predictions_baseline = rnd_clf.predict(train_features)
test_predictions_baseline = rnd_clf.predict(test_features)

plot_cm(test_labels, test_predictions_baseline)
```

```
f1 Score 0.010405053883314752

Irrelevant Documents Detected (True Negatives):  35505
Irrelevant Documents Incorrectly Detected (False Positives):  0
Relevant Documents Missed (False Negatives):  2663
Relevant Documents Detected (True Positives):  14
Total Relevant Documents:  2677
```



[ ]:
```
test_predictions_baseline = rnd_clf.predict(test)
test_predictions_baseline = test_predictions_baseline.round(0)
test_predictions_baseline = test_predictions_baseline.astype(int)
test_predictions_baseline
```

[ ]: array([0, 0, 0, …, 0, 0, 0])

[ ]:
```
predictions_baseline= pd.DataFrame(test_predictions_baseline)
predictions_baseline['Id'] = predictions_baseline.index
predictions_baseline.rename(columns={ predictions_baseline.columns[0]: "psrel"␣
↪}, inplace = True)
predictions_baseline = predictions_baseline[['Id','psrel']]
predictions_baseline
```

[ ]:

	Id	psrel
0	0	0
1	1	0
2	2	0
3	3	0

```
4          4      0
…     …     …
4995   4995      0
4996   4996      0
4997   4997      0
4998   4998      0
4999   4999      0

[5000 rows x 2 columns]
```

[ ]:
```
predictions_baseline['psrel'].value_counts()
```

[ ]:
```
0    5000
Name: psrel, dtype: int64
```

[ ]:
```
predictions_baseline.to_csv('Random Forest colab predictions.csv', index=False)
```

Data is still currently too skewed for standard machine learning model to accurately predict true positives. Will use large batch sizes for neural network training to try and ensure some positive values are included per batch, as well as other methods detailed below

6.2.1 Three Layer Model Baseline

[ ]:
```
EPOCHS = 100
BATCH_SIZE = 2048

early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_precision',
    verbose=1,
    patience=10,
    mode='max',
    restore_best_weights=True)

# I've replaced val_auc for val_tp for monitor to see if getting more true␣
↪positives will improve performance
```

Three Layer Model function

[ ]:
```
# Three Layer Learning Model function
def build_three_layer_model(n_hidden=3, n_neurons=30, learning_rate=3e-4,␣
↪metrics=METRICS, output_bias=None, input_shape=train_features.shape[1:]):
    if output_bias is not None:
      output_bias = tf.keras.initializers.Constant(output_bias)
    model = keras.models.Sequential()
    model.add(keras.layers.InputLayer(input_shape=input_shape))
    for layer in range(n_hidden):
        model.add(RegularizedDense(n_neurons))
        model.add(keras.layers.BatchNormalization())
```

```
        model.add(keras.layers.Dropout(rate=0.3)),
    model.add(keras.layers.Dense(1, activation="sigmoid",␣
↪bias_initializer=output_bias))

    optimizer = keras.optimizers.Nadam(lr=learning_rate)
    model.compile(loss="binary_crossentropy", optimizer=optimizer,␣
↪metrics=metrics)

    return model
```

[ ]:
```
# Create a default three layer model using the build_three_layer_model function

three_layer_keras_reg = keras.wrappers.scikit_learn.
↪KerasRegressor(build_three_layer_model)

three_layer_model = build_three_layer_model()
three_layer_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 30)                2250
_________________________________________________________________
batch_normalization (BatchNo (None, 30)                120
_________________________________________________________________
dropout (Dropout)            (None, 30)                0
_________________________________________________________________
dense_1 (Dense)              (None, 30)                930
_________________________________________________________________
batch_normalization_1 (Batch (None, 30)                120
_________________________________________________________________
dropout_1 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_2 (Dense)              (None, 30)                930
_________________________________________________________________
batch_normalization_2 (Batch (None, 30)                120
_________________________________________________________________
dropout_2 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 31
=================================================================
Total params: 4,501
Trainable params: 4,321
Non-trainable params: 180
_________________________________________________________________
```

[ ]:
```
# Create onecycle for models
onecycle = OneCycleScheduler(math.ceil(len(train_labels) / BATCH_SIZE) *␣
↪EPOCHS, max_rate=0.05)
```

Test run to compare predictions on train set vs actual values (naive predictions)

[ ]:
```
three_layer_model.predict(train_features[:10])
```

[ ]:
```
array([[0.8346735 ],
       [0.27901396],
       [0.43054563],
       [0.3553014 ],
       [0.7721624 ],
       [0.781099  ],
       [0.5588717 ],
       [0.8045237 ],
       [0.96360946],
       [0.604001  ]], dtype=float32)
```

[ ]:
```
train_labels[:10]
```

[ ]:
```
array([0, 0, 1, 0, 0, 0, 0, 0, 0, 0])
```

Every prediction was wrong so we'll try some methods to improve this

Adjusting bias Set correct initial bias to stop the algorithm from overfitting on the 0's

[ ]:
```
# Current Loss

results = three_layer_model.evaluate(train_features, train_labels,␣
↪batch_size=BATCH_SIZE, verbose=0)
print("Loss: {:0.4f}".format(results[0]))
```

```
Loss: 9.7782
```

[ ]:
```
# What Loss should be, derived from equations
initial_bias = np.log([pos/neg])
initial_bias
```

[ ]:
```
array([-2.7612479])
```

[ ]:
```
pos/total
```

[ ]:
```
0.059454545454545454
```

[ ]:
```
three_layer_model = build_three_layer_model(output_bias=initial_bias)
three_layer_model.predict(train_features[:10])
```

[ ]:
```
array([[0.52869797],
       [0.03223044],
       [0.02136847],
       [0.08165911],
       [0.06045404],
       [0.13303357],
       [0.0526365 ],
       [0.04584333],
       [0.06245753],
       [0.0207577 ]], dtype=float32)
```

[ ]:
```
# As a result the initial loss is much less reducng the time needed for the␣
↪neural network to initialise

results = three_layer_model.evaluate(train_features, train_labels,␣
↪batch_size=BATCH_SIZE, verbose=0)
print("Loss: {:0.4f}".format(results[0]))
```

```
Loss: 8.9992
```

To make the various training runs more comparable, keep the initial model's weights in a checkpoint file, and load them into each model before training.

[ ]:
```
initial_weights = os.path.join(tempfile.mkdtemp(), 'initial_weights')
three_layer_model.save_weights(initial_weights)
```

Before moving on, confirm quick that the careful bias initialisation actually helped.

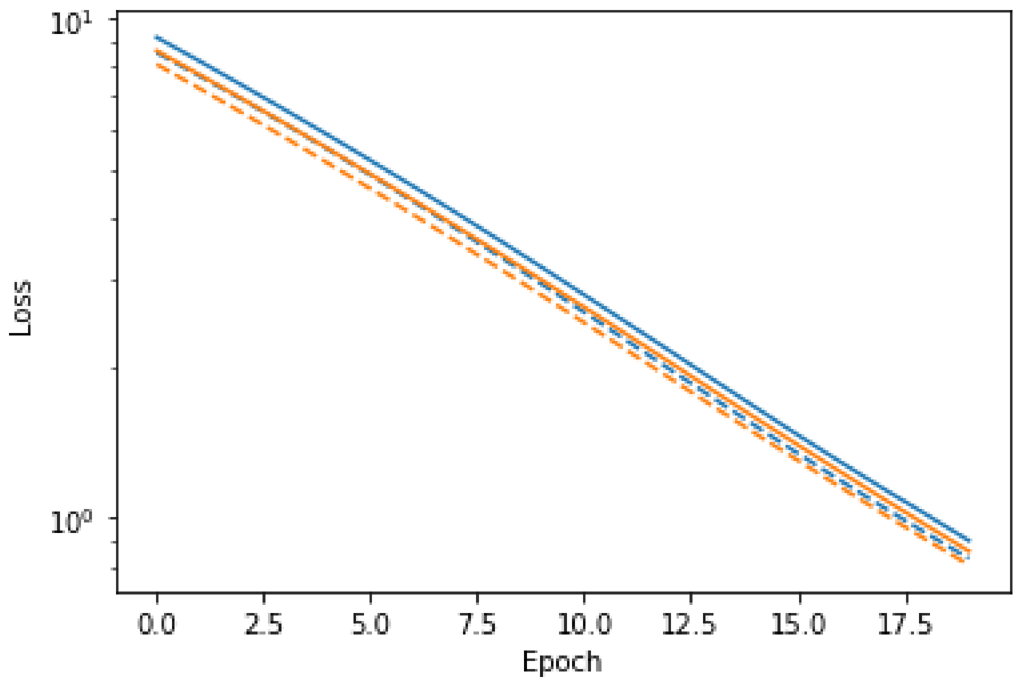
Train the model for 20 epochs, with and without this careful initialisation, and compare the losses:

[ ]:
```
# Without bias initialisation

three_layer_model = build_three_layer_model()
three_layer_model.load_weights(initial_weights)
three_layer_model.layers[-1].bias.assign([0.0])
zero_bias_history = three_layer_model.fit(
    train_features,
    train_labels,
    batch_size=BATCH_SIZE,
    epochs=20,
    validation_data=(val_features, val_labels),
    verbose=0)
```

[ ]:
```
# With bias initialisation

three_layer_model = build_three_layer_model()
three_layer_model.load_weights(initial_weights)
careful_bias_history = three_layer_model.fit(
    train_features,
```

```
    train_labels,
    batch_size=BATCH_SIZE,
    epochs=20,
    validation_data=(val_features, val_labels),
    verbose=0)
```

[ ]:
```
plot_loss(zero_bias_history, "Zero Bias", 0) #blue
plot_loss(careful_bias_history, "Careful Bias", 1) #orange
```



Train a model with adjusted biases

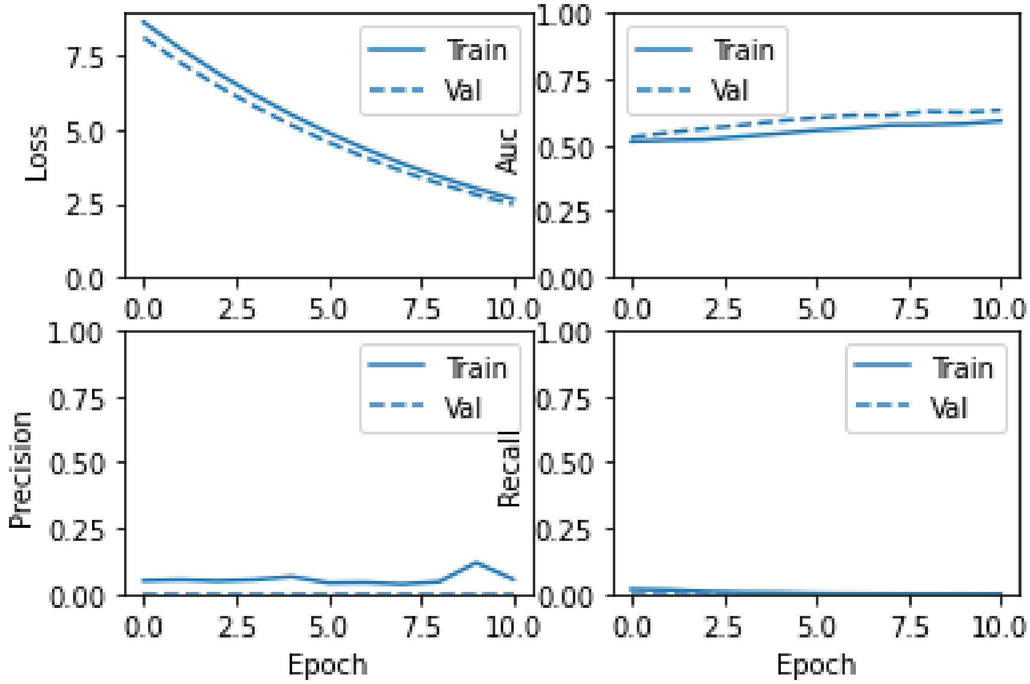
[ ]:
```
three_layer_model = build_three_layer_model()
three_layer_model.load_weights(initial_weights)
baseline_history = three_layer_model.fit(
    train_features,
    train_labels,
    batch_size=BATCH_SIZE,
    epochs=EPOCHS,
    callbacks=[early_stopping],
    validation_data=(val_features, val_labels))
```

```
Epoch 1/100
60/60 [==============================] - 6s 37ms/step - loss: 8.8345 - tp:
104.9344 - fp: 2083.7705 - tn: 85106.7213 - fn: 6681.0164 - accuracy: 0.9085 -
precision: 0.0459 - recall: 0.0139 - auc: 0.5368 - val_loss: 8.0972 - val_tp:
0.0000e+00 - val_fp: 25.0000 - val_tn: 28336.0000 - val_fn: 2184.0000 -
```

```
val_accuracy: 0.9277 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.5302
Epoch 2/100
60/60 [==============================] - 1s 21ms/step - loss: 7.9342 - tp:
77.3934 - fp: 1336.8852 - tn: 57450.1803 - fn: 4566.9836 - accuracy: 0.9055 -
precision: 0.0558 - recall: 0.0178 - auc: 0.5139 - val_loss: 7.2461 - val_tp:
0.0000e+00 - val_fp: 2.0000 - val_tn: 28359.0000 - val_fn: 2184.0000 -
val_accuracy: 0.9284 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.5476
Epoch 3/100
60/60 [==============================] - 1s 21ms/step - loss: 7.0935 - tp:
45.2623 - fp: 863.1311 - tn: 57959.3279 - fn: 4563.7213 - accuracy: 0.9147 -
precision: 0.0486 - recall: 0.0100 - auc: 0.5158 - val_loss: 6.4770 - val_tp:
0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000 -
val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.5632
Epoch 4/100
60/60 [==============================] - 1s 25ms/step - loss: 6.3396 - tp:
26.7869 - fp: 526.2787 - tn: 58287.2459 - fn: 4591.1311 - accuracy: 0.9184 -
precision: 0.0454 - recall: 0.0056 - auc: 0.5282 - val_loss: 5.7780 - val_tp:
0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000 -
val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.5762
Epoch 5/100
60/60 [==============================] - 1s 21ms/step - loss: 5.6476 - tp:
22.0656 - fp: 351.6066 - tn: 58485.8033 - fn: 4571.9672 - accuracy: 0.9225 -
precision: 0.0579 - recall: 0.0049 - auc: 0.5411 - val_loss: 5.1424 - val_tp:
0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000 -
val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.5924
Epoch 6/100
60/60 [==============================] - 1s 21ms/step - loss: 5.0231 - tp:
9.8197 - fp: 236.3115 - tn: 58587.8033 - fn: 4597.5082 - accuracy: 0.9240 -
precision: 0.0396 - recall: 0.0022 - auc: 0.5542 - val_loss: 4.5689 - val_tp:
0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000 -
val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.6043
Epoch 7/100
60/60 [==============================] - 1s 22ms/step - loss: 4.4665 - tp:
5.8197 - fp: 144.8689 - tn: 58611.3770 - fn: 4669.3770 - accuracy: 0.9236 -
precision: 0.0376 - recall: 0.0013 - auc: 0.5623 - val_loss: 4.0511 - val_tp:
0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000 -
val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.6135
Epoch 8/100
60/60 [==============================] - 1s 21ms/step - loss: 3.9552 - tp:
2.7541 - fp: 103.0656 - tn: 58686.6066 - fn: 4639.0164 - accuracy: 0.9254 -
precision: 0.0235 - recall: 5.4982e-04 - auc: 0.5736 - val_loss: 3.5852 -
```

```
val_tp: 0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000
- val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.6127
Epoch 9/100
60/60 [==============================] - 1s 20ms/step - loss: 3.4984 - tp:
2.2951 - fp: 58.1639 - tn: 58744.4262 - fn: 4626.5574 - accuracy: 0.9261 -
precision: 0.0315 - recall: 4.2355e-04 - auc: 0.5794 - val_loss: 3.1677 -
val_tp: 0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000
- val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.6282
Epoch 10/100
60/60 [==============================] - 1s 21ms/step - loss: 3.0874 - tp:
3.7705 - fp: 26.8361 - tn: 58805.1311 - fn: 4595.7049 - accuracy: 0.9277 -
precision: 0.1080 - recall: 7.2174e-04 - auc: 0.5862 - val_loss: 2.7956 -
val_tp: 0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000
- val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.6241
Epoch 11/100
60/60 [==============================] - 1s 21ms/step - loss: 2.7247 - tp:
2.0492 - fp: 27.0656 - tn: 58828.8197 - fn: 4573.5082 - accuracy: 0.9276 -
precision: 0.0687 - recall: 4.0854e-04 - auc: 0.5892 - val_loss: 2.4641 -
val_tp: 0.0000e+00 - val_fp: 0.0000e+00 - val_tn: 28361.0000 - val_fn: 2184.0000
- val_accuracy: 0.9285 - val_precision: 0.0000e+00 - val_recall: 0.0000e+00 -
val_auc: 0.6331
Restoring model weights from the end of the best epoch.
Epoch 00011: early stopping
```

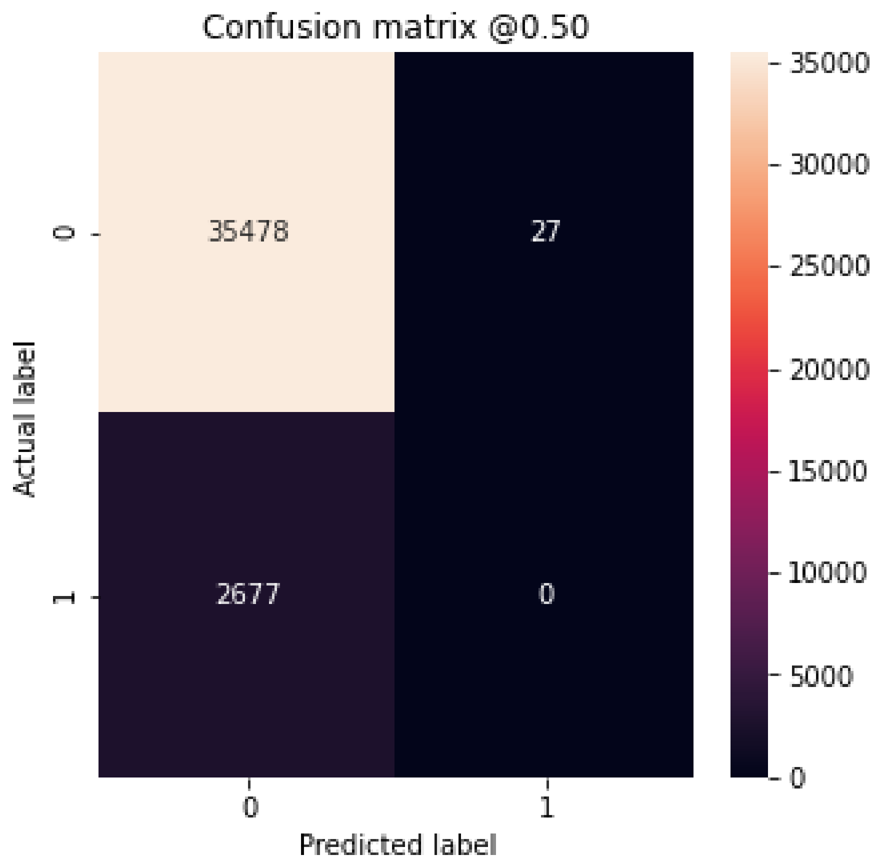
[ ]:
```
# produce plots of model's accuracy and loss on the training and validation set
 ↪- also includes some other metrics
plot_metrics(baseline_history)
```



[ ]:
```
train_predictions_baseline = three_layer_model.predict(train_features,␣
↪batch_size=BATCH_SIZE)
test_predictions_baseline = three_layer_model.predict(test_features,␣
↪batch_size=BATCH_SIZE)

# Print out scores for test values and confusion matrix

baseline_results = three_layer_model.evaluate(test_features, test_labels,
                                  batch_size=BATCH_SIZE, verbose=0)
for name, value in zip(three_layer_model.metrics_names, baseline_results):
  print(name, ': ', value)
print()

plot_cm(test_labels, test_predictions_baseline)
```

```
loss :  8.092643737792969
tp :  0.0
fp :  27.0
tn :  35478.0
fn :  2677.0
accuracy :  0.9291812777519226
precision :  0.0
recall :  0.0
auc :  0.5336455702781677
```

```
f1 Score 0.0

Irrelevant Documents Detected (True Negatives):  35478
Irrelevant Documents Incorrectly Detected (False Positives):  27
Relevant Documents Missed (False Negatives):  2677
Relevant Documents Detected (True Positives):  0
Total Relevant Documents:  2677
```



[ ]:
```
(three_layer_model.metrics_names[0], baseline_results[0])
```

[ ]:
```
('loss', 8.092643737792969)
```

[ ]:
```
pred_labels = three_layer_model.predict(test_features)
pred_labels = pred_labels.round(0)
pred_labels = pred_labels.astype(int)

tl_bias = {'Model': 'Adjusted Bias Three Layer Model',
                'Loss': baseline_results[0],
                'Accuracy': accuracy_score(test_labels, pred_labels),
                'Precision': precision_score(test_labels, pred_labels),
```

```
                 'Recall': recall_score(test_labels, pred_labels),
                 'F1 Score': f1_score(test_labels, pred_labels)}

tl_bias
```

[ ]:
```
{'Accuracy': 0.9291812896129066,
 'F1 Score': 0.0,
 'Loss': 8.092643737792969,
 'Model': 'Adjusted Bias Three Layer Model',
 'Precision': 0.0,
 'Recall': 0.0}
```

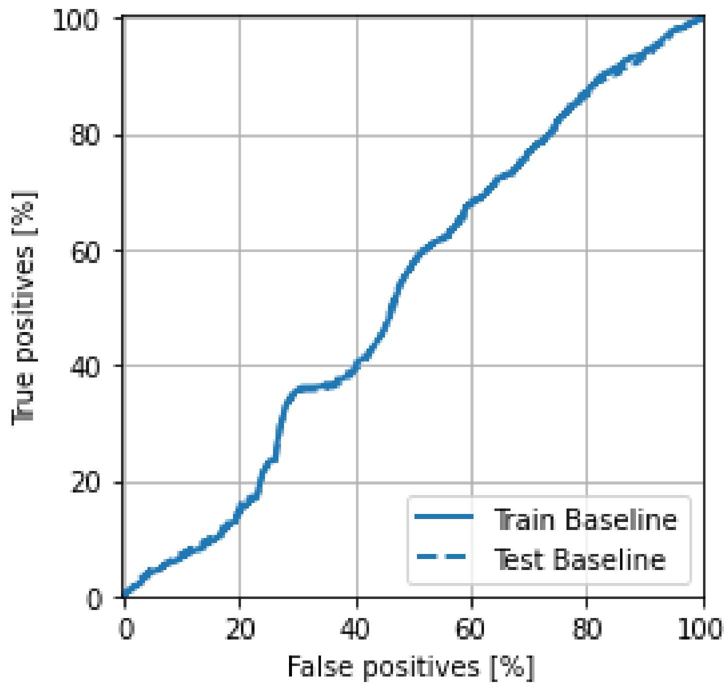
[ ]:
```
!mkdir -p saved_model
three_layer_model.save('saved_model/three_layer_adjusted_bias_model')
```

```
INFO:tensorflow:Assets written to:
saved_model/three_layer_adjusted_bias_model/assets
```

If the model had predicted everything perfectly, this would be a diagonal matrix where values off the main diagonal, indicating incorrect predictions, would be zero. In this case the matrix shows that you have relatively few false positives, meaning that there were relatively few irrelevant documents that were incorrectly flagged. However, you would likely want to have even fewer false negatives despite the cost of increasing the number of false positives.

[ ]:
```
# Now plot the ROC. This plot is useful because it shows, at a glance, the␣
↪range of performance the model can reach just by tuning the output threshold.

plot_roc("Train Baseline", train_labels, train_predictions_baseline,␣
↪color=colors[0])
plot_roc("Test Baseline", test_labels, test_predictions_baseline,␣
↪color=colors[0], linestyle='--')
plt.legend(loc='lower right')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f750efe7f10>
```



Tweaking Class Weights The goal is to identify relevant documents, but you don't have very many of those positive samples to work with, so you would want to have the classifier heavily weight the few examples that are available. You can do this by passing Keras weights for each class through a parameter. These will cause the model to "pay more attention" to examples from an under-represented class.

[ ]:
```
# Scaling by total/2 helps keep the loss to a similar magnitude.
# The sum of the weights of all examples stays the same.
weight_for_0 = (1 / neg)*(total)/2.0
weight_for_1 = (1 / pos)*(total)/2.0

class_weight = {0: weight_for_0, 1: weight_for_1}

print('Weight for class 0: {:.2f}'.format(weight_for_0))
print('Weight for class 1: {:.2f}'.format(weight_for_1))
```

```
Weight for class 0: 0.53
Weight for class 1: 8.41
```

Train a model with class weights Now try re-training and evaluating the model with class weights to see how that affects the predictions.

Note: Using `class_weights` changes the range of the loss. This may affect the stability of the training depending on the optimizer. Optimizers whose step size is dependent on the magnitude of the gradient, like `optimizers.SGD`, may fail. The optimizer used here, `optimizers.Nadam`, is unaffected by the scaling change. Also note that because of the weighting, the total losses are not comparable between the two models.

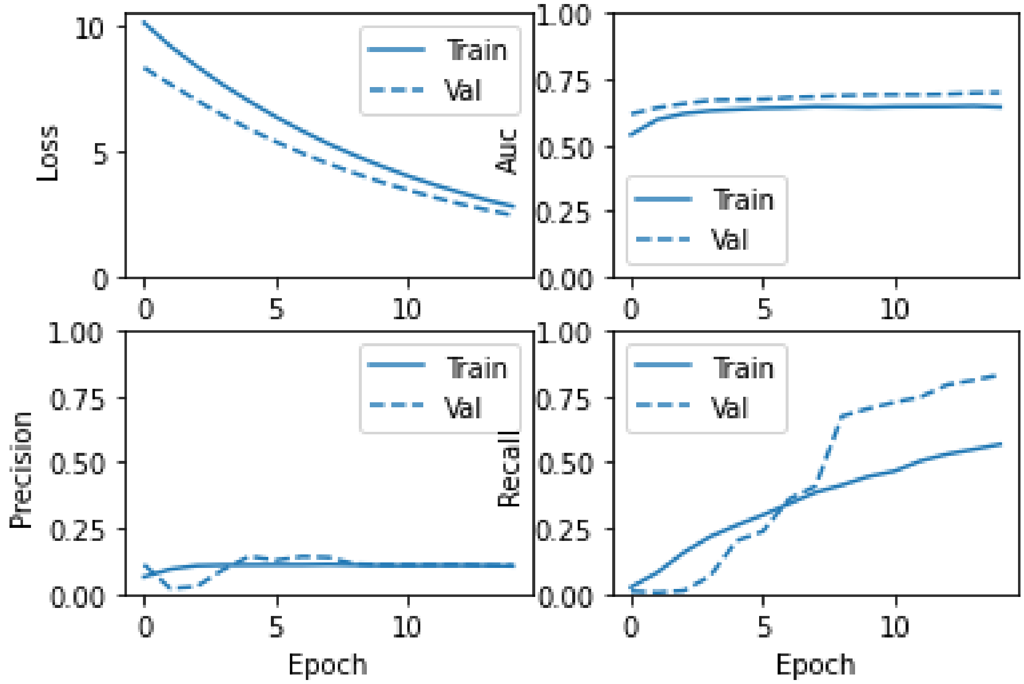
[ ]:
```
weighted_three_layer_model = build_three_layer_model()
weighted_three_layer_model.load_weights(initial_weights)

weighted_history = weighted_three_layer_model.fit(
    train_features,
    train_labels,
    batch_size=BATCH_SIZE,
    epochs=EPOCHS,
    callbacks=[early_stopping],
    validation_data=(val_features, val_labels),
    class_weight=class_weight)
```

```
Epoch 1/100
60/60 [==============================] - 6s 43ms/step - loss: 10.3057 - tp:
138.9672 - fp: 2236.7869 - tn: 92102.2459 - fn: 7135.4426 - accuracy: 0.9097 -
precision: 0.0545 - recall: 0.0169 - auc: 0.5273 - val_loss: 8.2965 - val_tp:
22.0000 - val_fp: 176.0000 - val_tn: 28185.0000 - val_fn: 2162.0000 -
val_accuracy: 0.9235 - val_precision: 0.1111 - val_recall: 0.0101 - val_auc:
0.6183
Epoch 2/100
60/60 [==============================] - 1s 20ms/step - loss: 9.3726 - tp:
321.5574 - fp: 3239.5082 - tn: 55544.8361 - fn: 4325.5410 - accuracy: 0.8838 -
precision: 0.0876 - recall: 0.0626 - auc: 0.5873 - val_loss: 7.6420 - val_tp:
12.0000 - val_fp: 576.0000 - val_tn: 27785.0000 - val_fn: 2172.0000 -
val_accuracy: 0.9100 - val_precision: 0.0204 - val_recall: 0.0055 - val_auc:
0.6420
Epoch 3/100
60/60 [==============================] - 1s 21ms/step - loss: 8.5441 - tp:
668.1148 - fp: 5703.0000 - tn: 53098.1967 - fn: 3962.1311 - accuracy: 0.8498 -
precision: 0.1023 - recall: 0.1370 - auc: 0.6119 - val_loss: 7.0059 - val_tp:
27.0000 - val_fp: 924.0000 - val_tn: 27437.0000 - val_fn: 2157.0000 -
val_accuracy: 0.8991 - val_precision: 0.0284 - val_recall: 0.0124 - val_auc:
0.6574
Epoch 4/100
60/60 [==============================] - 1s 21ms/step - loss: 7.7920 - tp:
957.4754 - fp: 7838.1967 - tn: 50982.0328 - fn: 3653.7377 - accuracy: 0.8212 -
precision: 0.1094 - recall: 0.2035 - auc: 0.6276 - val_loss: 6.4118 - val_tp:
148.0000 - val_fp: 1465.0000 - val_tn: 26896.0000 - val_fn: 2036.0000 -
val_accuracy: 0.8854 - val_precision: 0.0918 - val_recall: 0.0678 - val_auc:
0.6702
Epoch 5/100
60/60 [==============================] - 1s 20ms/step - loss: 7.1512 - tp:
1172.9344 - fp: 9485.6557 - tn: 49293.3115 - fn: 3479.5410 - accuracy: 0.7963 -
precision: 0.1108 - recall: 0.2505 - auc: 0.6321 - val_loss: 5.8646 - val_tp:
440.0000 - val_fp: 2641.0000 - val_tn: 25720.0000 - val_fn: 1744.0000 -
```

```
val_accuracy: 0.8564 - val_precision: 0.1428 - val_recall: 0.2015 - val_auc:
0.6727
Epoch 6/100
60/60 [==============================] - 1s 21ms/step - loss: 6.5053 - tp:
1368.3443 - fp: 10874.6885 - tn: 47922.9836 - fn: 3265.4262 - accuracy: 0.7790 -
precision: 0.1128 - recall: 0.2915 - auc: 0.6419 - val_loss: 5.3683 - val_tp:
518.0000 - val_fp: 3545.0000 - val_tn: 24816.0000 - val_fn: 1666.0000 -
val_accuracy: 0.8294 - val_precision: 0.1275 - val_recall: 0.2372 - val_auc:
0.6745
Epoch 7/100
60/60 [==============================] - 1s 21ms/step - loss: 5.9404 - tp:
1567.7049 - fp: 12564.8033 - tn: 46269.6721 - fn: 3029.2623 - accuracy: 0.7556 -
precision: 0.1128 - recall: 0.3401 - auc: 0.6421 - val_loss: 4.9131 - val_tp:
786.0000 - val_fp: 4769.0000 - val_tn: 23592.0000 - val_fn: 1398.0000 -
val_accuracy: 0.7981 - val_precision: 0.1415 - val_recall: 0.3599 - val_auc:
0.6808
Epoch 8/100
60/60 [==============================] - 1s 20ms/step - loss: 5.4045 - tp:
1724.4754 - fp: 13908.8852 - tn: 44912.4262 - fn: 2885.6557 - accuracy: 0.7374 -
precision: 0.1108 - recall: 0.3703 - auc: 0.6453 - val_loss: 4.4966 - val_tp:
892.0000 - val_fp: 5537.0000 - val_tn: 22824.0000 - val_fn: 1292.0000 -
val_accuracy: 0.7764 - val_precision: 0.1387 - val_recall: 0.4084 - val_auc:
0.6838
Epoch 9/100
60/60 [==============================] - 1s 21ms/step - loss: 4.9015 - tp:
1862.5082 - fp: 15216.6393 - tn: 43654.0820 - fn: 2698.2131 - accuracy: 0.7194 -
precision: 0.1094 - recall: 0.4115 - auc: 0.6501 - val_loss: 4.1190 - val_tp:
1470.0000 - val_fp: 11500.0000 - val_tn: 16861.0000 - val_fn: 714.0000 -
val_accuracy: 0.6001 - val_precision: 0.1133 - val_recall: 0.6731 - val_auc:
0.6881
Epoch 10/100
60/60 [==============================] - 1s 22ms/step - loss: 4.4885 - tp:
1999.1148 - fp: 16633.3934 - tn: 42198.9672 - fn: 2599.9672 - accuracy: 0.6988 -
precision: 0.1054 - recall: 0.4240 - auc: 0.6432 - val_loss: 3.7676 - val_tp:
1533.0000 - val_fp: 12303.0000 - val_tn: 16058.0000 - val_fn: 651.0000 -
val_accuracy: 0.5759 - val_precision: 0.1108 - val_recall: 0.7019 - val_auc:
0.6908
Epoch 11/100
60/60 [==============================] - 1s 21ms/step - loss: 4.1046 - tp:
2103.6557 - fp: 17569.8033 - tn: 41252.3934 - fn: 2505.5902 - accuracy: 0.6848 -
precision: 0.1070 - recall: 0.4534 - auc: 0.6456 - val_loss: 3.4532 - val_tp:
1585.0000 - val_fp: 12741.0000 - val_tn: 15620.0000 - val_fn: 599.0000 -
val_accuracy: 0.5633 - val_precision: 0.1106 - val_recall: 0.7257 - val_auc:
0.6917
Epoch 12/100
60/60 [==============================] - 1s 21ms/step - loss: 3.7452 - tp:
2298.8689 - fp: 18923.8852 - tn: 39899.4590 - fn: 2309.2295 - accuracy: 0.6659 -
precision: 0.1072 - recall: 0.4931 - auc: 0.6452 - val_loss: 3.1652 - val_tp:
```

```
1631.0000 - val_fp: 13142.0000 - val_tn: 15219.0000 - val_fn: 553.0000 -
val_accuracy: 0.5516 - val_precision: 0.1104 - val_recall: 0.7468 - val_auc:
0.6913
Epoch 13/100
60/60 [==============================] - 1s 21ms/step - loss: 3.4217 - tp:
2427.4754 - fp: 19871.7377 - tn: 38961.5410 - fn: 2170.6885 - accuracy: 0.6527 -
precision: 0.1089 - recall: 0.5272 - auc: 0.6472 - val_loss: 2.8987 - val_tp:
1731.0000 - val_fp: 13816.0000 - val_tn: 14545.0000 - val_fn: 453.0000 -
val_accuracy: 0.5329 - val_precision: 0.1113 - val_recall: 0.7926 - val_auc:
0.6937
Epoch 14/100
60/60 [==============================] - 1s 21ms/step - loss: 3.1272 - tp:
2495.2295 - fp: 20675.4754 - tn: 38134.8525 - fn: 2125.8852 - accuracy: 0.6405 -
precision: 0.1075 - recall: 0.5385 - auc: 0.6458 - val_loss: 2.6647 - val_tp:
1768.0000 - val_fp: 14517.0000 - val_tn: 13844.0000 - val_fn: 416.0000 -
val_accuracy: 0.5111 - val_precision: 0.1086 - val_recall: 0.8095 - val_auc:
0.6980
Epoch 15/100
60/60 [==============================] - 1s 21ms/step - loss: 2.8622 - tp:
2573.6393 - fp: 21872.7377 - tn: 36985.1803 - fn: 1999.8852 - accuracy: 0.6243 -
precision: 0.1042 - recall: 0.5576 - auc: 0.6425 - val_loss: 2.4529 - val_tp:
1812.0000 - val_fp: 14911.0000 - val_tn: 13450.0000 - val_fn: 372.0000 -
val_accuracy: 0.4997 - val_precision: 0.1084 - val_recall: 0.8297 - val_auc:
0.6995
Restoring model weights from the end of the best epoch.
Epoch 00015: early stopping
```

[ ]:
```
plot_metrics(weighted_history)
```

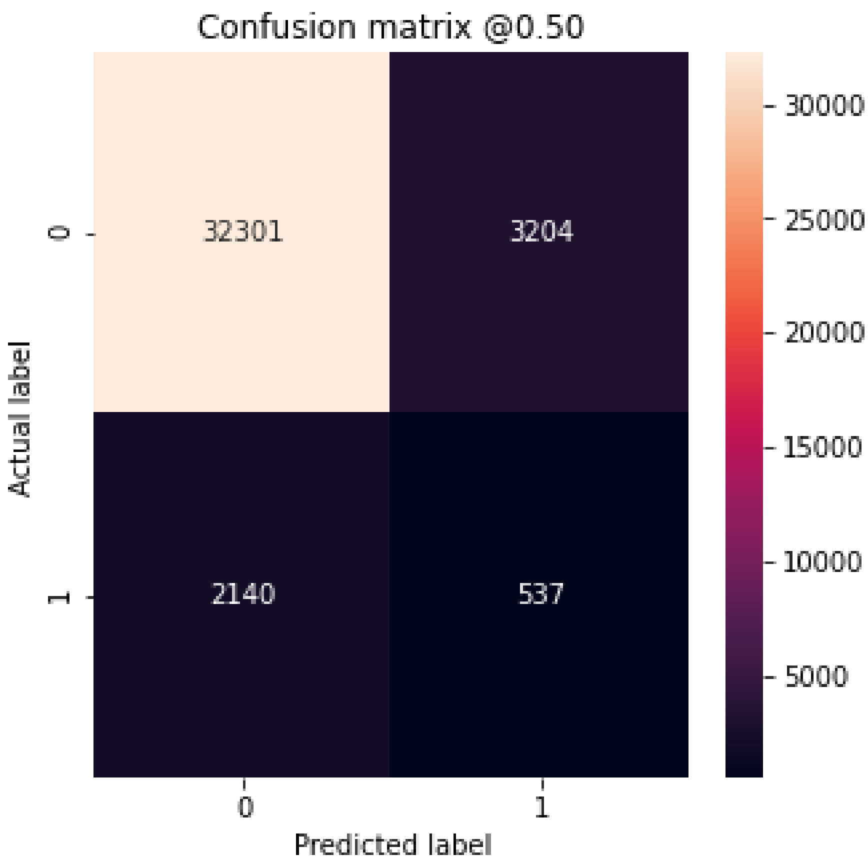


[ ]:
```
train_predictions_weighted = weighted_three_layer_model.predict(train_features,␣
↪batch_size=BATCH_SIZE)
test_predictions_weighted = weighted_three_layer_model.predict(test_features,␣
↪batch_size=BATCH_SIZE)
```

[ ]:
```
weighted_results = weighted_three_layer_model.evaluate(test_features,␣
↪test_labels,
                                             batch_size=BATCH_SIZE, verbose=0)
for name, value in zip(weighted_three_layer_model.metrics_names,␣
↪weighted_results):
  print(name, ': ', value)
print()

plot_cm(test_labels, test_predictions_weighted)
```

```
loss :  5.860197067260742
tp :  537.0
fp :  3204.0
tn :  32301.0
fn :  2140.0
accuracy :  0.8600387573242188
precision :  0.1435445100069046
recall :  0.20059768855571747
auc :  0.6826937198638916
```

```
f1 Score 0.16734185104393892

Irrelevant Documents Detected (True Negatives):  32301
Irrelevant Documents Incorrectly Detected (False Positives):  3204
Relevant Documents Missed (False Negatives):  2140
Relevant Documents Detected (True Positives):  537
Total Relevant Documents:  2677
```



[ ]:
```
pred_labels = weighted_three_layer_model.predict(test_features)
pred_labels = pred_labels.round(0)
pred_labels = pred_labels.astype(int)

tl_wt = {'Model': 'Adjusted Weights Three Layer Model',
                'Loss': weighted_results[0],
                'Accuracy': accuracy_score(test_labels, pred_labels),
                'Precision': precision_score(test_labels, pred_labels),
                'Recall': recall_score(test_labels, pred_labels),
                'F1 Score': f1_score(test_labels, pred_labels)}
```

```
tl_wt
```

[ ]:
```
{'Accuracy': 0.8600387617201822,
 'F1 Score': 0.16734185104393892,
 'Loss': 5.860197067260742,
 'Model': 'Adjusted Weights Three Layer Model',
 'Precision': 0.14354450681635927,
 'Recall': 0.20059768397459843}
```

[ ]:
```
test_predictions = weighted_three_layer_model.predict(test)
```

[ ]:
```
test_predictions = test_predictions.round(0)
test_predictions = test_predictions.astype(int)
test_predictions
```

[ ]:
```
array([[0],
       [0],
       [0],
       …,
       [0],
       [0],
       [0]])
```

[ ]:
```
predictions= pd.DataFrame(test_predictions)
predictions['Id'] = predictions.index
predictions.rename(columns={ predictions.columns[0]: "psrel" }, inplace = True)
predictions = predictions[['Id','psrel']]
predictions
```

[ ]:
```
        Id  psrel
0        0      0
1        1      0
2        2      0
3        3      0
4        4      0
…     …    …
4995  4995      0
4996  4996      0
4997  4997      0
4998  4998      0
4999  4999      0

[5000 rows x 2 columns]
```

[ ]:
```
predictions['psrel'].value_counts()
```

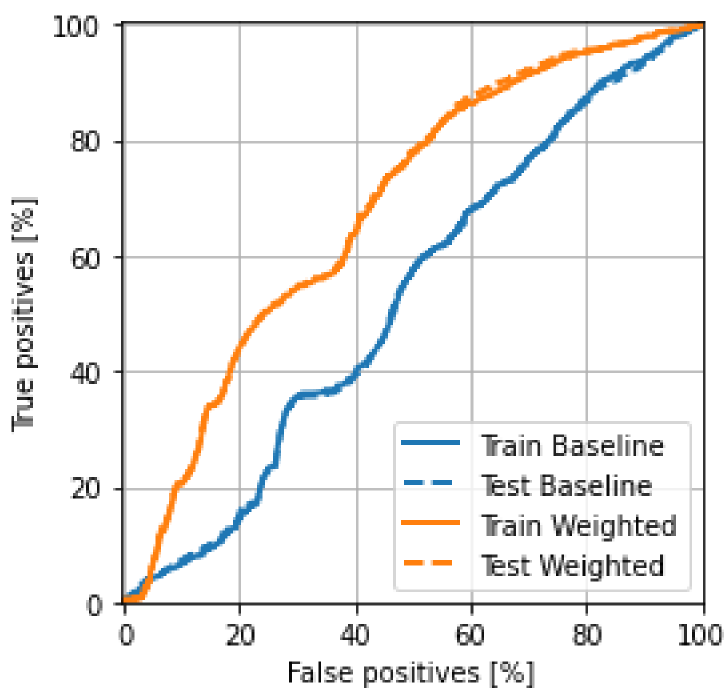
[ ]:
```
0    4711
1     289
Name: psrel, dtype: int64
```

[ ]:
```
predictions.to_csv('adjusted class weights colab predictions class weights.
↪csv', index=False)
```

Here you can see that with class weights the accuracy and precision are lower because there are more false positives, but conversely the recall and AUC are higher because the model also found more true positives. Despite having lower accuracy, this model has higher recall.

[ ]:
```
plot_roc("Train Baseline", train_labels, train_predictions_baseline,␣
↪color=colors[0])
plot_roc("Test Baseline", test_labels, test_predictions_baseline,␣
↪color=colors[0], linestyle='--')

plot_roc("Train Weighted", train_labels, train_predictions_weighted,␣
↪color=colors[1])
plot_roc("Test Weighted", test_labels, test_predictions_weighted,␣
↪color=colors[1], linestyle='--')


plt.legend(loc='lower right')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f7510aed510>
```



[ ]:
```
!mkdir -p saved_model
weighted_three_layer_model.save('saved_model/weighted_three_layer_model')
```

```
INFO:tensorflow:Assets written to: saved_model/weighted_three_layer_model/assets
```

Oversample the minority class A related approach would be to resample the dataset by oversampling the minority class. This helps the model to recognise what a relevant document looks like

[ ]:
```
pos_features = train_features[bool_train_labels]
neg_features = train_features[~bool_train_labels]

pos_labels = train_labels[bool_train_labels]
neg_labels = train_labels[~bool_train_labels]
```

[ ]:
```
# Use Numpy to generate new 'relevant' samples
ids = np.arange(len(pos_features))
choices = np.random.choice(ids, len(neg_features))

res_pos_features = pos_features[choices]
res_pos_labels = pos_labels[choices]

res_pos_features.shape
```

[ ]: (113299, 74)

[ ]:
```
resampled_features = np.concatenate([res_pos_features, neg_features], axis=0)
resampled_labels = np.concatenate([res_pos_labels, neg_labels], axis=0)

order = np.arange(len(resampled_labels))
np.random.shuffle(order)
resampled_features = resampled_features[order]
resampled_labels = resampled_labels[order]

resampled_features.shape
```

[ ]: (226598, 74)

[ ]:
```
# Use tf.data to merge positive and negative dataframes
BUFFER_SIZE = 100000

def make_ds(features, labels):
  ds = tf.data.Dataset.from_tensor_slices((features, labels))#.cache()
  ds = ds.shuffle(BUFFER_SIZE).repeat()
  return ds

pos_ds = make_ds(pos_features, pos_labels)
neg_ds = make_ds(neg_features, neg_labels)
```

```
[ ]: # Each dataset provides (feature, label) pairs:
for features, label in pos_ds.take(1):
  print("Features:\n", features.numpy())
  print()
  print("Label: ", label.numpy())
```

```
Features:
 [-0.31494735 -0.22480333 -0.35316283  0.5158269  -0.47299417  0.82892249
 -0.10434731 -0.45014672 -0.54346398 -0.31365016 -0.43049886 -0.1641563
 -0.069837   -0.06791763 -0.02774807  1.01496725 -0.49997698 -0.07420054
 -0.06537769 -0.1215902  -0.02774807 -0.04427166 -0.24920441  0.25407715
 -0.01458931 -0.73106047 -0.26347516 -0.30608251 -0.02932804 -0.05977517
 -0.02478367 -0.04635734 -0.01311139 -0.05929057 -0.01786913 -0.04944702
 -0.02759997 -0.07536263 -0.08439168 -0.10410658 -0.07216581 -0.10566194
 -0.06882387 -0.03575538 -0.05541193 -0.06989614 -0.01213864 -0.07864309
 -0.03470738 -0.10366385  0.90503443 -0.15992708 -0.11977513 -0.06742941
 -0.04818352 -0.05132459 -0.05313653 -0.05915139 -0.10924712 -0.07001429
 -0.06512468 -0.269587   -0.26484034 -0.13666075 -0.06512468 -0.0164368
 -0.06455184 -0.24527183 -0.12591953 -0.12033636 -0.14459002 -0.09408335
 -0.09670439 -0.0551139 ]

Label:  1
```

```
[ ]: resampled_ds = tf.data.experimental.sample_from_datasets([pos_ds, neg_ds],␣
 ↪weights=[0.5, 0.5])
resampled_ds = resampled_ds.batch(BATCH_SIZE).prefetch(2)
```

```
[ ]: # To use this dataset, you'll need the number of steps per epoch. Define as␣
 ↪number of batches to see each value of 1 once
resampled_steps_per_epoch = np.ceil(2.0*neg/BATCH_SIZE)
resampled_steps_per_epoch
```

```
[ ]: 31.0
```

Train a Model with Oversampled Data Training the model with the resampled data set instead of using class weights to see how these methods compare.

Note: Because the data was balanced by replicating the positive examples, the total dataset size is larger, and each epoch runs for more training steps.

```
[ ]: resampled_three_layer_model = build_three_layer_model()
resampled_three_layer_model.load_weights(initial_weights)

# Reset the bias to zero, since this dataset is balanced.
output_layer = resampled_three_layer_model.layers[-1]
output_layer.bias.assign([0])

val_ds = tf.data.Dataset.from_tensor_slices((val_features, val_labels)).cache()
```

```
val_ds = val_ds.batch(BATCH_SIZE).prefetch(2)

resampled_history = resampled_three_layer_model.fit(
    resampled_ds,
    epochs=EPOCHS,
    steps_per_epoch=resampled_steps_per_epoch,
    callbacks=[early_stopping],
    validation_data=val_ds)
```

```
Epoch 1/100
31/31 [==============================] - 5s 68ms/step - loss: 9.5194 - tp:
9385.6562 - fp: 11888.5000 - tn: 40592.1250 - fn: 10043.7188 - accuracy: 0.7096
- precision: 0.4165 - recall: 0.4618 - auc: 0.6823 - val_loss: 9.0466 - val_tp:
1393.0000 - val_fp: 16330.0000 - val_tn: 12031.0000 - val_fn: 791.0000 -
val_accuracy: 0.4395 - val_precision: 0.0786 - val_recall: 0.6378 - val_auc:
0.5335
Epoch 2/100
31/31 [==============================] - 1s 36ms/step - loss: 9.0495 - tp:
9315.6250 - fp: 8538.5312 - tn: 8269.3438 - fn: 7604.5000 - accuracy: 0.5203 -
precision: 0.5211 - recall: 0.5487 - auc: 0.5220 - val_loss: 8.6236 - val_tp:
1523.0000 - val_fp: 17169.0000 - val_tn: 11192.0000 - val_fn: 661.0000 -
val_accuracy: 0.4163 - val_precision: 0.0815 - val_recall: 0.6973 - val_auc:
0.5629
Epoch 3/100
31/31 [==============================] - 1s 37ms/step - loss: 8.5716 - tp:
9468.8750 - fp: 8530.3750 - tn: 8470.3750 - fn: 7258.3750 - accuracy: 0.5313 -
precision: 0.5252 - recall: 0.5648 - auc: 0.5374 - val_loss: 8.1928 - val_tp:
1589.0000 - val_fp: 17250.0000 - val_tn: 11111.0000 - val_fn: 595.0000 -
val_accuracy: 0.4158 - val_precision: 0.0843 - val_recall: 0.7276 - val_auc:
0.5799
Epoch 4/100
31/31 [==============================] - 1s 37ms/step - loss: 8.1289 - tp:
9582.0312 - fp: 8414.1562 - tn: 8571.9375 - fn: 7159.8750 - accuracy: 0.5391 -
precision: 0.5327 - recall: 0.5734 - auc: 0.5444 - val_loss: 7.7765 - val_tp:
1639.0000 - val_fp: 17319.0000 - val_tn: 11042.0000 - val_fn: 545.0000 -
val_accuracy: 0.4152 - val_precision: 0.0865 - val_recall: 0.7505 - val_auc:
0.5918
Epoch 5/100
31/31 [==============================] - 1s 37ms/step - loss: 7.7070 - tp:
9536.2812 - fp: 8427.2188 - tn: 8619.8125 - fn: 7144.6875 - accuracy: 0.5350 -
precision: 0.5265 - recall: 0.5685 - auc: 0.5444 - val_loss: 7.3784 - val_tp:
1688.0000 - val_fp: 17189.0000 - val_tn: 11172.0000 - val_fn: 496.0000 -
val_accuracy: 0.4210 - val_precision: 0.0894 - val_recall: 0.7729 - val_auc:
0.5990
Epoch 6/100
31/31 [==============================] - 1s 38ms/step - loss: 7.2957 - tp:
9867.9062 - fp: 8335.7812 - tn: 8493.0000 - fn: 7031.3125 - accuracy: 0.5445 -
precision: 0.5425 - recall: 0.5835 - auc: 0.5534 - val_loss: 7.0061 - val_tp:
```

```
1715.0000 - val_fp: 17391.0000 - val_tn: 10970.0000 - val_fn: 469.0000 -
val_accuracy: 0.4153 - val_precision: 0.0898 - val_recall: 0.7853 - val_auc:
0.6057
Epoch 7/100
31/31 [==============================] - 1s 38ms/step - loss: 6.9091 - tp:
10166.5625 - fp: 8351.0000 - tn: 8438.7188 - fn: 6771.7188 - accuracy: 0.5538 -
precision: 0.5524 - recall: 0.6014 - auc: 0.5630 - val_loss: 6.6473 - val_tp:
1725.0000 - val_fp: 17333.0000 - val_tn: 11028.0000 - val_fn: 459.0000 -
val_accuracy: 0.4175 - val_precision: 0.0905 - val_recall: 0.7898 - val_auc:
0.6127
Epoch 8/100
31/31 [==============================] - 1s 37ms/step - loss: 6.5414 - tp:
10254.6562 - fp: 8428.7812 - tn: 8435.5625 - fn: 6609.0000 - accuracy: 0.5530 -
precision: 0.5480 - recall: 0.6065 - auc: 0.5632 - val_loss: 6.2940 - val_tp:
1722.0000 - val_fp: 17203.0000 - val_tn: 11158.0000 - val_fn: 462.0000 -
val_accuracy: 0.4217 - val_precision: 0.0910 - val_recall: 0.7885 - val_auc:
0.6174
Epoch 9/100
31/31 [==============================] - 1s 37ms/step - loss: 6.1925 - tp:
10399.1562 - fp: 8385.6250 - tn: 8439.4375 - fn: 6503.7812 - accuracy: 0.5580 -
precision: 0.5523 - recall: 0.6144 - auc: 0.5690 - val_loss: 5.9618 - val_tp:
1728.0000 - val_fp: 17142.0000 - val_tn: 11219.0000 - val_fn: 456.0000 -
val_accuracy: 0.4239 - val_precision: 0.0916 - val_recall: 0.7912 - val_auc:
0.6230
Epoch 10/100
31/31 [==============================] - 1s 36ms/step - loss: 5.8587 - tp:
10563.5312 - fp: 8395.1562 - tn: 8451.0000 - fn: 6318.3125 - accuracy: 0.5644 -
precision: 0.5569 - recall: 0.6264 - auc: 0.5739 - val_loss: 5.6436 - val_tp:
1757.0000 - val_fp: 17073.0000 - val_tn: 11288.0000 - val_fn: 427.0000 -
val_accuracy: 0.4271 - val_precision: 0.0933 - val_recall: 0.8045 - val_auc:
0.6279
Epoch 11/100
31/31 [==============================] - 1s 37ms/step - loss: 5.5368 - tp:
10636.7500 - fp: 8403.7812 - tn: 8536.0938 - fn: 6151.3750 - accuracy: 0.5693 -
precision: 0.5588 - recall: 0.6346 - auc: 0.5814 - val_loss: 5.3398 - val_tp:
1751.0000 - val_fp: 16861.0000 - val_tn: 11500.0000 - val_fn: 433.0000 -
val_accuracy: 0.4338 - val_precision: 0.0941 - val_recall: 0.8017 - val_auc:
0.6331
Epoch 12/100
31/31 [==============================] - 1s 38ms/step - loss: 5.2361 - tp:
10780.5625 - fp: 8272.3438 - tn: 8621.6875 - fn: 6053.4062 - accuracy: 0.5754 -
precision: 0.5653 - recall: 0.6392 - auc: 0.5898 - val_loss: 5.0553 - val_tp:
1746.0000 - val_fp: 16767.0000 - val_tn: 11594.0000 - val_fn: 438.0000 -
val_accuracy: 0.4367 - val_precision: 0.0943 - val_recall: 0.7995 - val_auc:
0.6377
Epoch 13/100
31/31 [==============================] - 1s 38ms/step - loss: 4.9485 - tp:
10986.7812 - fp: 8357.8125 - tn: 8491.5938 - fn: 5891.8125 - accuracy: 0.5775 -
```

```
precision: 0.5674 - recall: 0.6511 - auc: 0.5922 - val_loss: 4.7820 - val_tp:
1758.0000 - val_fp: 16652.0000 - val_tn: 11709.0000 - val_fn: 426.0000 -
val_accuracy: 0.4409 - val_precision: 0.0955 - val_recall: 0.8049 - val_auc:
0.6493
Epoch 14/100
31/31 [==============================] - 1s 38ms/step - loss: 4.6762 - tp:
11058.5312 - fp: 8523.2812 - tn: 8421.6875 - fn: 5724.5000 - accuracy: 0.5785 -
precision: 0.5666 - recall: 0.6604 - auc: 0.5974 - val_loss: 4.5149 - val_tp:
1742.0000 - val_fp: 16046.0000 - val_tn: 12315.0000 - val_fn: 442.0000 -
val_accuracy: 0.4602 - val_precision: 0.0979 - val_recall: 0.7976 - val_auc:
0.6515
Epoch 15/100
31/31 [==============================] - 1s 37ms/step - loss: 4.4203 - tp:
11088.4688 - fp: 8415.3438 - tn: 8483.5625 - fn: 5740.6250 - accuracy: 0.5785 -
precision: 0.5666 - recall: 0.6582 - auc: 0.5964 - val_loss: 4.2661 - val_tp:
1744.0000 - val_fp: 15906.0000 - val_tn: 12455.0000 - val_fn: 440.0000 -
val_accuracy: 0.4649 - val_precision: 0.0988 - val_recall: 0.7985 - val_auc:
0.6536
Epoch 16/100
31/31 [==============================] - 1s 37ms/step - loss: 4.1801 - tp:
11032.6250 - fp: 8477.7812 - tn: 8570.1562 - fn: 5647.4375 - accuracy: 0.5814 -
precision: 0.5647 - recall: 0.6623 - auc: 0.5975 - val_loss: 4.0292 - val_tp:
1726.0000 - val_fp: 15618.0000 - val_tn: 12743.0000 - val_fn: 458.0000 -
val_accuracy: 0.4737 - val_precision: 0.0995 - val_recall: 0.7903 - val_auc:
0.6561
Epoch 17/100
31/31 [==============================] - 1s 36ms/step - loss: 3.9448 - tp:
11346.4062 - fp: 8190.4688 - tn: 8566.3438 - fn: 5624.7812 - accuracy: 0.5914 -
precision: 0.5821 - recall: 0.6686 - auc: 0.6067 - val_loss: 3.8128 - val_tp:
1742.0000 - val_fp: 15553.0000 - val_tn: 12808.0000 - val_fn: 442.0000 -
val_accuracy: 0.4763 - val_precision: 0.1007 - val_recall: 0.7976 - val_auc:
0.6577
Epoch 18/100
31/31 [==============================] - 1s 38ms/step - loss: 3.7238 - tp:
11382.2812 - fp: 8454.4062 - tn: 8479.5000 - fn: 5411.8125 - accuracy: 0.5891 -
precision: 0.5744 - recall: 0.6785 - auc: 0.6115 - val_loss: 3.6000 - val_tp:
1735.0000 - val_fp: 15356.0000 - val_tn: 13005.0000 - val_fn: 449.0000 -
val_accuracy: 0.4826 - val_precision: 0.1015 - val_recall: 0.7944 - val_auc:
0.6607
Epoch 19/100
31/31 [==============================] - 1s 37ms/step - loss: 3.5194 - tp:
11524.9062 - fp: 8246.9688 - tn: 8480.8750 - fn: 5475.2500 - accuracy: 0.5944 -
precision: 0.5840 - recall: 0.6780 - auc: 0.6130 - val_loss: 3.4069 - val_tp:
1767.0000 - val_fp: 15477.0000 - val_tn: 12884.0000 - val_fn: 417.0000 -
val_accuracy: 0.4797 - val_precision: 0.1025 - val_recall: 0.8091 - val_auc:
0.6628
Epoch 20/100
31/31 [==============================] - 1s 38ms/step - loss: 3.3259 - tp:
```

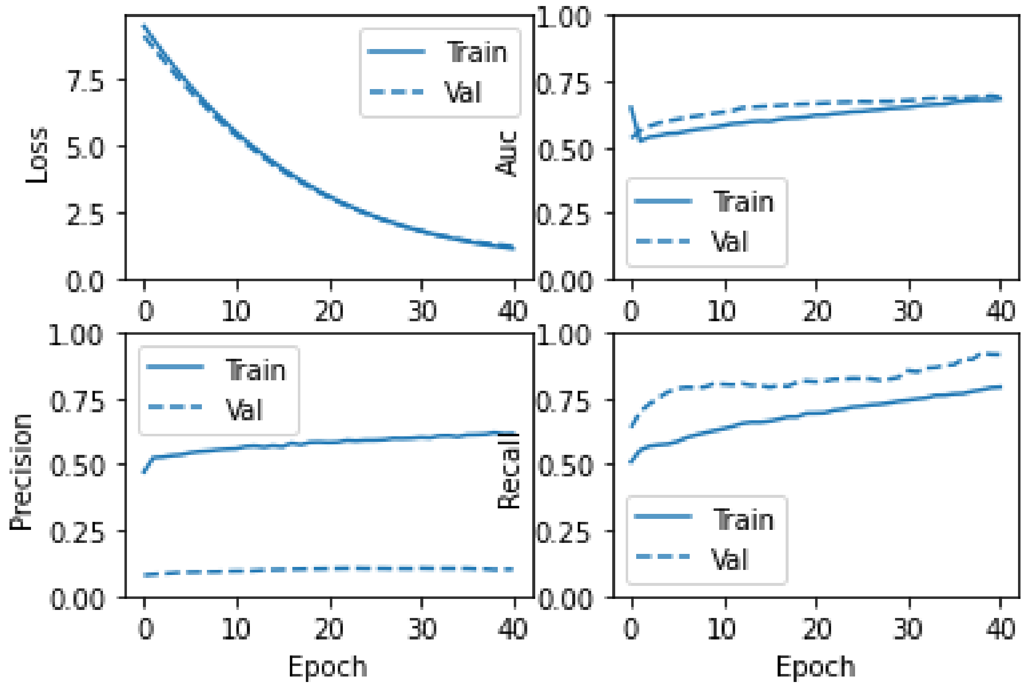
```
11737.2188 - fp: 8415.3750 - tn: 8334.0625 - fn: 5241.3438 - accuracy: 0.5944 -
precision: 0.5823 - recall: 0.6907 - auc: 0.6134 - val_loss: 3.2237 - val_tp:
1779.0000 - val_fp: 15572.0000 - val_tn: 12789.0000 - val_fn: 405.0000 -
val_accuracy: 0.4769 - val_precision: 0.1025 - val_recall: 0.8146 - val_auc:
0.6642
Epoch 21/100
31/31 [==============================] - 1s 38ms/step - loss: 3.1411 - tp:
11614.4688 - fp: 8401.1875 - tn: 8527.9688 - fn: 5184.3750 - accuracy: 0.5966 -
precision: 0.5799 - recall: 0.6907 - auc: 0.6185 - val_loss: 3.0446 - val_tp:
1772.0000 - val_fp: 15381.0000 - val_tn: 12980.0000 - val_fn: 412.0000 -
val_accuracy: 0.4830 - val_precision: 0.1033 - val_recall: 0.8114 - val_auc:
0.6655
Epoch 22/100
31/31 [==============================] - 1s 38ms/step - loss: 2.9675 - tp:
11588.3750 - fp: 8440.6250 - tn: 8544.7812 - fn: 5154.2188 - accuracy: 0.5958 -
precision: 0.5759 - recall: 0.6920 - auc: 0.6200 - val_loss: 2.8771 - val_tp:
1778.0000 - val_fp: 15338.0000 - val_tn: 13023.0000 - val_fn: 406.0000 -
val_accuracy: 0.4846 - val_precision: 0.1039 - val_recall: 0.8141 - val_auc:
0.6672
Epoch 23/100
31/31 [==============================] - 1s 38ms/step - loss: 2.8008 - tp:
11900.9375 - fp: 8233.2188 - tn: 8518.7812 - fn: 5075.0625 - accuracy: 0.6054 -
precision: 0.5913 - recall: 0.6992 - auc: 0.6282 - val_loss: 2.7263 - val_tp:
1792.0000 - val_fp: 15345.0000 - val_tn: 13016.0000 - val_fn: 392.0000 -
val_accuracy: 0.4848 - val_precision: 0.1046 - val_recall: 0.8205 - val_auc:
0.6691
Epoch 24/100
31/31 [==============================] - 1s 37ms/step - loss: 2.6514 - tp:
11854.5625 - fp: 8408.8125 - tn: 8502.1875 - fn: 4962.4375 - accuracy: 0.6027 -
precision: 0.5831 - recall: 0.7044 - auc: 0.6259 - val_loss: 2.5828 - val_tp:
1793.0000 - val_fp: 15322.0000 - val_tn: 13039.0000 - val_fn: 391.0000 -
val_accuracy: 0.4856 - val_precision: 0.1048 - val_recall: 0.8210 - val_auc:
0.6703
Epoch 25/100
31/31 [==============================] - 1s 37ms/step - loss: 2.5050 - tp:
12016.2188 - fp: 8380.8750 - tn: 8508.2500 - fn: 4822.6562 - accuracy: 0.6082 -
precision: 0.5897 - recall: 0.7123 - auc: 0.6310 - val_loss: 2.4444 - val_tp:
1800.0000 - val_fp: 15484.0000 - val_tn: 12877.0000 - val_fn: 384.0000 -
val_accuracy: 0.4805 - val_precision: 0.1041 - val_recall: 0.8242 - val_auc:
0.6712
Epoch 26/100
31/31 [==============================] - 1s 38ms/step - loss: 2.3666 - tp:
12083.2188 - fp: 8370.4688 - tn: 8535.8438 - fn: 4738.4688 - accuracy: 0.6116 -
precision: 0.5900 - recall: 0.7194 - auc: 0.6368 - val_loss: 2.3160 - val_tp:
1798.0000 - val_fp: 15489.0000 - val_tn: 12872.0000 - val_fn: 386.0000 -
val_accuracy: 0.4803 - val_precision: 0.1040 - val_recall: 0.8233 - val_auc:
0.6726
Epoch 27/100
```

```
31/31 [==============================] - 1s 38ms/step - loss: 2.2401 - tp:
12169.6875 - fp: 8367.4062 - tn: 8530.8438 - fn: 4660.0625 - accuracy: 0.6133 -
precision: 0.5916 - recall: 0.7232 - auc: 0.6387 - val_loss: 2.1945 - val_tp:
1796.0000 - val_fp: 15467.0000 - val_tn: 12894.0000 - val_fn: 388.0000 -
val_accuracy: 0.4809 - val_precision: 0.1040 - val_recall: 0.8223 - val_auc:
0.6716
Epoch 28/100
31/31 [==============================] - 1s 40ms/step - loss: 2.1237 - tp:
12277.0625 - fp: 8243.9688 - tn: 8549.2812 - fn: 4657.6875 - accuracy: 0.6168 -
precision: 0.5976 - recall: 0.7233 - auc: 0.6414 - val_loss: 2.0850 - val_tp:
1784.0000 - val_fp: 15522.0000 - val_tn: 12839.0000 - val_fn: 400.0000 -
val_accuracy: 0.4787 - val_precision: 0.1031 - val_recall: 0.8168 - val_auc:
0.6733
Epoch 29/100
31/31 [==============================] - 1s 37ms/step - loss: 2.0108 - tp:
12308.7188 - fp: 8331.0625 - tn: 8587.5000 - fn: 4500.7188 - accuracy: 0.6200 -
precision: 0.5958 - recall: 0.7336 - auc: 0.6490 - val_loss: 1.9801 - val_tp:
1793.0000 - val_fp: 15505.0000 - val_tn: 12856.0000 - val_fn: 391.0000 -
val_accuracy: 0.4796 - val_precision: 0.1037 - val_recall: 0.8210 - val_auc:
0.6731
Epoch 30/100
31/31 [==============================] - 1s 38ms/step - loss: 1.9082 - tp:
12403.9375 - fp: 8299.5312 - tn: 8612.2500 - fn: 4412.2812 - accuracy: 0.6238 -
precision: 0.5992 - recall: 0.7376 - auc: 0.6499 - val_loss: 1.8829 - val_tp:
1808.0000 - val_fp: 15688.0000 - val_tn: 12673.0000 - val_fn: 376.0000 -
val_accuracy: 0.4741 - val_precision: 0.1033 - val_recall: 0.8278 - val_auc:
0.6753
Epoch 31/100
31/31 [==============================] - 1s 38ms/step - loss: 1.8153 - tp:
12489.9688 - fp: 8342.9062 - tn: 8521.3750 - fn: 4373.7500 - accuracy: 0.6222 -
precision: 0.5985 - recall: 0.7413 - auc: 0.6481 - val_loss: 1.7952 - val_tp:
1865.0000 - val_fp: 15885.0000 - val_tn: 12476.0000 - val_fn: 319.0000 -
val_accuracy: 0.4695 - val_precision: 0.1051 - val_recall: 0.8539 - val_auc:
0.6772
Epoch 32/100
31/31 [==============================] - 1s 39ms/step - loss: 1.7230 - tp:
12503.0312 - fp: 8347.6875 - tn: 8561.8750 - fn: 4315.4062 - accuracy: 0.6250 -
precision: 0.6002 - recall: 0.7425 - auc: 0.6581 - val_loss: 1.7075 - val_tp:
1853.0000 - val_fp: 15909.0000 - val_tn: 12452.0000 - val_fn: 331.0000 -
val_accuracy: 0.4683 - val_precision: 0.1043 - val_recall: 0.8484 - val_auc:
0.6801
Epoch 33/100
31/31 [==============================] - 1s 37ms/step - loss: 1.6419 - tp:
12683.1250 - fp: 8210.7500 - tn: 8573.6250 - fn: 4260.5000 - accuracy: 0.6299 -
precision: 0.6079 - recall: 0.7476 - auc: 0.6571 - val_loss: 1.6311 - val_tp:
1885.0000 - val_fp: 16218.0000 - val_tn: 12143.0000 - val_fn: 299.0000 -
val_accuracy: 0.4593 - val_precision: 0.1041 - val_recall: 0.8631 - val_auc:
0.6836
```

```
Epoch 34/100
31/31 [==============================] - 1s 38ms/step - loss: 1.5641 - tp:
12862.7188 - fp: 8276.0000 - tn: 8442.6875 - fn: 4146.5938 - accuracy: 0.6309 -
precision: 0.6087 - recall: 0.7547 - auc: 0.6608 - val_loss: 1.5623 - val_tp:
1890.0000 - val_fp: 16285.0000 - val_tn: 12076.0000 - val_fn: 294.0000 -
val_accuracy: 0.4572 - val_precision: 0.1040 - val_recall: 0.8654 - val_auc:
0.6857
Epoch 35/100
31/31 [==============================] - 1s 39ms/step - loss: 1.4907 - tp:
12694.9062 - fp: 8422.8438 - tn: 8576.1875 - fn: 4034.0625 - accuracy: 0.6306 -
precision: 0.5998 - recall: 0.7589 - auc: 0.6626 - val_loss: 1.4937 - val_tp:
1908.0000 - val_fp: 16472.0000 - val_tn: 11889.0000 - val_fn: 276.0000 -
val_accuracy: 0.4517 - val_precision: 0.1038 - val_recall: 0.8736 - val_auc:
0.6848
Epoch 36/100
31/31 [==============================] - 1s 39ms/step - loss: 1.4206 - tp:
12856.5312 - fp: 8243.3750 - tn: 8650.7812 - fn: 3977.3125 - accuracy: 0.6383 -
precision: 0.6099 - recall: 0.7642 - auc: 0.6708 - val_loss: 1.4339 - val_tp:
1913.0000 - val_fp: 16486.0000 - val_tn: 11875.0000 - val_fn: 271.0000 -
val_accuracy: 0.4514 - val_precision: 0.1040 - val_recall: 0.8759 - val_auc:
0.6864
Epoch 37/100
31/31 [==============================] - 1s 38ms/step - loss: 1.3564 - tp:
12869.4688 - fp: 8217.2188 - tn: 8684.5938 - fn: 3956.7188 - accuracy: 0.6380 -
precision: 0.6085 - recall: 0.7640 - auc: 0.6734 - val_loss: 1.3816 - val_tp:
1962.0000 - val_fp: 17228.0000 - val_tn: 11133.0000 - val_fn: 222.0000 -
val_accuracy: 0.4287 - val_precision: 0.1022 - val_recall: 0.8984 - val_auc:
0.6866
Epoch 38/100
31/31 [==============================] - 1s 39ms/step - loss: 1.2952 - tp:
13093.5938 - fp: 8252.8438 - tn: 8612.6562 - fn: 3768.9062 - accuracy: 0.6441 -
precision: 0.6144 - recall: 0.7769 - auc: 0.6771 - val_loss: 1.3356 - val_tp:
1956.0000 - val_fp: 17250.0000 - val_tn: 11111.0000 - val_fn: 228.0000 -
val_accuracy: 0.4278 - val_precision: 0.1018 - val_recall: 0.8956 - val_auc:
0.6885
Epoch 39/100
31/31 [==============================] - 1s 39ms/step - loss: 1.2409 - tp:
13298.6562 - fp: 8152.7812 - tn: 8556.3438 - fn: 3720.2188 - accuracy: 0.6488 -
precision: 0.6206 - recall: 0.7813 - auc: 0.6821 - val_loss: 1.2949 - val_tp:
2011.0000 - val_fp: 18243.0000 - val_tn: 10118.0000 - val_fn: 173.0000 -
val_accuracy: 0.3971 - val_precision: 0.0993 - val_recall: 0.9208 - val_auc:
0.6909
Epoch 40/100
31/31 [==============================] - 1s 40ms/step - loss: 1.1943 - tp:
13250.2500 - fp: 8439.0938 - tn: 8461.0000 - fn: 3577.6562 - accuracy: 0.6420 -
precision: 0.6093 - recall: 0.7864 - auc: 0.6769 - val_loss: 1.2531 - val_tp:
1999.0000 - val_fp: 17979.0000 - val_tn: 10382.0000 - val_fn: 185.0000 -
val_accuracy: 0.4053 - val_precision: 0.1001 - val_recall: 0.9153 - val_auc:
```

```
0.6947
Epoch 41/100
31/31 [==============================] - 1s 38ms/step - loss: 1.1453 - tp:
13321.3438 - fp: 8354.4375 - tn: 8516.0938 - fn: 3536.1250 - accuracy: 0.6472 -
precision: 0.6156 - recall: 0.7892 - auc: 0.6841 - val_loss: 1.2138 - val_tp:
1997.0000 - val_fp: 17768.0000 - val_tn: 10593.0000 - val_fn: 187.0000 -
val_accuracy: 0.4122 - val_precision: 0.1010 - val_recall: 0.9144 - val_auc:
0.6903
Restoring model weights from the end of the best epoch.
Epoch 00041: early stopping
```

[ ]:
```
plot_metrics(resampled_history)

# This model seems to have performed the best by far
```



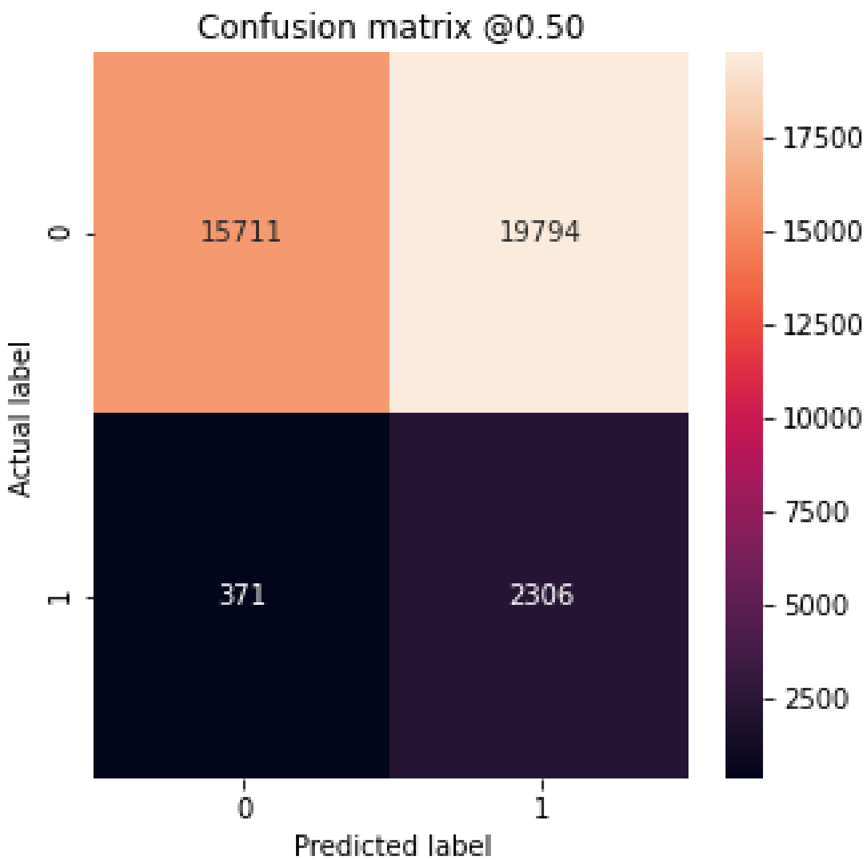
[ ]:
```
!mkdir -p saved_model
resampled_three_layer_model.save('saved_model/resampled_three_layer_model')
```

```
INFO:tensorflow:Assets written to:
saved_model/resampled_three_layer_model/assets
```

[ ]:
```
train_predictions_resampled = resampled_three_layer_model.
 ↪predict(train_features, batch_size=BATCH_SIZE)
test_predictions_resampled = resampled_three_layer_model.predict(test_features,␣
 ↪batch_size=BATCH_SIZE)
```

[ ]:
```
resampled_results = resampled_three_layer_model.evaluate(test_features,␣
↪test_labels,
                                             batch_size=BATCH_SIZE, verbose=0)
for name, value in zip(resampled_three_layer_model.metrics_names,␣
↪resampled_results):
  print(name, ': ', value)
print()

plot_cm(test_labels, test_predictions_resampled)
```

```
loss :  1.7949222326278687
tp :  2306.0
fp :  19794.0
tn :  15711.0
fn :  371.0
accuracy :  0.471871554851532
precision :  0.10434389114379883
recall :  0.8614120483398438
auc :  0.6911264061927795

f1 Score 0.1861403721193042

Irrelevant Documents Detected (True Negatives):  15711
Irrelevant Documents Incorrectly Detected (False Positives):  19794
Relevant Documents Missed (False Negatives):  371
Relevant Documents Detected (True Positives):  2306
Total Relevant Documents:  2677
```



[ ]:
```
pred_labels = resampled_three_layer_model.predict(test_features)
pred_labels = pred_labels.round(0)
pred_labels = pred_labels.astype(int)

tl_resampled = {'Model': 'Resampled Three Layer Model',
                'Loss': resampled_results[0],
                'Accuracy': accuracy_score(test_labels, pred_labels),
                'Precision': precision_score(test_labels, pred_labels),
                'Recall': recall_score(test_labels, pred_labels),
                'F1 Score': f1_score(test_labels, pred_labels)}

tl_resampled
```

[ ]:
```
{'Accuracy': 0.47187156251636897,
 'F1 Score': 0.1861403721193042,
 'Loss': 1.7949222326278687,
 'Model': 'Resampled Three Layer Model',
 'Precision': 0.10434389140271494,
 'Recall': 0.8614120283899888}
```

[ ]:
```
test_predictions_baseline = resampled_three_layer_model.predict(test)
```

[ ]:
```
test_predictions_baseline = test_predictions_baseline.round(0)
test_predictions_baseline = test_predictions_baseline.astype(int)
test_predictions_baseline
```

[ ]:
```
array([[1],
       [0],
       [1],
       …,
       [0],
       [0],
       [0]])
```

[ ]:
```
predictions_baseline= pd.DataFrame(test_predictions_baseline)
predictions_baseline['Id'] = predictions_baseline.index
predictions_baseline.rename(columns={ predictions_baseline.columns[0]: "psrel"␣
 ↪}, inplace = True)
predictions_baseline = predictions_baseline[['Id','psrel']]
predictions_baseline
```

[ ]:

	Id	psrel
0	0	1
1	1	0
2	2	1
3	3	1
4	4	1
…	…	…
4995	4995	1
4996	4996	1
4997	4997	0
4998	4998	0
4999	4999	0

[5000 rows x 2 columns]

[ ]:
```
predictions_baseline['psrel'].value_counts()
```

[ ]:
```
0    2663
1    2337
Name: psrel, dtype: int64
```

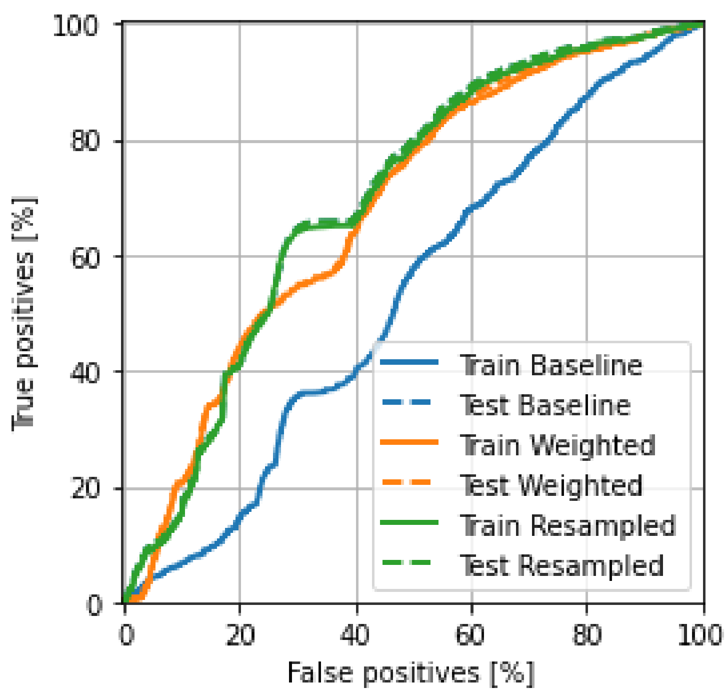
[ ]:
```
predictions_baseline.to_csv('Resampled colab predictions.csv', index=False)
```

[ ]:
```
test_predictions_baseline = resampled_three_layer_model.predict(test_features,␣
 ↪batch_size=BATCH_SIZE)
```

Final Evaluation

[ ]:
```
plot_roc("Train Baseline", train_labels, train_predictions_baseline,␣
 ↪color=colors[0])
plot_roc("Test Baseline", test_labels, test_predictions_baseline,␣
 ↪color=colors[0], linestyle='--')

plot_roc("Train Weighted", train_labels, train_predictions_weighted,␣
 ↪color=colors[1])
plot_roc("Test Weighted", test_labels, test_predictions_weighted,␣
 ↪color=colors[1], linestyle='--')

plot_roc("Train Resampled", train_labels, train_predictions_resampled,␣
 ↪color=colors[2])
plot_roc("Test Resampled", test_labels, test_predictions_resampled,␣
 ↪color=colors[2], linestyle='--')
plt.legend(loc='lower right')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f7509537d50>
```



[ ]:
```
keras.backend.clear_session()
```

Predictions

[ ]:
```
weighted_three_layer_model = tf.keras.models.load_model('saved_model/
 ↪weighted_three_layer_model')
```

[ ]:
```
test_predictions = weighted_three_layer_model.predict(test)
```

[ ]:
```
test_predictions = test_predictions.round(0)
test_predictions = test_predictions.astype(int)
test_predictions
```

[ ]:
```
array([[0],
       [0],
       [0],
       …,
       [0],
       [0],
       [0]])
```

[ ]:
```
predictions_baseline= pd.DataFrame(test_predictions)
predictions_baseline['Id'] = predictions_baseline.index
predictions_baseline.rename(columns={ predictions_baseline.columns[0]: "psrel"␣
 ↪}, inplace = True)
predictions_baseline = predictions_baseline[['Id','psrel']]
```

[ ]:
```
predictions_baseline['psrel'].value_counts()
```

[ ]:
```
0    4711
1     289
Name: psrel, dtype: int64
```

[ ]:
```
# create output file
predictions_baseline.to_csv('three-layer predictions.csv', index=False)
```

6.2.2 Random Forest with Updated Class Weights

[ ]:
```
wt_rnd_clf = RandomForestClassifier(criterion = "gini",
                                 n_estimators=200,
                                 max_leaf_nodes=100,
                                 min_samples_leaf=1,
                                 max_features="sqrt",
                                 class_weight=class_weight,
                                 n_jobs=-1)
```

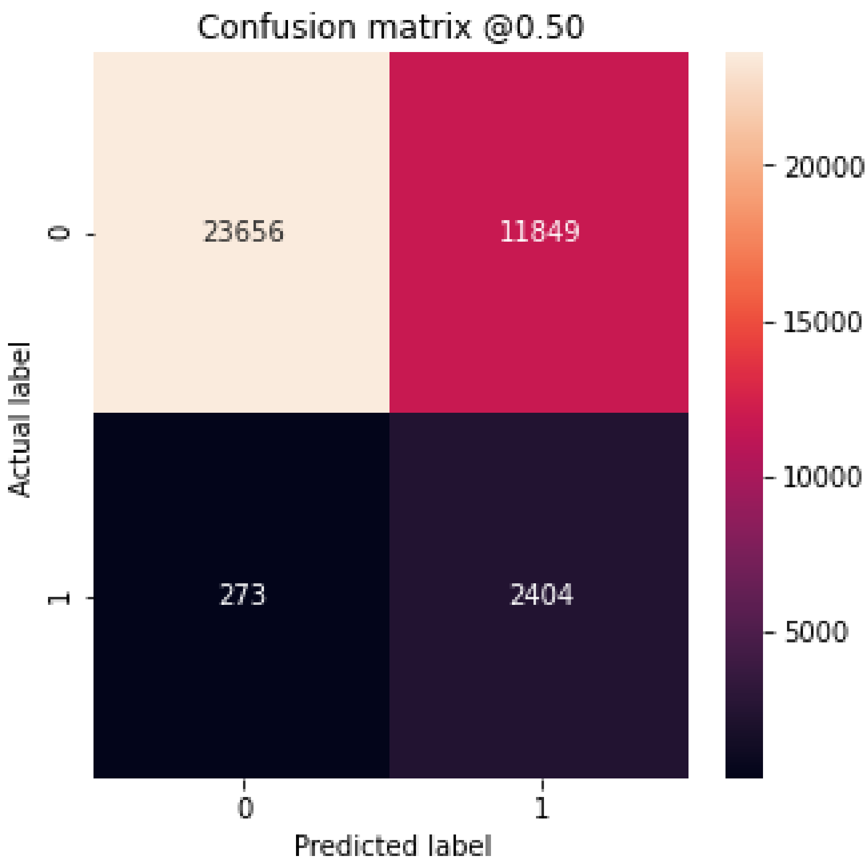
[ ]:
```
wt_rnd_clf.fit(train_features, train_labels)

pred_labels = wt_rnd_clf.predict(test_features)

scores = cross_validate(wt_rnd_clf, train_features, train_labels,
                        scoring=("accuracy","precision","recall","f1"),cv=10)

wt_rnd = {'Model': 'Weighted Random Forest',
```

```
                 'Loss': 0,
                 'Accuracy': accuracy_score(test_labels, pred_labels),
                 'Precision': precision_score(test_labels, pred_labels),
                 'Recall': recall_score(test_labels, pred_labels),
                 'F1 Score': f1_score(test_labels, pred_labels)}

wt_rnd
```

[ ]:
```
{'Accuracy': 0.6825205594259075,
 'F1 Score': 0.2839929119905493,
 'Loss': 0,
 'Model': 'Weighted Random Forest',
 'Precision': 0.1686662457026591,
 'Recall': 0.8980201718341427}
```

[ ]:
```
train_predictions_wt_rnd_clf = wt_rnd_clf.predict(train_features)
test_predictions_wt_rnd_clf = wt_rnd_clf.predict(test_features)

plot_cm(test_labels, test_predictions_wt_rnd_clf)
```

```
f1 Score 0.2839929119905493

Irrelevant Documents Detected (True Negatives):  23656
Irrelevant Documents Incorrectly Detected (False Positives):  11849
Relevant Documents Missed (False Negatives):  273
Relevant Documents Detected (True Positives):  2404
Total Relevant Documents:  2677
```




```
[ ]: test_predictions_wt_rnd_clf = wt_rnd_clf.predict(test)
     test_predictions_wt_rnd_clf = test_predictions_wt_rnd_clf.round(0)
     test_predictions_wt_rnd_clf = test_predictions_wt_rnd_clf.astype(int)
     test_predictions_wt_rnd_clf
```

```
[ ]: array([0, 0, 0, …, 0, 0, 0])
```

```
[ ]: predictions_wt_rnd_clf= pd.DataFrame(test_predictions_wt_rnd_clf)
     predictions_wt_rnd_clf['Id'] = predictions_wt_rnd_clf.index
     predictions_wt_rnd_clf.rename(columns={ predictions_wt_rnd_clf.columns[0]:␣
      ↪"psrel" }, inplace = True)
     predictions_wt_rnd_clf = predictions_wt_rnd_clf[['Id','psrel']]
     predictions_wt_rnd_clf
```

[ ]:

	Id	psrel
0	0	0
1	1	0
2	2	0
3	3	0

```
4         4       0
…     …     …
4995   4995       0
4996   4996       0
4997   4997       0
4998   4998       0
4999   4999       0

[5000 rows x 2 columns]
```

[ ]:
```
predictions_wt_rnd_clf['psrel'].value_counts()
```

[ ]:
```
0    4198
1     802
Name: psrel, dtype: int64
```

[ ]:
```
predictions_wt_rnd_clf.to_csv('Reweighted Random Forest colab predictions.csv',␣
↪index=False)
```

Baseline Model also performs much better with updated weights

6.2.3 Deep Network Model

Dense Deep Model Function

[ ]:
```
early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_precision',
    verbose=1,
    patience=10,
    mode='max',
    restore_best_weights=True)
```

[ ]:
```
def build_dense_deep(n_hidden=5, n_neurons=30, learning_rate=3e-4,␣
↪metrics=METRICS, output_bias=None, input_shape=train_features.shape[1:]):
  if output_bias is not None:
    output_bias = tf.keras.initializers.Constant(output_bias)
  model = keras.models.Sequential()
  model.add(keras.layers.InputLayer(input_shape=input_shape))
  for layer in range(n_hidden):
    model.add(RegularizedDense(n_neurons))
    model.add(keras.layers.BatchNormalization())
    model.add(keras.layers.Dropout(rate=0.3))
  model.add(keras.layers.Dense(1, activation="sigmoid",␣
↪bias_initializer=output_bias))

  optimizer = keras.optimizers.Nadam(lr=learning_rate)
  model.compile(loss="binary_crossentropy", optimizer=optimizer,␣
↪metrics=metrics)
  return model
```

[ ]:
```python
# Create a default dense deep model using the build_dense_deep function

dense_deep_keras_reg = keras.wrappers.scikit_learn.
 ↪KerasRegressor(build_dense_deep)

dense_deep_model = build_dense_deep()
dense_deep_model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 30)                2250
_________________________________________________________________
batch_normalization (BatchNo (None, 30)                120
_________________________________________________________________
dropout (Dropout)            (None, 30)                0
_________________________________________________________________
dense_1 (Dense)              (None, 30)                930
_________________________________________________________________
batch_normalization_1 (Batch (None, 30)                120
_________________________________________________________________
dropout_1 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_2 (Dense)              (None, 30)                930
_________________________________________________________________
batch_normalization_2 (Batch (None, 30)                120
_________________________________________________________________
dropout_2 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_3 (Dense)              (None, 30)                930
_________________________________________________________________
batch_normalization_3 (Batch (None, 30)                120
_________________________________________________________________
dropout_3 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_4 (Dense)              (None, 30)                930
_________________________________________________________________
batch_normalization_4 (Batch (None, 30)                120
_________________________________________________________________
dropout_4 (Dropout)          (None, 30)                0
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 31
=================================================================
Total params: 6,601
Trainable params: 6,301
Non-trainable params: 300
_________________________________________________________________
```

With Class Weights

```
[ ]: # Find initial weights
initial_weights = os.path.join(tempfile.mkdtemp(), 'initial_weights')
dense_deep_model.save_weights(initial_weights)
```

```
[ ]: # Load in previously calculated weights

dense_deep_model.load_weights(initial_weights)

dense_deep_history = dense_deep_model.fit(
    train_features,
    train_labels,
    batch_size=BATCH_SIZE,
    epochs=EPOCHS,
    callbacks=[early_stopping],
    validation_data=(val_features, val_labels),
    class_weight=class_weight)
```

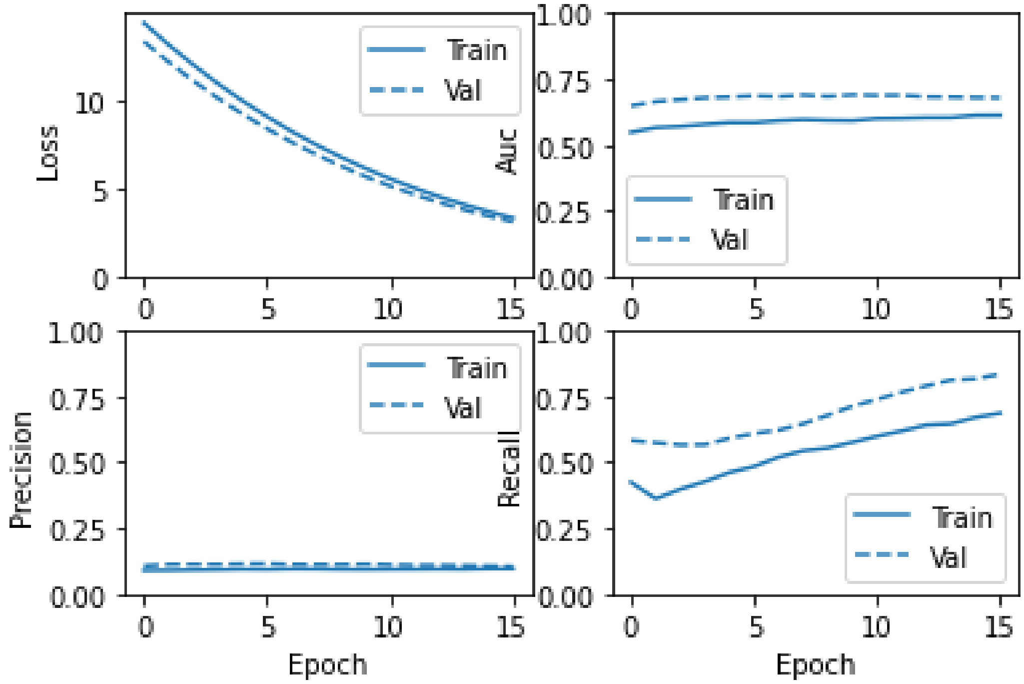
```
Epoch 1/100
60/60 [==============================] - 8s 47ms/step - loss: 14.6585 - tp:
3616.5246 - fp: 35217.3115 - tn: 59074.1803 - fn: 3705.4262 - accuracy: 0.6030 -
precision: 0.0941 - recall: 0.5294 - auc: 0.5715 - val_loss: 13.3116 - val_tp:
1271.0000 - val_fp: 10698.0000 - val_tn: 17663.0000 - val_fn: 913.0000 -
val_accuracy: 0.6199 - val_precision: 0.1062 - val_recall: 0.5820 - val_auc:
0.6492
Epoch 2/100
60/60 [==============================] - 2s 29ms/step - loss: 13.4353 - tp:
1630.4590 - fp: 16644.7541 - tn: 42142.6557 - fn: 3013.5738 - accuracy: 0.6911 -
precision: 0.0886 - recall: 0.3431 - auc: 0.5612 - val_loss: 12.1671 - val_tp:
1252.0000 - val_fp: 9969.0000 - val_tn: 18392.0000 - val_fn: 932.0000 -
val_accuracy: 0.6431 - val_precision: 0.1116 - val_recall: 0.5733 - val_auc:
0.6655
Epoch 3/100
60/60 [==============================] - 2s 28ms/step - loss: 12.2787 - tp:
1793.7213 - fp: 18013.9180 - tn: 40797.0656 - fn: 2826.7377 - accuracy: 0.6726 -
precision: 0.0905 - recall: 0.3852 - auc: 0.5681 - val_loss: 11.1066 - val_tp:
1234.0000 - val_fp: 9766.0000 - val_tn: 18595.0000 - val_fn: 950.0000 -
val_accuracy: 0.6492 - val_precision: 0.1122 - val_recall: 0.5650 - val_auc:
0.6729
Epoch 4/100
60/60 [==============================] - 2s 29ms/step - loss: 11.1970 - tp:
1974.0984 - fp: 19124.2787 - tn: 39676.0656 - fn: 2657.0000 - accuracy: 0.6576 -
precision: 0.0947 - recall: 0.4282 - auc: 0.5814 - val_loss: 10.1292 - val_tp:
1236.0000 - val_fp: 9803.0000 - val_tn: 18558.0000 - val_fn: 948.0000 -
val_accuracy: 0.6480 - val_precision: 0.1120 - val_recall: 0.5659 - val_auc:
0.6799
Epoch 5/100
60/60 [==============================] - 2s 28ms/step - loss: 10.1948 - tp:
```

2121.7869 - fp: 20261.2459 - tn: 38539.9180 - fn: 2508.4918 - accuracy: 0.6417 - precision: 0.0945 - recall: 0.4594 - auc: 0.5883 - val_loss: 9.2339 - val_tp: 1289.0000 - val_fp: 10017.0000 - val_tn: 18344.0000 - val_fn: 895.0000 - val_accuracy: 0.6428 - val_precision: 0.1140 - val_recall: 0.5902 - val_auc: 0.6829
Epoch 6/100
60/60 [==============================] - 2s 28ms/step - loss: 9.2845 - tp: 2197.9180 - fp: 21408.1967 - tn: 37432.3115 - fn: 2393.0164 - accuracy: 0.6276 - precision: 0.0943 - recall: 0.4811 - auc: 0.5894 - val_loss: 8.3992 - val_tp: 1328.0000 - val_fp: 10256.0000 - val_tn: 18105.0000 - val_fn: 856.0000 - val_accuracy: 0.6362 - val_precision: 0.1146 - val_recall: 0.6081 - val_auc: 0.6873
Epoch 7/100
60/60 [==============================] - 2s 29ms/step - loss: 8.4356 - tp: 2361.4590 - fp: 22568.6230 - tn: 36268.6721 - fn: 2232.6885 - accuracy: 0.6100 - precision: 0.0942 - recall: 0.5105 - auc: 0.5922 - val_loss: 7.6385 - val_tp: 1356.0000 - val_fp: 10743.0000 - val_tn: 17618.0000 - val_fn: 828.0000 - val_accuracy: 0.6212 - val_precision: 0.1121 - val_recall: 0.6209 - val_auc: 0.6845
Epoch 8/100
60/60 [==============================] - 2s 29ms/step - loss: 7.6606 - tp: 2475.4754 - fp: 23691.3443 - tn: 35152.9836 - fn: 2111.6393 - accuracy: 0.5942 - precision: 0.0944 - recall: 0.5386 - auc: 0.5975 - val_loss: 6.9359 - val_tp: 1408.0000 - val_fp: 11220.0000 - val_tn: 17141.0000 - val_fn: 776.0000 - val_accuracy: 0.6073 - val_precision: 0.1115 - val_recall: 0.6447 - val_auc: 0.6903
Epoch 9/100
60/60 [==============================] - 2s 28ms/step - loss: 6.9635 - tp: 2531.4754 - fp: 24526.3770 - tn: 34286.1639 - fn: 2087.4262 - accuracy: 0.5813 - precision: 0.0940 - recall: 0.5461 - auc: 0.5927 - val_loss: 6.2910 - val_tp: 1478.0000 - val_fp: 11809.0000 - val_tn: 16552.0000 - val_fn: 706.0000 - val_accuracy: 0.5903 - val_precision: 0.1112 - val_recall: 0.6767 - val_auc: 0.6852
Epoch 10/100
60/60 [==============================] - 2s 28ms/step - loss: 6.3074 - tp: 2640.5410 - fp: 25753.3770 - tn: 33056.2131 - fn: 1981.3115 - accuracy: 0.5635 - precision: 0.0940 - recall: 0.5729 - auc: 0.5936 - val_loss: 5.6959 - val_tp: 1553.0000 - val_fp: 12209.0000 - val_tn: 16152.0000 - val_fn: 631.0000 - val_accuracy: 0.5796 - val_precision: 0.1128 - val_recall: 0.7111 - val_auc: 0.6908
Epoch 11/100
60/60 [==============================] - 2s 29ms/step - loss: 5.6998 - tp: 2730.7705 - fp: 26445.6230 - tn: 32406.8361 - fn: 1848.2131 - accuracy: 0.5555 - precision: 0.0936 - recall: 0.5956 - auc: 0.5981 - val_loss: 5.1588 - val_tp: 1609.0000 - val_fp: 12947.0000 - val_tn: 15414.0000 - val_fn: 575.0000 - val_accuracy: 0.5573 - val_precision: 0.1105 - val_recall: 0.7367 - val_auc: 0.6889
Epoch 12/100

```
60/60 [==============================] - 2s 28ms/step - loss: 5.1496 - tp:
2847.0328 - fp: 27379.5246 - tn: 31464.2951 - fn: 1740.5902 - accuracy: 0.5409 -
precision: 0.0944 - recall: 0.6225 - auc: 0.6066 - val_loss: 4.6687 - val_tp:
1669.0000 - val_fp: 13723.0000 - val_tn: 14638.0000 - val_fn: 515.0000 -
val_accuracy: 0.5339 - val_precision: 0.1084 - val_recall: 0.7642 - val_auc:
0.6895
Epoch 13/100
60/60 [==============================] - 2s 28ms/step - loss: 4.6602 - tp:
2966.0492 - fp: 28095.0328 - tn: 30691.3443 - fn: 1679.0164 - accuracy: 0.5319 -
precision: 0.0959 - recall: 0.6400 - auc: 0.6078 - val_loss: 4.2259 - val_tp:
1721.0000 - val_fp: 14163.0000 - val_tn: 14198.0000 - val_fn: 463.0000 -
val_accuracy: 0.5212 - val_precision: 0.1083 - val_recall: 0.7880 - val_auc:
0.6835
Epoch 14/100
60/60 [==============================] - 2s 30ms/step - loss: 4.2143 - tp:
2948.1475 - fp: 28530.0656 - tn: 30310.3443 - fn: 1642.8852 - accuracy: 0.5251 -
precision: 0.0941 - recall: 0.6418 - auc: 0.6038 - val_loss: 3.8231 - val_tp:
1769.0000 - val_fp: 14811.0000 - val_tn: 13550.0000 - val_fn: 415.0000 -
val_accuracy: 0.5015 - val_precision: 0.1067 - val_recall: 0.8100 - val_auc:
0.6827
Epoch 15/100
60/60 [==============================] - 2s 28ms/step - loss: 3.8034 - tp:
3065.7705 - fp: 28955.5738 - tn: 29842.8689 - fn: 1567.2295 - accuracy: 0.5202 -
precision: 0.0956 - recall: 0.6595 - auc: 0.6091 - val_loss: 3.4566 - val_tp:
1780.0000 - val_fp: 15138.0000 - val_tn: 13223.0000 - val_fn: 404.0000 -
val_accuracy: 0.4912 - val_precision: 0.1052 - val_recall: 0.8150 - val_auc:
0.6809
Epoch 16/100
60/60 [==============================] - 2s 28ms/step - loss: 3.4391 - tp:
3141.0820 - fp: 29640.2295 - tn: 29164.3770 - fn: 1485.7541 - accuracy: 0.5095 -
precision: 0.0960 - recall: 0.6766 - auc: 0.6098 - val_loss: 3.1283 - val_tp:
1818.0000 - val_fp: 15753.0000 - val_tn: 12608.0000 - val_fn: 366.0000 -
val_accuracy: 0.4723 - val_precision: 0.1035 - val_recall: 0.8324 - val_auc:
0.6802
Restoring model weights from the end of the best epoch.
Epoch 00016: early stopping
```

Evaluation

[ ]:
```
plot_metrics(dense_deep_history)
```

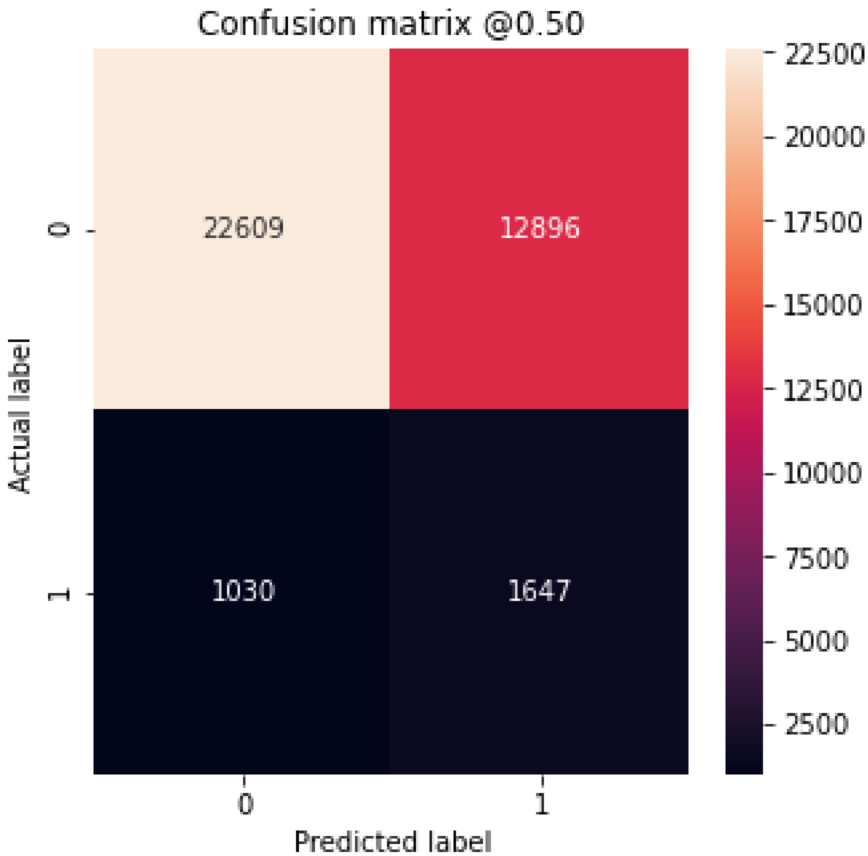



```
[ ]: train_predictions_dense_deep_model = dense_deep_model.predict(train_features,␣
      ↪batch_size=BATCH_SIZE)
     test_predictions_dense_deep_model = dense_deep_model.predict(test_features,␣
      ↪batch_size=BATCH_SIZE)
```

```
[ ]: dense_deep_results = dense_deep_model.evaluate(test_features, test_labels,
                                                     batch_size=BATCH_SIZE, verbose=0)
     for name, value in zip(dense_deep_model.metrics_names, dense_deep_results):
       print(name, ': ', value)
     print()

     plot_cm(test_labels, test_predictions_dense_deep_model)
```

```
loss :  8.398951530456543
tp :  1647.0
fp :  12896.0
tn :  22609.0
fn :  1030.0
accuracy :  0.6352731585502625
precision :  0.11325035989284515
recall :  0.6152409315109253
auc :  0.6954426765441895

f1 Score 0.19128919860627178
```

```
Irrelevant Documents Detected (True Negatives):  22609
Irrelevant Documents Incorrectly Detected (False Positives):  12896
Relevant Documents Missed (False Negatives):  1030
Relevant Documents Detected (True Positives):  1647
Total Relevant Documents:  2677
```



[ ]:
```
pred_labels = dense_deep_model.predict(test_features)
pred_labels = pred_labels.round(0)
pred_labels = pred_labels.astype(int)

dense_deep = {'Model': 'Dense Deep Model',
                'Loss': dense_deep_results[0],
                'Accuracy': accuracy_score(test_labels, pred_labels),
                'Precision': precision_score(test_labels, pred_labels),
                'Recall': recall_score(test_labels, pred_labels),
                'F1 Score': f1_score(test_labels, pred_labels)}

dense_deep
```

```
[ ]: {'Accuracy': 0.6352731653658792,
      'F1 Score': 0.19128919860627178,
      'Loss': 8.398951530456543,
      'Model': 'Dense Deep Model',
      'Precision': 0.11325036099841848,
      'Recall': 0.61524094135226}
```

Predictions

```
[ ]: test_predictions = dense_deep_model.predict(test)
```

```
[ ]: test_predictions = test_predictions.round(0)
     test_predictions = test_predictions.astype(int)
     test_predictions
```

```
[ ]: array([[0],
            [0],
            [0],
            …,
            [0],
            [0],
            [0]])
```

```
[ ]: predictions= pd.DataFrame(test_predictions)
     predictions['Id'] = predictions.index
     predictions.rename(columns={ predictions.columns[0]: "psrel" }, inplace = True)
     predictions = predictions[['Id','psrel']]
     predictions
```

```
[ ]:         Id  psrel
     0        0      0
     1        1      0
     2        2      0
     3        3      0
     4        4      0
     …      …    …
     4995  4995      0
     4996  4996      0
     4997  4997      0
     4998  4998      0
     4999  4999      0

     [5000 rows x 2 columns]
```

```
[ ]: predictions['psrel'].value_counts()
```

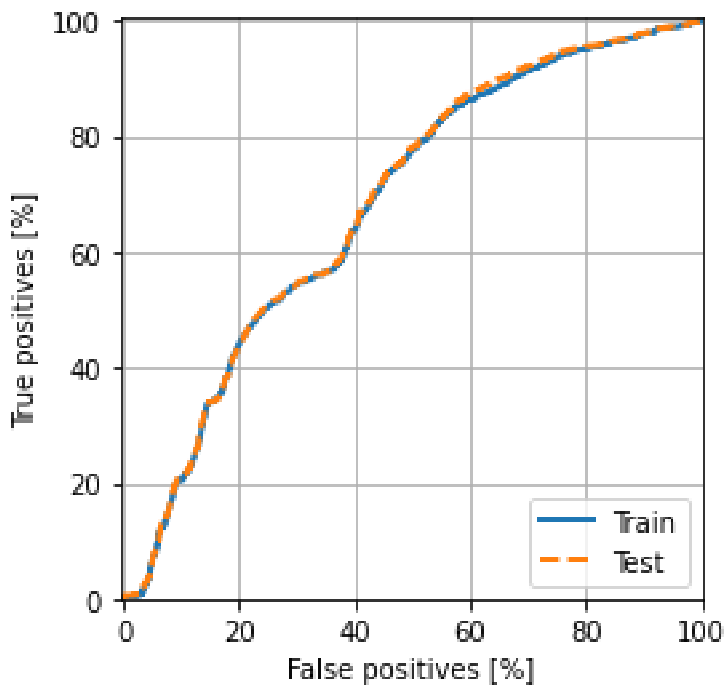
```
[ ]: 0    4846
     1     154
```

```
Name: psrel, dtype: int64
```

[ ]:
```python
predictions.to_csv('dense deep colab predictions.csv', index=False)
```

[ ]:
```python
plot_roc("Train", train_labels, train_predictions_weighted, color=colors[0])
plot_roc("Test", test_labels, test_predictions_weighted, color=colors[1],␣
 ↪linestyle='--')

plt.legend(loc='lower right')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f75064c9d10>
```



With Resampled Dataset

[ ]:
```python
resampled_dense_deep_model = build_dense_deep()
resampled_dense_deep_model.load_weights(initial_weights)

# Reset the bias to zero, since this dataset is balanced.
output_layer = resampled_dense_deep_model.layers[-1]
output_layer.bias.assign([0])

val_ds = tf.data.Dataset.from_tensor_slices((val_features, val_labels)).cache()
val_ds = val_ds.batch(BATCH_SIZE).prefetch(2)
```

[ ]:
```
resampled_history = resampled_dense_deep_model.fit(
    resampled_ds,
    epochs=EPOCHS,
    steps_per_epoch=resampled_steps_per_epoch,
    callbacks=[early_stopping],
    validation_data=val_ds)
```

```
Epoch 1/100
31/31 [==============================] - 7s 78ms/step - loss: 14.5880 - tp:
10774.3438 - fp: 21328.6562 - tn: 31063.3438 - fn: 8743.6562 - accuracy: 0.5865
- precision: 0.3148 - recall: 0.5557 - auc: 0.6043 - val_loss: 14.1993 - val_tp:
1688.0000 - val_fp: 19565.0000 - val_tn: 8796.0000 - val_fn: 496.0000 -
val_accuracy: 0.3432 - val_precision: 0.0794 - val_recall: 0.7729 - val_auc:
0.6140
Epoch 2/100
31/31 [==============================] - 1s 46ms/step - loss: 13.9093 - tp:
9287.8750 - fp: 8257.7188 - tn: 8541.5312 - fn: 7640.8750 - accuracy: 0.5278 -
precision: 0.5282 - recall: 0.5479 - auc: 0.5381 - val_loss: 13.4347 - val_tp:
1654.0000 - val_fp: 18796.0000 - val_tn: 9565.0000 - val_fn: 530.0000 -
val_accuracy: 0.3673 - val_precision: 0.0809 - val_recall: 0.7573 - val_auc:
0.6336
Epoch 3/100
31/31 [==============================] - 1s 43ms/step - loss: 13.2239 - tp:
9313.3438 - fp: 8249.5312 - tn: 8645.2188 - fn: 7519.9062 - accuracy: 0.5314 -
precision: 0.5277 - recall: 0.5532 - auc: 0.5423 - val_loss: 12.7215 - val_tp:
1659.0000 - val_fp: 17240.0000 - val_tn: 11121.0000 - val_fn: 525.0000 -
val_accuracy: 0.4184 - val_precision: 0.0878 - val_recall: 0.7596 - val_auc:
0.6463
Epoch 4/100
31/31 [==============================] - 1s 43ms/step - loss: 12.5606 - tp:
9411.9688 - fp: 8249.3125 - tn: 8686.1250 - fn: 7380.5938 - accuracy: 0.5365 -
precision: 0.5315 - recall: 0.5617 - auc: 0.5500 - val_loss: 12.0530 - val_tp:
1616.0000 - val_fp: 16119.0000 - val_tn: 12242.0000 - val_fn: 568.0000 -
val_accuracy: 0.4537 - val_precision: 0.0911 - val_recall: 0.7399 - val_auc:
0.6497
Epoch 5/100
31/31 [==============================] - 1s 44ms/step - loss: 11.9228 - tp:
9435.5938 - fp: 8052.0000 - tn: 8811.7500 - fn: 7428.6562 - accuracy: 0.5400 -
precision: 0.5395 - recall: 0.5587 - auc: 0.5570 - val_loss: 11.4267 - val_tp:
1603.0000 - val_fp: 14924.0000 - val_tn: 13437.0000 - val_fn: 581.0000 -
val_accuracy: 0.4924 - val_precision: 0.0970 - val_recall: 0.7340 - val_auc:
0.6556
Epoch 6/100
31/31 [==============================] - 1s 45ms/step - loss: 11.3310 - tp:
9502.2188 - fp: 8140.2188 - tn: 8733.1562 - fn: 7352.4062 - accuracy: 0.5388 -
precision: 0.5367 - recall: 0.5617 - auc: 0.5520 - val_loss: 10.8358 - val_tp:
1578.0000 - val_fp: 14371.0000 - val_tn: 13990.0000 - val_fn: 606.0000 -
val_accuracy: 0.5097 - val_precision: 0.0989 - val_recall: 0.7225 - val_auc:
```

```
0.6586
Epoch 7/100
31/31 [==============================] - 1s 44ms/step - loss: 10.7534 - tp:
9678.0625 - fp: 8104.1875 - tn: 8700.1875 - fn: 7245.5625 - accuracy: 0.5434 -
precision: 0.5420 - recall: 0.5718 - auc: 0.5580 - val_loss: 10.2789 - val_tp:
1566.0000 - val_fp: 13896.0000 - val_tn: 14465.0000 - val_fn: 618.0000 -
val_accuracy: 0.5248 - val_precision: 0.1013 - val_recall: 0.7170 - val_auc:
0.6635
Epoch 8/100
31/31 [==============================] - 1s 44ms/step - loss: 10.2039 - tp:
9652.8438 - fp: 8150.0000 - tn: 8798.4688 - fn: 7126.6875 - accuracy: 0.5480 -
precision: 0.5421 - recall: 0.5768 - auc: 0.5593 - val_loss: 9.7444 - val_tp:
1541.0000 - val_fp: 13392.0000 - val_tn: 14969.0000 - val_fn: 643.0000 -
val_accuracy: 0.5405 - val_precision: 0.1032 - val_recall: 0.7056 - val_auc:
0.6646
Epoch 9/100
31/31 [==============================] - 1s 43ms/step - loss: 9.6737 - tp:
9677.7500 - fp: 8053.6875 - tn: 8821.9375 - fn: 7174.6250 - accuracy: 0.5486 -
precision: 0.5458 - recall: 0.5740 - auc: 0.5663 - val_loss: 9.2399 - val_tp:
1541.0000 - val_fp: 13149.0000 - val_tn: 15212.0000 - val_fn: 643.0000 -
val_accuracy: 0.5485 - val_precision: 0.1049 - val_recall: 0.7056 - val_auc:
0.6682
Epoch 10/100
31/31 [==============================] - 1s 44ms/step - loss: 9.1797 - tp:
9745.1250 - fp: 8036.3125 - tn: 8755.7188 - fn: 7190.8438 - accuracy: 0.5477 -
precision: 0.5468 - recall: 0.5743 - auc: 0.5611 - val_loss: 8.7586 - val_tp:
1535.0000 - val_fp: 12866.0000 - val_tn: 15495.0000 - val_fn: 649.0000 -
val_accuracy: 0.5575 - val_precision: 0.1066 - val_recall: 0.7028 - val_auc:
0.6689
Epoch 11/100
31/31 [==============================] - 1s 46ms/step - loss: 8.6948 - tp:
9794.0000 - fp: 8126.5312 - tn: 8796.5938 - fn: 7010.8750 - accuracy: 0.5530 -
precision: 0.5468 - recall: 0.5862 - auc: 0.5701 - val_loss: 8.2989 - val_tp:
1542.0000 - val_fp: 12969.0000 - val_tn: 15392.0000 - val_fn: 642.0000 -
val_accuracy: 0.5544 - val_precision: 0.1063 - val_recall: 0.7060 - val_auc:
0.6679
Epoch 12/100
31/31 [==============================] - 1s 43ms/step - loss: 8.2461 - tp:
9798.4375 - fp: 8098.3438 - tn: 8724.5625 - fn: 7106.6562 - accuracy: 0.5488 -
precision: 0.5477 - recall: 0.5785 - auc: 0.5657 - val_loss: 7.8618 - val_tp:
1549.0000 - val_fp: 12897.0000 - val_tn: 15464.0000 - val_fn: 635.0000 -
val_accuracy: 0.5570 - val_precision: 0.1072 - val_recall: 0.7092 - val_auc:
0.6740
Epoch 13/100
31/31 [==============================] - 1s 44ms/step - loss: 7.8074 - tp:
10076.7188 - fp: 8077.2188 - tn: 8694.2812 - fn: 6879.7812 - accuracy: 0.5567 -
precision: 0.5550 - recall: 0.5941 - auc: 0.5733 - val_loss: 7.4464 - val_tp:
1542.0000 - val_fp: 12920.0000 - val_tn: 15441.0000 - val_fn: 642.0000 -
```

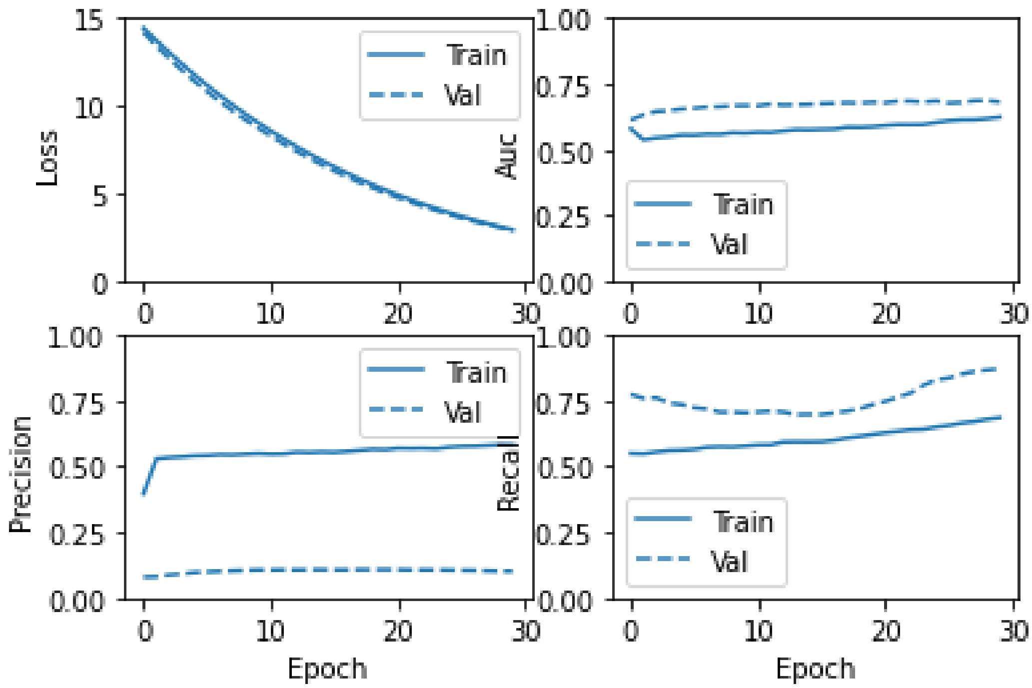
```
val_accuracy: 0.5560 - val_precision: 0.1066 - val_recall: 0.7060 - val_auc:
0.6704
Epoch 14/100
31/31 [==============================] - 1s 45ms/step - loss: 7.3888 - tp:
9936.7188 - fp: 8056.1875 - tn: 8950.4062 - fn: 6784.6875 - accuracy: 0.5601 -
precision: 0.5511 - recall: 0.5951 - auc: 0.5803 - val_loss: 7.0450 - val_tp:
1519.0000 - val_fp: 12618.0000 - val_tn: 15743.0000 - val_fn: 665.0000 -
val_accuracy: 0.5651 - val_precision: 0.1074 - val_recall: 0.6955 - val_auc:
0.6717
Epoch 15/100
31/31 [==============================] - 1s 45ms/step - loss: 6.9973 - tp:
9999.6250 - fp: 8007.9688 - tn: 8896.9062 - fn: 6823.5000 - accuracy: 0.5617 -
precision: 0.5570 - recall: 0.5959 - auc: 0.5795 - val_loss: 6.6669 - val_tp:
1521.0000 - val_fp: 12598.0000 - val_tn: 15763.0000 - val_fn: 663.0000 -
val_accuracy: 0.5659 - val_precision: 0.1077 - val_recall: 0.6964 - val_auc:
0.6731
Epoch 16/100
31/31 [==============================] - 1s 44ms/step - loss: 6.6257 - tp:
9946.8125 - fp: 8059.6562 - tn: 8861.3750 - fn: 6860.1562 - accuracy: 0.5574 -
precision: 0.5529 - recall: 0.5893 - auc: 0.5779 - val_loss: 6.3084 - val_tp:
1520.0000 - val_fp: 12694.0000 - val_tn: 15667.0000 - val_fn: 664.0000 -
val_accuracy: 0.5627 - val_precision: 0.1069 - val_recall: 0.6960 - val_auc:
0.6760
Epoch 17/100
31/31 [==============================] - 1s 43ms/step - loss: 6.2696 - tp:
10071.4375 - fp: 8054.4062 - tn: 8843.3750 - fn: 6758.7812 - accuracy: 0.5610 -
precision: 0.5554 - recall: 0.5990 - auc: 0.5781 - val_loss: 5.9717 - val_tp:
1534.0000 - val_fp: 12791.0000 - val_tn: 15570.0000 - val_fn: 650.0000 -
val_accuracy: 0.5600 - val_precision: 0.1071 - val_recall: 0.7024 - val_auc:
0.6777
Epoch 18/100
31/31 [==============================] - 1s 43ms/step - loss: 5.9266 - tp:
10224.3125 - fp: 7987.7812 - tn: 8896.7500 - fn: 6619.1562 - accuracy: 0.5676 -
precision: 0.5630 - recall: 0.6068 - auc: 0.5856 - val_loss: 5.6477 - val_tp:
1549.0000 - val_fp: 12811.0000 - val_tn: 15550.0000 - val_fn: 635.0000 -
val_accuracy: 0.5598 - val_precision: 0.1079 - val_recall: 0.7092 - val_auc:
0.6799
Epoch 19/100
31/31 [==============================] - 1s 44ms/step - loss: 5.6045 - tp:
10369.7812 - fp: 8019.5625 - tn: 8811.5625 - fn: 6527.0938 - accuracy: 0.5690 -
precision: 0.5616 - recall: 0.6150 - auc: 0.5885 - val_loss: 5.3459 - val_tp:
1569.0000 - val_fp: 12973.0000 - val_tn: 15388.0000 - val_fn: 615.0000 -
val_accuracy: 0.5551 - val_precision: 0.1079 - val_recall: 0.7184 - val_auc:
0.6784
Epoch 20/100
31/31 [==============================] - 1s 46ms/step - loss: 5.2986 - tp:
10395.1562 - fp: 8114.6562 - tn: 8773.9688 - fn: 6444.2188 - accuracy: 0.5681 -
precision: 0.5610 - recall: 0.6163 - auc: 0.5868 - val_loss: 5.0589 - val_tp:
```

```
1603.0000 - val_fp: 13188.0000 - val_tn: 15173.0000 - val_fn: 581.0000 -
val_accuracy: 0.5492 - val_precision: 0.1084 - val_recall: 0.7340 - val_auc:
0.6814
Epoch 21/100
31/31 [==============================] - 1s 45ms/step - loss: 5.0080 - tp:
10642.5625 - fp: 8125.6250 - tn: 8641.0938 - fn: 6318.7188 - accuracy: 0.5716 -
precision: 0.5670 - recall: 0.6282 - auc: 0.5908 - val_loss: 4.7854 - val_tp:
1629.0000 - val_fp: 13504.0000 - val_tn: 14857.0000 - val_fn: 555.0000 -
val_accuracy: 0.5397 - val_precision: 0.1076 - val_recall: 0.7459 - val_auc:
0.6794
Epoch 22/100
31/31 [==============================] - 1s 43ms/step - loss: 4.7329 - tp:
10647.7812 - fp: 8137.6562 - tn: 8738.5000 - fn: 6204.0625 - accuracy: 0.5738 -
precision: 0.5650 - recall: 0.6315 - auc: 0.5931 - val_loss: 4.5285 - val_tp:
1665.0000 - val_fp: 13923.0000 - val_tn: 14438.0000 - val_fn: 519.0000 -
val_accuracy: 0.5272 - val_precision: 0.1068 - val_recall: 0.7624 - val_auc:
0.6856
Epoch 23/100
31/31 [==============================] - 1s 43ms/step - loss: 4.4725 - tp:
10772.8438 - fp: 8138.7188 - tn: 8721.4688 - fn: 6094.9688 - accuracy: 0.5789 -
precision: 0.5720 - recall: 0.6392 - auc: 0.5959 - val_loss: 4.2840 - val_tp:
1699.0000 - val_fp: 14227.0000 - val_tn: 14134.0000 - val_fn: 485.0000 -
val_accuracy: 0.5184 - val_precision: 0.1067 - val_recall: 0.7779 - val_auc:
0.6855
Epoch 24/100
31/31 [==============================] - 1s 44ms/step - loss: 4.2255 - tp:
10762.0938 - fp: 8205.4688 - tn: 8697.7812 - fn: 6062.6562 - accuracy: 0.5760 -
precision: 0.5658 - recall: 0.6380 - auc: 0.5964 - val_loss: 4.0532 - val_tp:
1763.0000 - val_fp: 14770.0000 - val_tn: 13591.0000 - val_fn: 421.0000 -
val_accuracy: 0.5027 - val_precision: 0.1066 - val_recall: 0.8072 - val_auc:
0.6820
Epoch 25/100
31/31 [==============================] - 1s 44ms/step - loss: 3.9879 - tp:
10918.8125 - fp: 8165.8438 - tn: 8688.0625 - fn: 5955.2812 - accuracy: 0.5820 -
precision: 0.5728 - recall: 0.6472 - auc: 0.6047 - val_loss: 3.8358 - val_tp:
1808.0000 - val_fp: 15262.0000 - val_tn: 13099.0000 - val_fn: 376.0000 -
val_accuracy: 0.4880 - val_precision: 0.1059 - val_recall: 0.8278 - val_auc:
0.6861
Epoch 26/100
31/31 [==============================] - 1s 45ms/step - loss: 3.7656 - tp:
10972.8750 - fp: 8131.6562 - tn: 8759.3750 - fn: 5864.0938 - accuracy: 0.5841 -
precision: 0.5738 - recall: 0.6494 - auc: 0.6092 - val_loss: 3.6288 - val_tp:
1823.0000 - val_fp: 15494.0000 - val_tn: 12867.0000 - val_fn: 361.0000 -
val_accuracy: 0.4809 - val_precision: 0.1053 - val_recall: 0.8347 - val_auc:
0.6787
Epoch 27/100
31/31 [==============================] - 1s 44ms/step - loss: 3.5579 - tp:
11165.3125 - fp: 8160.1562 - tn: 8682.9375 - fn: 5719.5938 - accuracy: 0.5876 -
```

```
precision: 0.5776 - recall: 0.6601 - auc: 0.6114 - val_loss: 3.4350 - val_tp:
1856.0000 - val_fp: 15883.0000 - val_tn: 12478.0000 - val_fn: 328.0000 -
val_accuracy: 0.4693 - val_precision: 0.1046 - val_recall: 0.8498 - val_auc:
0.6807
Epoch 28/100
31/31 [==============================] - 1s 43ms/step - loss: 3.3642 - tp:
11304.6875 - fp: 8239.3438 - tn: 8598.7188 - fn: 5585.2500 - accuracy: 0.5884 -
precision: 0.5775 - recall: 0.6682 - auc: 0.6107 - val_loss: 3.2533 - val_tp:
1878.0000 - val_fp: 16313.0000 - val_tn: 12048.0000 - val_fn: 306.0000 -
val_accuracy: 0.4559 - val_precision: 0.1032 - val_recall: 0.8599 - val_auc:
0.6870
Epoch 29/100
31/31 [==============================] - 1s 43ms/step - loss: 3.1755 - tp:
11461.0625 - fp: 8191.7188 - tn: 8603.3750 - fn: 5471.8438 - accuracy: 0.5942 -
precision: 0.5838 - recall: 0.6758 - auc: 0.6177 - val_loss: 3.0824 - val_tp:
1890.0000 - val_fp: 16669.0000 - val_tn: 11692.0000 - val_fn: 294.0000 -
val_accuracy: 0.4447 - val_precision: 0.1018 - val_recall: 0.8654 - val_auc:
0.6879
Epoch 30/100
31/31 [==============================] - 1s 43ms/step - loss: 2.9993 - tp:
11445.4688 - fp: 8232.4375 - tn: 8750.4375 - fn: 5299.6562 - accuracy: 0.5979 -
precision: 0.5813 - recall: 0.6831 - auc: 0.6226 - val_loss: 2.9204 - val_tp:
1900.0000 - val_fp: 16773.0000 - val_tn: 11588.0000 - val_fn: 284.0000 -
val_accuracy: 0.4416 - val_precision: 0.1018 - val_recall: 0.8700 - val_auc:
0.6823
Restoring model weights from the end of the best epoch.
Epoch 00030: early stopping
```

Evaluation

[ ]:
```
plot_metrics(resampled_history)
```




```
[ ]: !mkdir -p saved_model
     resampled_dense_deep_model.save('saved_model/resampled_dense_deep_model')
```

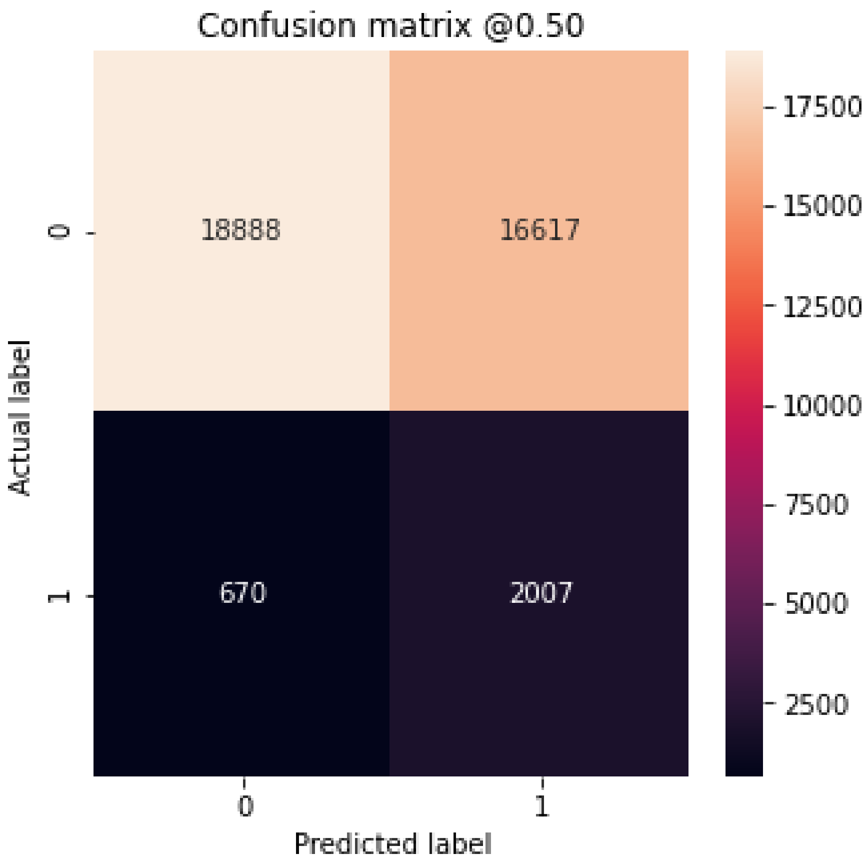
```
INFO:tensorflow:Assets written to: saved_model/resampled_dense_deep_model/assets
```

```
[ ]: dd_train_predictions_resampled = resampled_dense_deep_model.
      ↪predict(train_features, batch_size=BATCH_SIZE)
     dd_test_predictions_resampled = resampled_dense_deep_model.
      ↪predict(test_features, batch_size=BATCH_SIZE)
```

```
[ ]: resampled_results = resampled_dense_deep_model.evaluate(test_features,␣
      ↪test_labels,
                                                  batch_size=BATCH_SIZE, verbose=0)
     for name, value in zip(resampled_dense_deep_model.metrics_names,␣
      ↪resampled_results):
       print(name, ': ', value)
     print()

     plot_cm(test_labels, dd_test_predictions_resampled)
```

```
loss :  5.059300422668457
tp :  2007.0
fp :  16617.0
tn :  18888.0
fn :  670.0
```

```
accuracy :  0.5472474098205566
precision :  0.10776417702436447
recall :  0.7497198581695557
auc :  0.6902697086334229

f1 Score 0.1884418571898033

Irrelevant Documents Detected (True Negatives):  18888
Irrelevant Documents Incorrectly Detected (False Positives):  16617
Relevant Documents Missed (False Negatives):  670
Relevant Documents Detected (True Positives):  2007
Total Relevant Documents:  2677
```



[ ]:
```
pred_labels = resampled_dense_deep_model.predict(test_features)
pred_labels = pred_labels.round(0)
pred_labels = pred_labels.astype(int)

deep_dense_resampled = {'Model': 'Resampled Dense Deep Layer Model',
                'Loss': resampled_results[0],
```

```
                'Accuracy': accuracy_score(test_labels, pred_labels),
                'Precision': precision_score(test_labels, pred_labels),
                'Recall': recall_score(test_labels, pred_labels),
                'F1 Score': f1_score(test_labels, pred_labels)}

deep_dense_resampled
```

[ ]:
```
{'Accuracy': 0.5472473940600283,
 'F1 Score': 0.1884418571898033,
 'Loss': 5.059300422668457,
 'Model': 'Resampled Dense Deep Layer Model',
 'Precision': 0.10776417525773196,
 'Recall': 0.749719835636907}
```

Predictions

[ ]:
```
test_predictions = resampled_dense_deep_model.predict(test)
```

[ ]:
```
test_predictions = test_predictions.round(0)
test_predictions = test_predictions.astype(int)
test_predictions
```

[ ]:
```
array([[0],
       [0],
       [0],
       …,
       [0],
       [0],
       [0]])
```

[ ]:
```
predictions= pd.DataFrame(test_predictions)
predictions['Id'] = predictions.index
predictions.rename(columns={ predictions.columns[0]: "psrel" }, inplace = True)
predictions = predictions[['Id','psrel']]
predictions
```

[ ]:

	Id	psrel
0	0	0
1	1	0
2	2	0
3	3	0
4	4	0
…	…	…
4995	4995	0
4996	4996	0
4997	4997	0
4998	4998	0
4999	4999	0

[5000 rows x 2 columns]

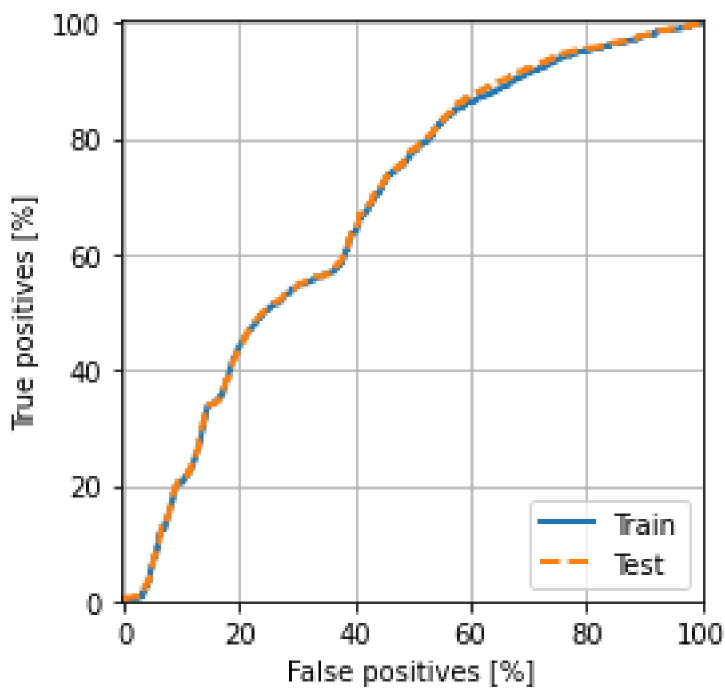
[ ]:
```
predictions['psrel'].value_counts()
```

[ ]:
```
0    4215
1     785
Name: psrel, dtype: int64
```

[ ]:
```
predictions.to_csv('resampled dense deep colab predictions.csv', index=False)
```

[ ]:
```
plot_roc("Train", train_labels, train_predictions_weighted, color=colors[0])
plot_roc("Test", test_labels, test_predictions_weighted, color=colors[1],␣
 ↪linestyle='--')

plt.legend(loc='lower right')
```

[ ]: <matplotlib.legend.Legend at 0x7f7503e7bd90>



6.2.4 Wide and Deep Model

[ ]:
```
input_wide = keras.layers.Input(shape=[23], name="wide_input")
input_deep = keras.layers.Input(shape=[74], name="deep_input")
```

[ ]:
```
wd_early_stopping = tf.keras.callbacks.EarlyStopping(
    monitor='val_loss',
    verbose=1,
    patience=10,
    mode='min',
    restore_best_weights=True)
```

Wide and Deep Model Class

[ ]:
```
# Wide and Deep Learning Model function
class WideAndDeepModel(keras.Model):
  def __init__(self, n_neurons=30, activation="elu", **kwargs):
    super().__init__(**kwargs)
    self.hidden1 = WDRegularizedDense(n_neurons)
    self.hidden2 = WDRegularizedDense(n_neurons)
    self.main_output = keras.layers.Dense(1, activation="sigmoid")

  def call(self, inputs):
    input_wide, input_deep = inputs
    hidden1 = self.hidden1(input_deep)
    hidden2 = self.hidden2(hidden1)
    concat = keras.layers.concatenate([input_wide, hidden2])
    main_output = self.main_output(concat)

    return main_output
```

[ ]:
```
wide_train_features.shape
```

[ ]:
```
(122179, 23)
```

[ ]:
```
deep_train_features.shape
```

[ ]:
```
(122179, 74)
```

[ ]:
```
wd_model = WideAndDeepModel(n_neurons=30, activation="selu")

wd_model.compile(loss=["binary_crossentropy"], optimizer=keras.optimizers.
 ↪Nadam(lr=3e-4), metrics="accuracy")

wd_model_history = wd_model.fit([wide_train_features, deep_train_features],␣
 ↪train_labels,
                    epochs=40,
                    validation_data=([wide_val_features, deep_val_features],␣
 ↪val_labels),
                    callbacks=[wd_early_stopping],
                    verbose=1)

total_loss = wd_model.evaluate((wide_test_features, deep_test_features),
```

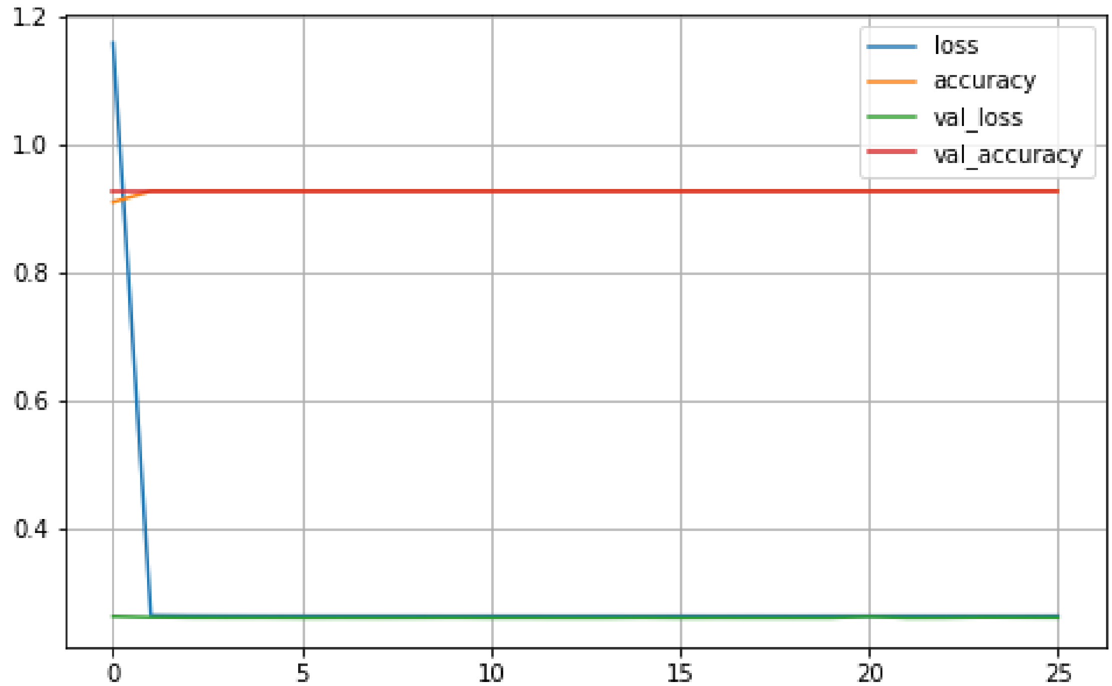
```
                                                                test_labels)
print(total_loss)
```

```
Epoch 1/40
3819/3819 [==============================] - 8s 2ms/step - loss: 2.6609 -
accuracy: 0.8517 - val_loss: 0.2607 - val_accuracy: 0.9285
Epoch 2/40
3819/3819 [==============================] - 7s 2ms/step - loss: 0.2645 -
accuracy: 0.9266 - val_loss: 0.2594 - val_accuracy: 0.9285
Epoch 3/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2616 -
accuracy: 0.9274 - val_loss: 0.2588 - val_accuracy: 0.9285
Epoch 4/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2603 -
accuracy: 0.9278 - val_loss: 0.2586 - val_accuracy: 0.9285
Epoch 5/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2578 -
accuracy: 0.9288 - val_loss: 0.2587 - val_accuracy: 0.9285
Epoch 6/40
3819/3819 [==============================] - 7s 2ms/step - loss: 0.2643 -
accuracy: 0.9262 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 7/40
3819/3819 [==============================] - 7s 2ms/step - loss: 0.2594 -
accuracy: 0.9281 - val_loss: 0.2585 - val_accuracy: 0.9285
Epoch 8/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2621 -
accuracy: 0.9270 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 9/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2618 -
accuracy: 0.9272 - val_loss: 0.2585 - val_accuracy: 0.9285
Epoch 10/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2652 -
accuracy: 0.9257 - val_loss: 0.2587 - val_accuracy: 0.9285
Epoch 11/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2589 -
accuracy: 0.9282 - val_loss: 0.2585 - val_accuracy: 0.9285
Epoch 12/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2614 -
accuracy: 0.9273 - val_loss: 0.2585 - val_accuracy: 0.9285
Epoch 13/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2644 -
accuracy: 0.9261 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 14/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2589 -
accuracy: 0.9283 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 15/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2589 -
accuracy: 0.9282 - val_loss: 0.2587 - val_accuracy: 0.9285
```

```
Epoch 16/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2608 -
accuracy: 0.9276 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 17/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2604 -
accuracy: 0.9277 - val_loss: 0.2585 - val_accuracy: 0.9285
Epoch 18/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2623 -
accuracy: 0.9270 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 19/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2592 -
accuracy: 0.9281 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 20/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2645 -
accuracy: 0.9261 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 21/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2573 -
accuracy: 0.9289 - val_loss: 0.2603 - val_accuracy: 0.9285
Epoch 22/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2590 -
accuracy: 0.9283 - val_loss: 0.2584 - val_accuracy: 0.9285
Epoch 23/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2592 -
accuracy: 0.9282 - val_loss: 0.2585 - val_accuracy: 0.9285
Epoch 24/40
3819/3819 [==============================] - 7s 2ms/step - loss: 0.2583 -
accuracy: 0.9285 - val_loss: 0.2591 - val_accuracy: 0.9285
Epoch 25/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2592 -
accuracy: 0.9282 - val_loss: 0.2589 - val_accuracy: 0.9285
Epoch 26/40
3819/3819 [==============================] - 6s 2ms/step - loss: 0.2599 -
accuracy: 0.9279 - val_loss: 0.2587 - val_accuracy: 0.9285
Restoring model weights from the end of the best epoch.
Epoch 00026: early stopping
1194/1194 [==============================] - 1s 1ms/step - loss: 0.2549 -
accuracy: 0.9299
[0.2549344301223755, 0.9298884272575378]
```

Evaluation

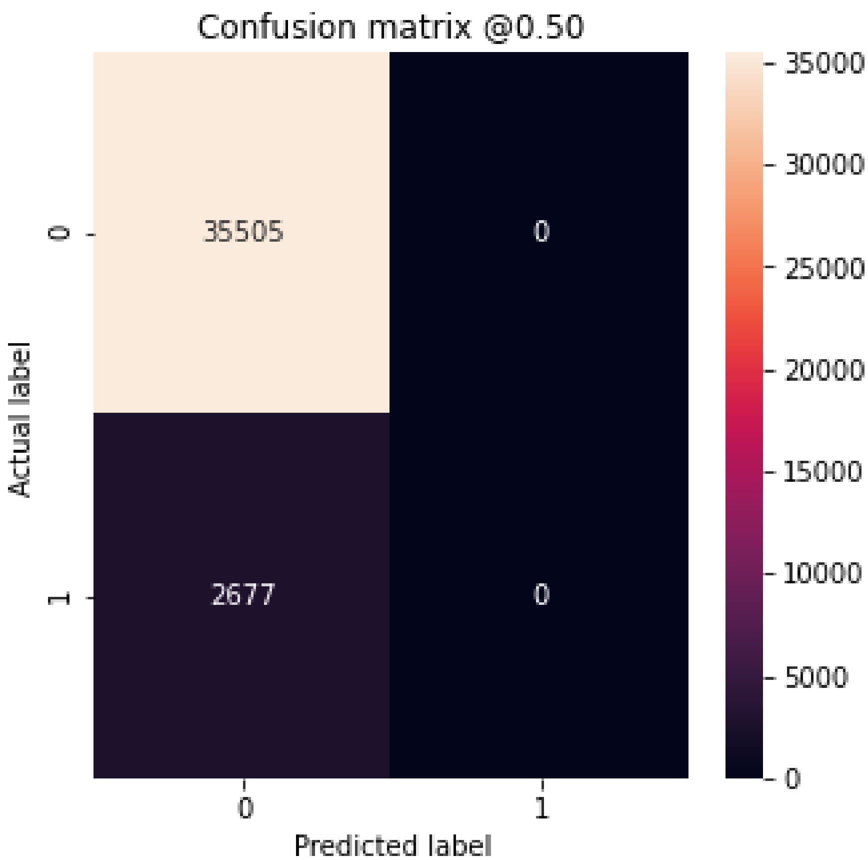
[ ]:
```
pd.DataFrame(wd_model_history.history).plot(figsize=(8, 5))
plt.grid(True)
plt.show()
```



[ ]:
```
train_predictions_wd_model = wd_model.predict((wide_train_features,␣
 ↪deep_train_features))
test_predictions_wd_model = wd_model.predict((wide_test_features,␣
 ↪deep_test_features))
```

[ ]:
```
wd_results = wd_model.evaluate((wide_test_features, deep_test_features),␣
 ↪test_labels, verbose=0)
for name, value in zip(wd_model.metrics_names, wd_results):
  print(name, ': ', value)
print()

plot_cm(test_labels, test_predictions_wd_model)
```

```
loss :  0.2549344301223755
accuracy :  0.9298884272575378

f1 Score 0.0

Irrelevant Documents Detected (True Negatives):  35505
Irrelevant Documents Incorrectly Detected (False Positives):  0
Relevant Documents Missed (False Negatives):  2677
Relevant Documents Detected (True Positives):  0
Total Relevant Documents:  2677
```



[ ]:
```
pred_labels = wd_model.predict((wide_test_features, deep_test_features))
pred_labels = pred_labels.round(0)
pred_labels = pred_labels.astype(int)

wd = {'Model': 'Wide and Deep Model',
               'Loss': wd_results[0],
               'Accuracy': accuracy_score(test_labels, pred_labels),
               'Precision': precision_score(test_labels, pred_labels),
               'Recall': recall_score(test_labels, pred_labels),
               'F1 Score': f1_score(test_labels, pred_labels)}


wd
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1272:
UndefinedMetricWarning: Precision is ill-defined and being set to 0.0 due to no
predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
[ ]: {'Accuracy': 0.9298884291027185,
      'F1 Score': 0.0,
      'Loss': 0.2549344301223755,
      'Model': 'Wide and Deep Model',
      'Precision': 0.0,
      'Recall': 0.0}
```

Predictions

```
[ ]: test_predictions = wd_model.predict((wide_test, deep_test))
     test_predictions
```

```
[ ]: array([[0.06221834],
            [0.05450538],
            [0.05234206],
            …,
            [0.07361767],
            [0.06896427],
            [0.06474838]], dtype=float32)
```

```
[ ]: test_predictions = test_predictions.round(0)
     test_predictions = test_predictions.astype(int)
     test_predictions
```

```
[ ]: array([[0],
            [0],
            [0],
            …,
            [0],
            [0],
            [0]])
```

```
[ ]: predictions= pd.DataFrame(test_predictions)
     predictions['Id'] = predictions.index
     predictions.rename(columns={ predictions.columns[0]: "psrel" }, inplace = True)
     predictions = predictions[['Id','psrel']]
     predictions
```

[ ]:

	Id	psrel
0	0	0
1	1	0
2	2	0
3	3	0
4	4	0
…	…	…
4995	4995	0
4996	4996	0
4997	4997	0

```
4998  4998      0
4999  4999      0

[5000 rows x 2 columns]
```

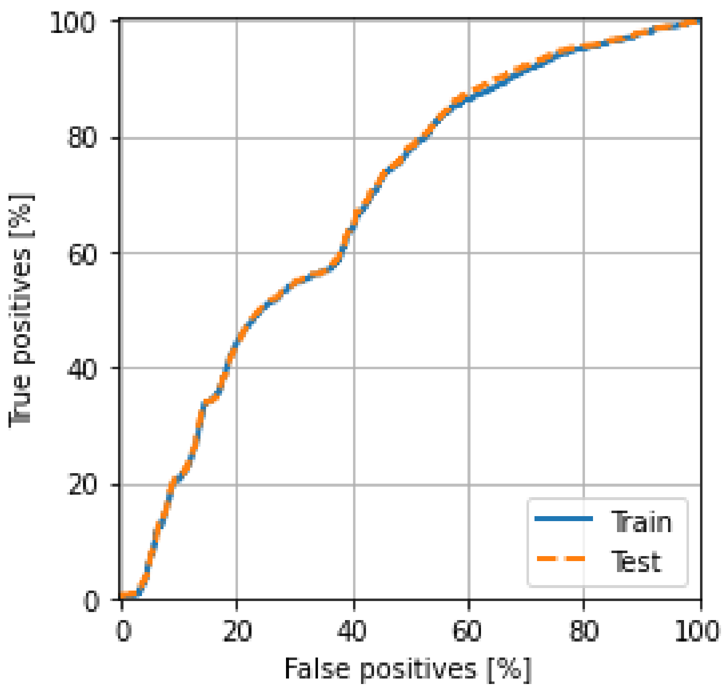
[ ]:
```
predictions['psrel'].value_counts()
```

[ ]:
```
0    5000
Name: psrel, dtype: int64
```

[ ]:
```
predictions.to_csv('wide and deep colab predictions.csv', index=False)
```

[ ]:
```
plot_roc("Train", train_labels, train_predictions_weighted, color=colors[0])
plot_roc("Test", test_labels, test_predictions_weighted, color=colors[1],␣
 ↪linestyle='--')

plt.legend(loc='lower right')
```

[ ]:
```
<matplotlib.legend.Legend at 0x7f75011567d0>
```



6.3 Any Additional Analysis

- Add in any additional analysis etc that you performed here.

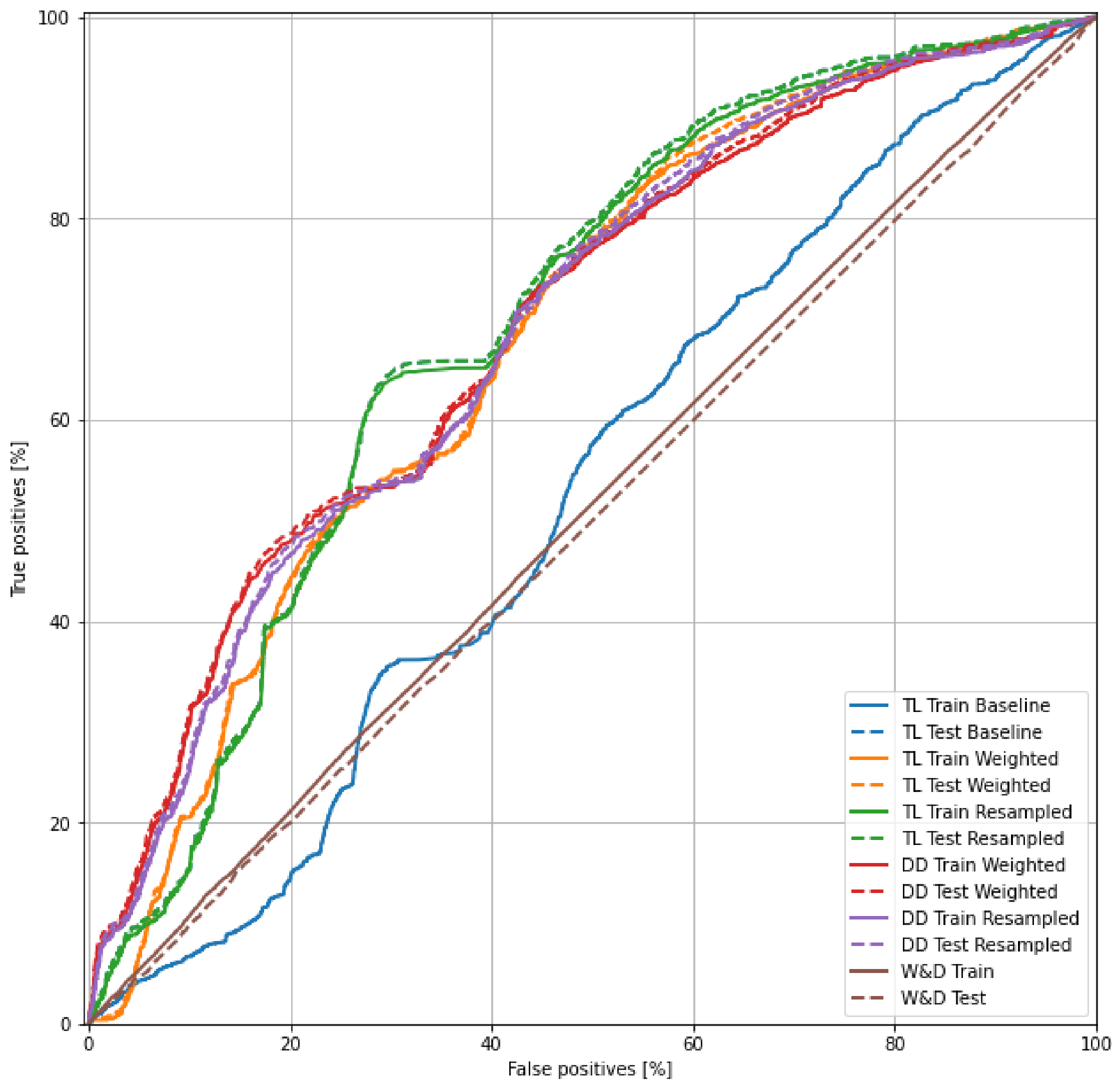
[ ]:
```python
### Create table of testing performance

model_dict = [unwt_rnd, wt_rnd, tl_bias, tl_wt, tl_resampled, dense_deep,␣
↪deep_dense_resampled, wd]
```

[ ]:
```python
model_df = pd.DataFrame(model_dict)
model_df
```

[ ]:
```
                                  Model      Loss  ...    Recall  F1 Score
0              Unweighted Random Forest  0.000000  ...  0.005230  0.010405
1                Weighted Random Forest  0.000000  ...  0.898020  0.283993
2      Adjusted Bias Three Layer Model  8.092644  ...  0.000000  0.000000
3   Adjusted Weights Three Layer Model  5.860197  ...  0.200598  0.167342
4          Resampled Three Layer Model  1.794922  ...  0.861412  0.186140
5                     Dense Deep Model  8.398952  ...  0.615241  0.191289
6     Resampled Dense Deep Layer Model  5.059300  ...  0.749720  0.188442
7                  Wide and Deep Model  0.254934  ...  0.000000  0.000000

[8 rows x 6 columns]
```

[ ]:
```python
plot_roc("TL Train Baseline", train_labels, train_predictions_baseline,␣
↪color=colors[0])
plot_roc("TL Test Baseline", test_labels, test_predictions_baseline,␣
↪color=colors[0], linestyle='--')

plot_roc("TL Train Weighted", train_labels, train_predictions_weighted,␣
↪color=colors[1])
plot_roc("TL Test Weighted", test_labels, test_predictions_weighted,␣
↪color=colors[1], linestyle='--')

plot_roc("TL Train Resampled", train_labels, train_predictions_resampled,␣
↪color=colors[2])
plot_roc("TL Test Resampled", test_labels, test_predictions_resampled,␣
↪color=colors[2], linestyle='--')

plot_roc("DD Train Weighted", train_labels, train_predictions_dense_deep_model,␣
↪color=colors[3])
plot_roc("DD Test Weighted", test_labels, test_predictions_dense_deep_model,␣
↪color=colors[3], linestyle='--')

plot_roc("DD Train Resampled", train_labels, dd_train_predictions_resampled,␣
↪color=colors[4])
plot_roc("DD Test Resampled", test_labels, dd_test_predictions_resampled,␣
↪color=colors[4], linestyle='--')

plot_roc("W&D Train", train_labels, train_predictions_wd_model, color=colors[5])
```

```
plot_roc("W&D Test", test_labels, test_predictions_wd_model, color=colors[5],␣
↪linestyle='--')

plt.legend(loc='lower right')


fig = plt.gcf()
fig.set_size_inches(18.5, 10.5)
fig.savefig('graph.png', dpi=100)
```



[ ]:
```
TL_HP = {"Model": "Three Layer Model",
         "Neurons per Layer": "30",
         "Number of Layers": "3",
```

```
           "Kernel Initializer": "He Initialization",
           "Activation Function": "ELU",
           "Normalization": "Batch Normalisation",
           "Regularisation": "l1 and l2 regularisation with Dropout if needed",
           "Optimizer": "Nadam",
           "Learning Rate Schedule": "1cycle"}

DD_HP = {"Model": "Dense Deep Model",
           "Neurons per Layer": "30",
           "Number of Layers": "5",
           "Kernel Initializer": "He Initialization",
           "Activation Function": "ELU",
           "Normalization": "Batch Normalisation",
           "Regularisation": "l1 and l2 regularisation with Dropout if needed",
           "Optimizer": "Nadam",
           "Learning Rate Schedule": "1cycle"}

WD_HP = {"Model": "Wide and Deep Model",
           "Neurons per Layer": "30",
           "Number of Layers": "5 (2 inputs, 2 dense and output)",
           "Kernel Initializer": "LeCun Initialization",
           "Activation Function": "SELU",
           "Normalization": "None (Self-Normalisation)",
           "Regularisation": "l1 and l2 regularisation",
           "Optimizer": "Nadam",
           "Learning Rate Schedule": "1cycle"}
```

[ ]:

```
hyp_dict = [TL_HP, DD_HP, WD_HP]

hyp_df = pd.DataFrame(hyp_dict)
hyp_df
```

[ ]:

```
                 Model Neurons per Layer  … Optimizer Learning Rate Schedule
0    Three Layer Model                30  …     Nadam                 1cycle
1      Dense Deep Model               30  …     Nadam                 1cycle
2   Wide and Deep Model               30  …     Nadam                 1cycle

[3 rows x 9 columns]
```