index

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1 Business Understanding

Sentiment analysis is one the of the most important tasks to understand user satisfaction. Most websites that offer products and services have various means of keeping track of user satisfaction criteria, such as stars-based system. However, most users are disincentivized to provide accurate rating for the products or services they purchased. In addition, manually sorting through users' comments to determine if the comments left by users/clients is positive or negative takes a lot of work. Therefore, the problem necessitates an automated way to determine sentiment analysis of clients.

2 Data Understanding

The data used in this project was obtained from Kaggle. The dataset contains four million comments (3.6 million training and 0.4 million test datasets). The files are presented in fastText format, which will be parsed to the required type of data for processing. Both the training and test datasets are labeled, which will help in quantify how the predictions measure with true labels.

The first step was to load and preprocess the training data, saved as B2Z zipped file. The preprocessing steps include: decontracting words, filter out email address and website URLs, splitting labels and statements, checking statements for spelling error, replace misspelled words by their closest approximated word (for example `caracters` was replaced by `characters`) and finally the cleaned statements are lemmatized and tagged with Part-Of-Speech.

Next, the words were vectorized using TfIdf, Count and GloVe word embedding vectorizers for model fitting. The minimum and maximum document frequencies were manually set to match GloVe vectorizer used for this project. The vectorized data were then applied to a grid of shallow models (naïve Bayes, logistic regression and random forest) and gradient boosting models (XGBoost and CatBoost).

For deep learning approaches, Long Short Term Memory (LSTM) models with and without word embedding were considered. In addition, a Convolutional Neural Network (CNN) model with Bidirectional Encoder Representations from Transformers (BERT) encoding was used as an alternative to transformer models.

Finally, models from each method with the best performance were fitted with the test data and final model was selected. The final model was then trained over the training dataset for more epochs to maximize prediction accuracy. The model was then tested on novel comments.

3 Data Preparation

The project depends on the following libraries to function. Users are advised to uncomment the following section to install the libraries.

[181]:
```
######## Uncomment to install libraries ###########
# ! pip install pyenchant
# ! pip install autocorrect
# ! pip install tensorflow_hub
# ! pip install transformers
# ! pip install eli5
```

```
# ! pip install wordcloud
# ! pip install lime
```

[270]:
```
# Import important libraries
import os
from os import remove
from os.path import exists
import wget
import zipfile
import pandas as pd
import numpy as np
import bz2
import nltk
from nltk import pos_tag
from nltk.corpus import wordnet, stopwords
from nltk.probability import FreqDist
from nltk.tokenize import regexp_tokenize, word_tokenize, RegexpTokenizer
import re
from collections import Counter
from autocorrect import Speller
from enchant import request_dict
from enchant.checker import SpellChecker
from enchant.tokenize import EmailFilter, URLFilter
from tqdm import tqdm
from tqdm.contrib.concurrent import process_map
from multiprocessing import Pool
from time import time
import itertools as it
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
from sklearn.model_selection import train_test_split
from sklearn.base import clone
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.utils.class_weight import compute_class_weight
from imblearn.over_sampling import SMOTE, RandomOverSampler, ADASYN
from sklearn.model_selection import train_test_split, StratifiedKFold,␣
↪GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from xgboost.sklearn import XGBClassifier
from catboost import CatBoostClassifier
import tensorflow as tf
from tensorflow import keras
from tensorflow.python.keras import models, layers, optimizers
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
from transformers import DistilBertTokenizer
from lime.lime_text import LimeTextExplainer
from wordcloud import WordCloud, ImageColorGenerator
from sklearn.metrics import precision_score,accuracy_score,recall_score
from sklearn.metrics import␣
↪f1_score,roc_auc_score,log_loss,roc_curve,auc,confusion_matrix
import dill as pickle
import matplotlib.pyplot as plt
import seaborn as sns

# Define 'ClassType' for pickled models
pickle._dill._reverse_typemap['ClassType'] = type

# Enable inline ploting
%matplotlib inline
SEED = 123
```

Useful packaged from NLTK are downloaded.

[3]:
```
# Load NLTK packages
nltk.download('tagsets')
nltk.download('wordnet')
nltk.download('stopwords')
```

```
[nltk_data] Downloading package tagsets to
[nltk_data]     C:\Users\zeaps\AppData\Roaming\nltk_data…
[nltk_data]   Package tagsets is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\zeaps\AppData\Roaming\nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\zeaps\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[3]: True

Now, lets build a function that automatically imports B2Z zipped file and see the contents.

[4]:
```
# Function to load B2Z file
def load_data(b2z_file_loc):
    '''
    Function to read B2Z file
    b2z_file_loc: location of file
    '''
    file = bz2.BZ2File(b2z_file_loc)
    # Read lines with progress bar
    t = tqdm(file.readlines())
    # Add description to loading file
```

```
    t.set_description('Loading '+b2z_file_loc.split('/')[-1].split('.')[0]+'␣
↪data')
    # Return 'utf-8' version of the file
    return [x.decode('utf-8') for x in t]

train_file_lines = load_data('data/train.ft.txt.bz2')
```

```
Loading train data: 100%|      | 3600000/3600000 [00:03<00:00,
1139600.91it/s]
```

We can now look at the contents of the file.

[5]:
```
# Show the first 5 lines
train_file_lines[:5]
```

[5]:
```
['__label__2 Stuning even for the non-gamer: This sound track was beautiful! It
paints the senery in your mind so well I would recomend it even to people who
hate vid. game music! I have played the game Chrono Cross but out of all of the
games I have ever played it has the best music! It backs away from crude
keyboarding and takes a fresher step with grate guitars and soulful orchestras.
It would impress anyone who cares to listen! ^_^\n',
 "__label__2 The best soundtrack ever to anything.: I'm reading a lot of reviews
saying that this is the best 'game soundtrack' and I figured that I'd write a
review to disagree a bit. This in my opinino is Yasunori Mitsuda's ultimate
masterpiece. The music is timeless and I'm been listening to it for years now
and its beauty simply refuses to fade.The price tag on this is pretty staggering
I must say, but if you are going to buy any cd for this much money, this is the
only one that I feel would be worth every penny.\n",
 '__label__2 Amazing!: This soundtrack is my favorite music of all time, hands
down. The intense sadness of "Prisoners of Fate" (which means all the more if
you\'ve played the game) and the hope in "A Distant Promise" and "Girl who Stole
the Star" have been an important inspiration to me personally throughout my teen
years. The higher energy tracks like "Chrono Cross ~ Time\'s Scar~", "Time of
the Dreamwatch", and "Chronomantique" (indefinably remeniscent of Chrono
Trigger) are all absolutely superb as well.This soundtrack is amazing music,
probably the best of this composer\'s work (I haven\'t heard the Xenogears
soundtrack, so I can\'t say for sure), and even if you\'ve never played the
game, it would be worth twice the price to buy it.I wish I could give it 6
stars.\n',
 "__label__2 Excellent Soundtrack: I truly like this soundtrack and I enjoy
video game music. I have played this game and most of the music on here I enjoy
and it's truly relaxing and peaceful.On disk one. my favorites are Scars Of
Time, Between Life and Death, Forest Of Illusion, Fortress of Ancient Dragons,
Lost Fragment, and Drowned Valley.Disk Two: The Draggons, Galdorb - Home,
Chronomantique, Prisoners of Fate, Gale, and my girlfriend likes ZelbessDisk
Three: The best of the three. Garden Of God, Chronopolis, Fates, Jellyfish sea,
Burning Orphange, Dragon's Prayer, Tower Of Stars, Dragon God, and Radical
Dreamers - Unstealable Jewel.Overall, this is a excellent soundtrack and should
```

```
be brought by those that like video game music.Xander Cross\n",
 "__label__2 Remember, Pull Your Jaw Off The Floor After Hearing it: If you've
played the game, you know how divine the music is! Every single song tells a
story of the game, it's that good! The greatest songs are without a doubt,
Chrono Cross: Time's Scar, Magical Dreamers: The Wind, The Stars, and the Sea
and Radical Dreamers: Unstolen Jewel. (Translation varies) This music is perfect
if you ask me, the best it can be. Yasunori Mitsuda just poured his heart on and
wrote it down on paper.\n"]
```

[6]:
```
# Show more lines with negative reviews
train_file_lines[10:15]
```

[6]:
```
["__label__1 The Worst!: A complete waste of time. Typographical errors, poor
grammar, and a totally pathetic plot add up to absolutely nothing. I'm
embarrassed for this author and very disappointed I actually paid for this
book.\n",
 '__label__2 Great book: This was a great book,I just could not put it down,and
could not read it fast enough. Boy what a book the twist and turns in this just
keeps you guessing and wanting to know what is going to happen next. This book
makes you fall in love and can heat you up,it can also make you so angery. this
book can make you go throu several of your emotions. This is a quick read
romance. It is something that you will want to end your day off with if you read
at night.\n',
 '__label__2 Great Read: I thought this book was brilliant, but yet realistic.
It showed me that to error is human. I loved the fact that this writer showed
the loving side of God and not the revengeful side of him. I loved how it
twisted and turned and I could not put it down. I also loved The glass
castle.\n',
 "__label__1 Oh please: I guess you have to be a romance novel lover for this
one, and not a very discerning one. All others beware! It is absolute drivel. I
figured I was in trouble when a typo is prominently featured on the back cover,
but the first page of the book removed all doubt. Wait - maybe I'm missing the
point. A quick re-read of the beginning now makes it clear. This has to be an
intentional churning of over-heated prose for satiric purposes. Phew, so glad I
didn't waste $10.95 after all.\n",
 '__label__1 Awful beyond belief!: I feel I have to write to keep others from
wasting their money. This book seems to have been written by a 7th grader with
poor grammatical skills for her age! As another reviewer points out, there is a
misspelling on the cover, and I believe there is at least one per chapter. For
example, it was mentioned twice that she had a "lean" on her house. I was so
distracted by the poor writing and weak plot, that I decided to read with a
pencil in hand to mark all of the horrible grammar and spelling. Please don\'t
waste your money. I too, believe that the good reviews must have been written by
the author\'s relatives. I will not put much faith in the reviews from now
on!\n']
```

Usually at this stage, visualization of which words are most frequent would aide to understand the processing stage. However, the file is just too large for such step.

In order to begin preprocessing, the following helper functions are written to streamline the process. The first is decontracting words, which converts words like `don't` to `do not`.

[7]:
```
# Function to decontract words
def decontracted(phrase):
    '''
    Function to decontract words.
    phrase: string with contracted words
    '''
    phrase = re.sub(r"n\'t", " not", phrase)
    phrase = re.sub(r"\'re", " are", phrase)
    phrase = re.sub(r"\'s", " is", phrase)
    phrase = re.sub(r"\'d", " would", phrase)
    phrase = re.sub(r"\'ll", " will", phrase)
    phrase = re.sub(r"\'t", " not", phrase)
    phrase = re.sub(r"\'ve", " have", phrase)
    phrase = re.sub(r"\'m", " am", phrase)
    return phrase
```

The following function converts NLTK POS tagging to wordnet. (This was adopted from the teaching material)

[8]:
```
# Function to change NLTK POS to wordnet tags
def get_wordnet_pos(treebank_tag):
    '''
    Translate NLTK POS to wordnet tags
    '''
    if treebank_tag.startswith('J'):
        return wordnet.ADJ
    elif treebank_tag.startswith('V'):
        return wordnet.VERB
    elif treebank_tag.startswith('N'):
        return wordnet.NOUN
    elif treebank_tag.startswith('R'):
        return wordnet.ADV
    else:
        return wordnet.NOUN
```

Now we can write a data cleaner function, that removes emails and URLs, performs spelling checks, tokenize, lemmatize and POS tags data.

[216]:
```
# Function to clean text
def data_cleaner(data, labeled=True, spell_check=True):
    '''
    Function to clean data
    data: String input
    '''
    # Create filter to remove emails and urls
```

```
    chkr = SpellChecker("en_US",filters=[EmailFilter,URLFilter])
    # Create RegEx pattern for tokenization
    pattern = "([a-zA-Z]+(?:'[a-z]+)?)"
    # Create RegexpTokenizer
    tokenizer = RegexpTokenizer(pattern)
    # Define stopwords from NLTK
    sw = stopwords.words('english')
    # Create lemmatizer object
    lemmatizer = nltk.stem.WordNetLemmatizer()
    # Split string at '__label__'
    splits = data.split('__label__')[-1]
    # Return lable and statement if labaled else return string alone
    if labeled:
        labels = int(splits[0])-1
        statement = decontracted(splits[1:].lower())
    else:
        labels = np.nan
        statement = decontracted(splits.lower())
    # Spell check statement
    if spell_check:
        # Create speller object
        spell = Speller(lang='en')
        # Spell check statement
        statement = spell(statement)
        chkr.set_text(statement)
        # Check for misspelled words
        for err in chkr:
            try:
                # Take the first correct spelling if it exists
                statement = statement.replace(err.word,request_dict(err.
↪word)[0])
            except:
                # Else skip word
                continue
    # Tokenize statement
    statement = tokenizer.tokenize(statement)
    # Remove stopwords
    statement = [w for w in statement if w not in sw]
    # Apply pos_tag to each token
    statement_tagged = [(token[0], get_wordnet_pos(token[1]))
                        for token in pos_tag(statement)]
    # Lemmatize statement
    statement_lemmed = [lemmatizer.lemmatize(token[0], token[1]) for token in␣
↪statement_tagged]
    # Return lemmed statement and labels
    return statement_lemmed, labels
```

Now, lets apply the function to the first training data entry.

[10]:
```
# Apply data cleaner to the first entry
statement, labels = data_cleaner(train_file_lines[0])
statement
```

[10]:
```
['tune',
 'even',
 'non',
 'gamer',
 'sound',
 'track',
 'beautiful',
 'paint',
 'scenery',
 'mind',
 'well',
 'would',
 'recommend',
 'even',
 'people',
 'hate',
 'vid',
 'game',
 'music',
 'play',
 'game',
 'chrono',
 'cross',
 'game',
 'ever',
 'play',
 'best',
 'music',
 'back',
 'away',
 'crude',
 'keyboardist',
 'take',
 'fresh',
 'step',
 'rate',
 'guitar',
 'soulful',
 'orchestra',
 'would',
 'impress',
```

```
'anyone',
'care',
'listen']
```

This looks good. However, there are 3.6 million training datasets. Hence, the data cleaner must be able to run on a as a multithread pool instead of running on a single core. The cleaned data can then be saved to file.

[11]:
```
# Function to save cleaned data
def save_to_file(file_lines, attrib):
    '''
    Function to apply data cleaning on a pool
    file_lines: Lines to be cleaned
    attrib: 'train' of 'test' attribute to save cleaned data
    '''
    # Deploy data cleaner on multiple pools
    currtime = time()
    results = process_map(data_cleaner, file_lines,
                          max_workers=Pool()._processes,
                          chunksize=Pool()._processes)
    # Collect results and labels from parallel pools
    statements = []
    labels = []
    for result in results:
        statements.append(result[0])
        labels.append(result[-1])
    # Create a dataframe of cleaned data
    df = pd.DataFrame(columns=['statements','labels'])
    df.statements = statements
    df.labels = labels
    # Save cleaned data to file in a zipped format
    df.to_csv(r'data/'+attrib+'.zip', index=False, compression='gzip')
    print('Parallel: time elapsed:', time() - currtime)
    return df
```

CAUTION: This operation takes over 12 hours to complete on 16 core computer with over 100 GB. Users are advised to download a cleaned version from this link. Unzip the file and copy files to data/ directory.

[302]:
```
# Check if 'data/train.zip' exists
if exists('data/train.zip'):
    # Remove lines if it exists to save memory
#     del train_file_lines
    # Load to dataframe from file
    train_df = pd.read_csv('data/train.zip', compression='gzip')
    # Remove square braces from each side
    def str_cleaner(line):
        return line[1:-1].replace("'",'').replace(' ','').replace(',',' ')
```

```python
    train_df.statements = train_df.statements.apply(str_cleaner)
else:
    # Else run save_to_file function
    train_df = save_to_file(train_file_lines, 'train')
    # Remove lines if it exists to save memory
    del train_file_lines
```

If loaded correctly, `train_df` should show the first five entries, like so:

[303]:
```python
train_df.head()
```

[303]:

	statements	labels
0	tune even non gamer sound track beautiful pain…	1
1	best soundtrack ever anything reading lot revi…	1
2	amaze soundtrack favorite music time hand inte…	1
3	excellent soundtrack truly like soundtrack enj…	1
4	remember pull jaw floor hear played game know …	1

[14]:
```python
train_df.labels.value_counts(normalize=True)
```

[14]:
```
1    0.5
0    0.5
Name: labels, dtype: float64
```

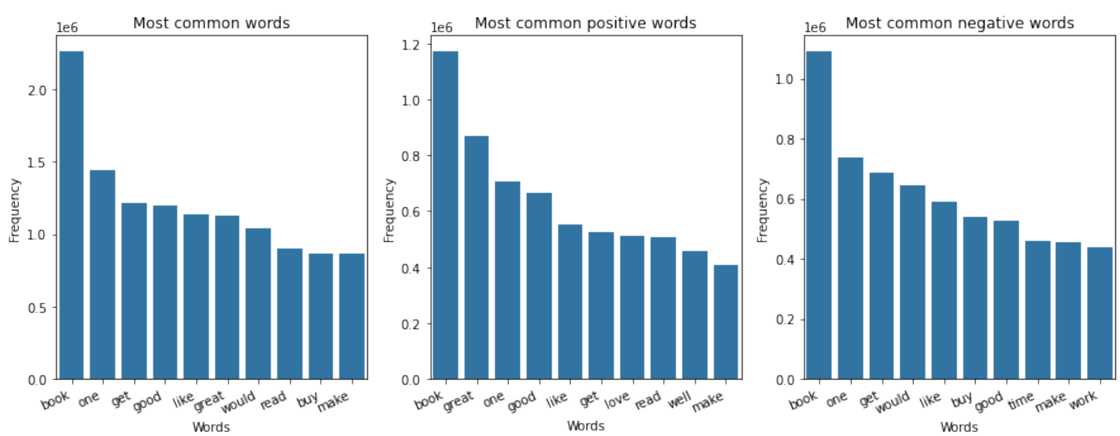
Our data is balanced. Therefore, there is no need for oversampling. Now data visualization can be applied.

[312]:
```python
# Find the most frequent words
all_words = (' '.join(train_df.statements.to_list())).split()
# Convert to dataframe
most_common_all = pd.DataFrame(FreqDist(all_words).most_common(10))
# Delete all words
del all_words

# Find the most frequent positive words
positive_words = (' '.join(train_df[train_df.labels==1].statements.to_list())).
 ↪split()
# Convert to dataframe
most_common_pos = pd.DataFrame(FreqDist(positive_words).most_common(10))
# Delete positive words
del positive_words

# Find the most frequent negative words
negative_words = (' '.join(train_df[train_df.labels==0].statements.to_list())).
 ↪split()
# Convert to dataframe
most_common_neg = pd.DataFrame(FreqDist(negative_words).most_common(10))
# Delete negative words
```

```
del negative_words

# Store all in a list
hist_words = [most_common_all, most_common_pos, most_common_neg]
```

Now we can plot the most frequent words in the training data.

[320]:
```
# Initialize figure
fig, axes = plt.subplots(1, 3, figsize=(15,5))
# Set title labels
labels = ['Most common words', 'Most common positive words',
          'Most common negative words']

# Iterate through each dataframe and plot word frequencies
for label, ax, hist_word in zip(labels, axes.flatten(), hist_words):
    # Rename columns of the dataframe
    hist_word.columns = ['Words', 'Frequency']
    # Plot frequency
    g = sns.barplot(data=hist_word, x='Words', y='Frequency',
                    ax=ax, color='tab:blue')
    # Rotate xtick labels for visibility
    g.set_xticklabels(g.get_xticklabels(), rotation=25,
                  horizontalalignment='right')
    # Set title
    ax.set_title(label)
```



For word embedding, `glove.6B.300d` is selected, which contains 300 vectors representing each word.

[17]:
```
# Check if pickled GloVe embedding file exists
if not exists('glove_embedding.pickle'):
    # If not, check if a zipped embedding text file exists
    if not exists('glove.6B.300d.txt'):
```

```
        # Download word embedding
        wget.download(url='https://nlp.stanford.edu/data/glove.6B.zip')
        # Unzip file
        zip_ = zipfile.ZipFile('glove.6B.zip')
        zip_.extract('glove.6B.300d.txt')
        zip_.close()
        # Remove zipped file from downloads
        remove('glove.6B.zip')
    embeddings_index = {}
    # Open glove embedding text
    f = open('glove.6B.300d.txt', encoding = "utf-8")
    # Iterate through each word and create an embedding dictionary
    for line in f:
        # First line after split is the word, followed by embedding vector
        values = line.split()
        word = values[0]
        # Convert embedding vector to float32
        coefs = np.asarray(values[1:], dtype='float32')
        # Populate the dictionary
        embeddings_index[word] = coefs
    f.close()
    # Remove text file after operation
    remove('glove.6B.300d.txt')
    # Save embedding dict to file
    with open('glove_embedding.pickle', 'wb') as f:
        pickle.dump(embeddings_index, f)
else:
    # Else load pickled file
    with open('glove_embedding.pickle', 'rb') as f:
        embeddings_index = pickle.load(f)
```

There are a total of 400,000 words in the GloVe embedding.

[18]:
```
len(embeddings_index.keys())
```

[18]: 400000

Training and test data are split to training and validation datasets. Relatively higher test_size is declared since the amount of data is generally large.

[179]:
```
# Train and validation split
X_train, X_valid, y_train, y_valid = train_test_split(train_df.statements,
                                                       train_df.labels,
                                                       random_state=SEED,
                                                       stratify = train_df.
 ↪labels,
                                                       test_size = 0.3)
```

Over 2.5 million training dataset to be used for modeling.

[20]:
```
X_train.shape
```

[20]: (2520000,)

Memory management is important in this project. Therefore, large variables are deleted after use.

[321]:
```
# Delete train_df
del train_df
```

4 Modeling

Most of the modeling tools used here require more computational resources. Therefore, one less than the number of CPUs are used for various models here. For gradient boost models, GPUs are used instead of CPUs.

[24]:
```
n_cpu = os.cpu_count()-1
print("Number of CPUs in the system:", n_cpu)
```

```
Number of CPUs in the system: 7
```

4.1 Preprocessing Class

A preprocessing class was written to load data from file or to vectorize the training data.

[22]:
```
class Preprocess():
    '''
    Preprocessing class for text vectorization
    '''
    def __init__(self, dataset=None,
                 transformer='tfidf',
                 cleaned=True,
                 ngram_range=(1,1),
                 max_features = 20000,
                 min_df = 0.05,
                 max_df = 0.95):
        '''
        Initialize parameters
        dataset: Type of dataset used
        transformer: Type of vectorizing transformer
        cleaned: Boolean if data is cleaned
        ngram_range: ngram tuple for vectorization
        max_features: Maximum allowed features
        min_df: Minimum document frequency
        max_df: Maximum document frequency
        '''
        self.dataset = dataset
        self.transformer = transformer
        self.cleaned = cleaned
```

```
        self.ngram_range = ngram_range
        self.max_features = max_features
        self.min_df = min_df
        self.max_df = max_df

    def load_data(self, n_pool, labeled, attrib):
        '''
        Function to load data in a raw format
        n_pool: Number of pools for parallel operation
        labeled: Boolean if data is labeled
        attrib: 'train' or 'test' attribute
        '''
        if not self.cleaned:
            statements = []
            labels = []
            # Check pool, if 1 run on single thread
            # else run on specified threads
            if n_pool==1:
                for data in self.dataset:
                    statement, label = data_cleaner(data)
                    statements.append(statement)
                    labels.append(label)
            else:
                results = process_map(data_cleaner, data,
                          max_workers=n_pool,
                          chunksize=n_pool)
                for result in results:
                    statements.append(result[0])
                    labels.append(result[-1])
            df = pd.DataFrame(columns=['statements','labels'])
            df.statements = statements
            df.labels = labels
            df.to_csv(r'data/'+attrib+'.zip', index=False, compression='gzip')
        else:
            df = pd.read_csv('data/'+attrib+'.zip', compression='gzip')
            def str_cleaner(line):
                return line[1:-1].replace("'",'').replace(' ','').replace(',',' 
↪')
            df.statements = df.statements.apply(str_cleaner)
        return df

    def transform(self, df, return_vectorizer=True):
        '''
        Function to transform/vectorize data
        df: Series object containing text
        return_vectorizer: Boolean to return vectorizer used
        '''
```

```python
        # Use TfidfVectorizer
        if self.transformer=='tfidf':
            vectorizer = TfidfVectorizer(max_features=self.max_features,
                                         ngram_range=self.ngram_range,
                                         min_df=self.min_df,
                                         max_df=self.max_df)
            if return_vectorizer:
                tokens = (vectorizer.fit_transform(df).toarray(),vectorizer)
            else:
                tokens = vectorizer.fit_transform(df).toarray()
        # Use CountVectorizer
        elif self.transformer=='count':
            vectorizer = CountVectorizer(max_features=self.max_features,
                                         ngram_range=self.ngram_range,
                                         min_df=self.min_df,
                                         max_df=self.max_df)
            if return_vectorizer:
                tokens = (vectorizer.fit_transform(df).toarray(),vectorizer)
            else:
                tokens = vectorizer.fit_transform(df).toarray()
        # If embed is specified, used embedding vector for each word,
        # sum and normalize
        elif self.transformer=='embed':
            def sent2vec(s):
                M = []
                for w in s:
                    try:
                        M.append(embeddings_index[w])
                    except:
                        continue
                M = np.array(M)
                v = M.sum(axis=0)
                if type(v) != np.ndarray:
                    return np.zeros(300)
                return v / np.sqrt((v ** 2).sum())
            # Tokenize based on GloVe embedding
            data = df.apply(word_tokenize)
            # Return token as numpy matrix
            tokens = np.array(data.apply(sent2vec).tolist())
        return tokens
```

TfIdf, Count and GloVe word embedding vectorizations are either preprocessed or loaded from file. Notice that `min_df` and `max_df` have been set to conform with embedding matrix. This avoids potential overfitting that could results in unfair advantage to embedding due to size.

[23]:
```python
# train_vec contains vectorization with tfidf, count and embedding vectorization
if not exists('train_vec.pickle'):
```

```
    # Apply TfIdf vectorization
    prep = Preprocess(transformer='tfidf',max_df=0.979,min_df=0.0201)
    X_train_tfidf, tfidf_vec = prep.transform(X_train)

    # Apply Count vectorization
    prep = Preprocess(transformer='count',max_df=0.979,min_df=0.0201)
    X_train_count, count_vec = prep.transform(X_train)

    # Apply embedding
    prep = Preprocess(transformer='embed')
    X_train_embed = prep.transform(X_train)

    # Add all three to X_train_vec
    X_train_vec = [X_train_tfidf, X_train_count, X_train_embed]
    vec_labels = ['TfIdf', 'Count', 'Embedding']
    vec_list = [tfidf_vec, count_vec]

    # Delete unused variables to save memory
    del X_train_tfidf, X_train_count, X_train_embed, tfidf_vec, count_vec

    # Save models to file
    with open('train_vec.pickle', 'wb') as f:
        pickle.dump(X_train_vec, f)
        pickle.dump(vec_labels, f)
        pickle.dump(y_train, f)
        pickle.dump(vec_list, f)
else:
    # Load models
    with open('train_vec.pickle', 'rb') as f:
        X_train_vec = pickle.load(f)
        vec_labels = pickle.load(f)
        y_train = pickle.load(f)
```

4.2 Grid Search Class

For this project, a custom grid search class was written so that important metrics such as ROC curves and metrics for model performances can be plotted.

[25]:
```
class Custom_GridSearchCV():
    def __init__(self, estimator, param_grid={}, cv=5):
        """
        Custom_GridSearchCV: A grid search that automatically returns
        various metrics for almost all sklearn, xgboost and catboost
        classification models.
        estimator: A string of the model
        param_grid: parametric grid for grid search. All entries should be in
        string format
```

```
        cv: Number of cross validation folds
        """
        # Initialize cv
        self.cv = cv
        # Initialize fitted, boolean if the grid of models have been fitted
        self.fitted = False
        # Initialize models list
        self.models = []
        # Initialize cross validation evaluations
        self.cross_eval = {}
        # Extract parameters for baseline model. Parameters with only one value
        # are selected.
        base_params = [k+"="+v[0] for k,v in param_grid.items() if len(v)==1]
        base_params = ','.join(base_params)
        # Initialize baseline model
        exec("self.baseline_model = "+estimator+"("+base_params+")")
        # Create a combinations of the parameter grid
        all_params = sorted(param_grid)
        combinations = it.product(*(param_grid[name] for name in all_params))
        # Iterate through the combinations and keys to create a list of models
        keys = list(param_grid.keys())
        for j, comb in enumerate(combinations):
            params = ""
            for i, key in enumerate(keys):
                params += key+"="+comb[i]+","
            # Append models
            exec("self.models.append("+estimator+"("+params[:-1]+"))")
        # Initialize predictions dataframe
        self.predictions = None
        # Best model
        self.best_model_ = None

    def cross_validate(self, X, y, scoring="accuracy", vectorization=None):
        """
        Cross validate data on training data and return dataset with the
        largest scoring.
        X: A list containing different vectorized training datasets
        y: Training labels
        scoring: The type of scoring used in cross validation. Valid entries
        are 'accuracy','precision','recall','f1' and 'roc_auc'
        vectorization: User specified corpus vectorization labels to serve
        as indices of report dataframe
        """
        # Set default scoring
        self.scoring = scoring
        # Weighted boolean
        weighted = False
```

```
        # Cross validation: run custom_cross_validate
        if self.cross_eval=={}:
            for i in range(len(X)):
                # Convert to dataframe
                X[i] = pd.DataFrame(X[i])
                # Run custom cross validate on each vectorizatized data
                train_dict, valid_dict = custom_cross_validate(self.
↪baseline_model,
                                                              X[i],
                                                              y,
                                                              cv=self.cv)
                # Append values
                self.cross_eval[vectorization[i]] = {'train':train_dict,
                                                     'cross_validate':valid_dict}
        # 'return_report' returns values from 'cross_eval' and 'scoring'
        return_report = {}
        for dataset in self.cross_eval.keys():
            return_report[dataset] = {}
            for report in self.cross_eval[dataset].keys():
                return_report[dataset][report] = self.
↪cross_eval[dataset][report][scoring]
        # 'report_dataframe': a dataframe where average values are selected
        report_dataframe = pd.DataFrame(return_report).applymap(np.mean)
        # Transpose the dataframe so that indices represent␣
↪'cross_eval_dataset'
        report_dataframe = report_dataframe.transpose()
        # Select the dataset with maximum score for training
        max_train = report_dataframe.train.max()
        max_train_score_dataset = report_dataframe.train[report_dataframe.
↪train==max_train].index
        max_train_score_dataset = max_train_score_dataset[0]
        # Select the dataset with maximum score for validation
        max_valid = report_dataframe.cross_validate.max()
        max_valid_score_dataset = report_dataframe.
↪cross_validate[report_dataframe.cross_validate==max_valid].index
        max_valid_score_dataset = max_valid_score_dataset[0]
        # Combine scores
        max_score_dataset = {'train':max_train_score_dataset,
                             'cross_validate':max_valid_score_dataset}
        # Return 'return_report' dictionary, 'report_dataframe' dataframe and
        # 'max_score_dataset' dataset string
        return return_report, report_dataframe, max_score_dataset

    def fit(self, X, y):
        """
        Fit training data to a grid of models.
        X: Training dataset
```

```
        y: Training labels
        """
        # Run if models are not fitted
        if not self.fitted:
            for model in self.models:
                # Iterate through each model and fit training data
                model.fit(X, y)
            # Set 'fitted' to True
            self.fitted = True

    def predict(self, X, y, train_test='test'):
        """
        Predict values: Unlike predict functions for sklearn estimators,
        this function takes y value as well, to report fitting metrics
        X: Training/test dataset
        y: Training/test labels
        train_test: only 'train' and 'test' values need to be specified.
        """
        # Dataframe to store prediction per 'train_test'
        tr_ts = None
        # Iterate through each model
        for model in self.models:
            # Calculate the probabilities of predictions
            prob_preds = model.predict_proba(X)
            # Check if the model has 'decision_function'
            score = prob_preds[:, 1]
            # Calculate predictions
            preds = np.array([round(i) for i in score])
            # Find fpr and tpr values
            fpr, tpr, threshold = roc_curve(y, score)
            # Dict to store values
            tmp = {}
            # Populate 'tmp_df' with values
            tmp['train_test'] = train_test
            tmp['preds'] = [preds]
            tmp['prob_preds'] = [prob_preds]
            tmp['log_loss_score'] = log_loss(y, preds)
            tmp['accuracy'] = accuracy_score(y, preds)
            tmp['precision'] = precision_score(y, preds)
            tmp['recall'] = recall_score(y, preds)
            tmp['f1'] = f1_score(y, preds)
            tmp['fpr'] = [fpr]
            tmp['tpr'] = [tpr]
            tmp['auc'] = auc(fpr, tpr)
            tmp['roc_auc'] = roc_auc_score(y, preds)
            # Create a temp dataframe with 'predictions' columns
            tmp_df = pd.DataFrame(tmp)
```

```
            # Concatenate 'tmp_df' and 'tmp_df'
            if not isinstance(tr_ts, pd.DataFrame):
                tr_ts = tmp_df.copy()
            else:
                tr_ts = pd.concat([tr_ts,tmp_df])
        # Reset indices
        tr_ts.index = np.arange(len(self.models))
        # Assign values to 'predictions'
        if not isinstance(self.predictions, pd.DataFrame):
            self.predictions = tr_ts.copy()
        else:
            self.predictions = pd.concat([self.predictions,tr_ts])

    def best_model(self, metrics=['accuracy'], valid_test='test'):
        """
        This function returns the best model and model metrics
        based on provided metrics from the test dataset.
        metrics: A list of metrics
        """
        # Select test cases only
        test_metrics = self.predictions.loc[self.predictions.
↪train_test==valid_test]
        # Sort test_metrics by metrics in descending order
        test_metrics = test_metrics.sort_values(by=metrics, ascending=False)
        # Reset indices
        test_metrics = test_metrics.reset_index()
        # Best model index
        idx = test_metrics.loc[0,:]['index']
        # Return best model and best model metrics
        if self.best_model_ is None:
            self.best_model_ = self.models[idx]
        return self.best_model_, test_metrics.loc[0,:]
```

To aide with custom grid search, a custom cross validation tool was adopted from the teaching material. The importance of developing such a tool is to perform oversampling within the training folds which will be then applied to the validation dataset.

[26]:
```
def custom_cross_validate(estimator, X, y, cv=5):
    """
    'custom_cross_validate' function that performs oversampling and cross
    validate results.
    X: Training dataset
    y: Training labels
    cv: The number of cross-validation folds
    """
    # Create dictionaries to hold the scores from each fold
    train_dict = {'log_loss_score':np.ndarray(cv), 'precision':np.ndarray(cv),
```

```python
                 'accuracy':np.ndarray(cv), 'recall':np.ndarray(cv),
                  'f1':np.ndarray(cv),'fpr':[],
                  'tpr':[], 'auc':np.ndarray(cv), 'roc_auc':np.ndarray(cv)
                 }
valid_dict = {'log_loss_score':np.ndarray(cv), 'precision':np.ndarray(cv),
                 'accuracy':np.ndarray(cv), 'recall':np.ndarray(cv),
                  'f1':np.ndarray(cv),'fpr':[],
                  'tpr':[], 'auc':np.ndarray(cv), 'roc_auc':np.ndarray(cv)
                 }

# Instantiate a splitter object and loop over its result
kfold = StratifiedKFold(n_splits=cv, shuffle=True)
for fold, (train_index, val_index) in enumerate(kfold.split(X, y)):
    # Extract train and validation subsets using the provided indices
    X_t, X_val = X.iloc[train_index], X.iloc[val_index]
    y_t, y_val = y.iloc[train_index], y.iloc[val_index]

    # Clone the provided model and fit it on the train subset
    temp_model = clone(estimator)

    # Fit the model
    temp_model.fit(X_t, y_t)

    # Find predictions and probabilities
    train_score = temp_model.predict_proba(X_t)[:,1]
    val_score = temp_model.predict_proba(X_val)[:,1]
    train_pred = np.array([round(i) for i in train_score])
    val_pred = np.array([round(i) for i in val_score])

    # Evaluate the provided model on the train and validation subsets
    # Log loss score
    train_dict['log_loss_score'][fold] = log_loss(y_t, train_pred)
    valid_dict['log_loss_score'][fold] = log_loss(y_val, val_pred)
    # Accuracy score
    train_dict['accuracy'][fold] = accuracy_score(y_t, train_pred)
    valid_dict['accuracy'][fold] = accuracy_score(y_val, val_pred)
    # Precision score
    train_dict['precision'][fold] = precision_score(y_t, train_pred)
    valid_dict['precision'][fold] = precision_score(y_val, val_pred)
    # Recall score
    train_dict['recall'][fold] = recall_score(y_t, train_pred)
    valid_dict['recall'][fold] = recall_score(y_val, val_pred)
    # F1 score
    train_dict['f1'][fold] = f1_score(y_t, train_pred)
    valid_dict['f1'][fold] = f1_score(y_val, val_pred)
    # FPR and TPR
    train_fpr, train_tpr, threshold = roc_curve(y_t, train_score)
```

```python
        valid_fpr, valid_tpr, threshold = roc_curve(y_val, val_score)
        train_dict['fpr'].append(train_fpr)
        train_dict['tpr'].append(train_tpr)
        valid_dict['fpr'].append(valid_fpr)
        valid_dict['tpr'].append(valid_tpr)
        # AUC
        train_dict['auc'][fold] = auc(train_fpr, train_tpr)
        valid_dict['auc'][fold] = auc(valid_fpr, valid_tpr)
        # ROC_AUC
        train_dict['roc_auc'][fold] = roc_auc_score(y_t, train_pred)
        valid_dict['roc_auc'][fold] = roc_auc_score(y_val, val_pred)

    # Return training and validation results
    return train_dict, valid_dict
```

4.3 Model Performance Visualization Functions

The following function helps in visualizing the log losses, combined ROC curves of training and cross-validation datasets, and performance metrics of training and validation datasets.

[27]:
```python
def prepare_metrics(model_grid, train_val='train'):
    """
    This function plots metrics on different datasets
    model_grid: Custom_GridSearchCV object
    Run this code after fitting.
    """
    # Convert cross_eval from Custom_GrisSearchCV into dataframe
    # Table is transposed to set dataset as columns
    tmp = pd.DataFrame(model_grid.cross_eval).transpose()
    tmp = pd.DataFrame(tmp[train_val].to_dict())
    # Initialize metrics dataframe
    metrics = pd.DataFrame(columns=list(tmp.columns)+['metric'])
    # Iterate through each metric in 'tmp' and assign to metrics dataframe
    for idx in tmp.index:
        # Create an empty dataframe
        metric = pd.DataFrame(tmp.loc[idx,:].to_dict())
        # Update type of metric
        metric['metric'] = idx
        # Append results
        metrics = pd.concat([metrics, metric])
    # Reset metrics
    metrics = metrics.reset_index()
    # Rename 'index' column to 'fold'
    metrics.rename(columns={'index':'fold'}, inplace=True)
    # Initialiaze squeezed metrics dataframe
    squeezed_metrics = pd.DataFrame(columns=['fold','metric','dataset',
                                             'value','train_val'])
```

```
    # Iterate through each column and populate 'squeezed_metrics'
    for col in model_grid.cross_eval.keys():
        # Create empty dataframe
        sq_met = pd.DataFrame(columns=squeezed_metrics.columns)
        # Populate 'sq_met'
        sq_met.fold = metrics.fold
        sq_met.metric = metrics.metric
        sq_met.dataset = col
        sq_met.value = metrics[col]
        sq_met.train_val = train_val
        # Append 'sq_met' to 'squeezed_metrics'
        squeezed_metrics = pd.concat([squeezed_metrics, sq_met],
                                     ignore_index=True)
    # Set log-loss to a variable and remove the column from 'squeezed_metrics'
    log_loss_vals =  squeezed_metrics.loc[squeezed_metrics.metric␣
↪=='log_loss_score']
    squeezed_metrics.drop(log_loss_vals.index, inplace=True)
    # Get fpr and tpr from 'squeezed_metrics'
    fpr = squeezed_metrics.loc[squeezed_metrics.metric=='fpr']
    tpr = squeezed_metrics.loc[squeezed_metrics.metric=='tpr']
    # Drop 'fpr' and 'tpr' from 'squeezed_metrics'
    squeezed_metrics.drop(fpr.index, inplace=True)
    squeezed_metrics.drop(tpr.index, inplace=True)
    # Find the longest fpr/tpr
    roc_max_len = fpr.value.apply(lambda x: len(x)).max()
    # Reset indices for 'fpr' and 'tpr'
    fpr = fpr.reset_index()
    tpr = tpr.reset_index()
    # Initialize 'fpr_mat' and 'tpr_mat'
    fpr_mat = np.zeros((len(fpr), roc_max_len))
    tpr_mat = np.zeros((len(tpr), roc_max_len))
    # Iteratre through each fpr and tpr, and interpolate values
    for i in range(len(fpr)):
        # Create a uniformly spaced 'fpr' values
        xvals = np.linspace(0, 1, roc_max_len)
        # Interpolate y values
        yinterp = np.interp(xvals, fpr.loc[i,'value'], tpr.loc[i,'value'])
        # Update fpr and tpr matrix
        fpr_mat[i,:] = xvals
        tpr_mat[i,:] = yinterp
    # Create roc_vals dictionary
    roc_vals = {}
    # Instead of taking the entire matrices, the mean and std values are
    # selected for 'fpr' and 'tpr'
    roc_vals['fpr_mean'] = fpr_mat.mean(axis=0)
    roc_vals['tpr_mean'] = tpr_mat.mean(axis=0)
    roc_vals['fpr_std'] = fpr_mat.std(axis=0)
```

```python
    roc_vals['tpr_std'] = tpr_mat.std(axis=0)
    # Return squeezed metrics, log loss and roc
    return squeezed_metrics, log_loss_vals, roc_vals


def plot_metrics(model_grid):
    """
    This function plots metrics on different datasets
    model_grid: Custom_GridSearchCV object
    Run this code after fitting.
    """
    # Get parameters for training
    tr_metrics, tr_log_loss, tr_roc_vals = prepare_metrics(model_grid,
                                                           'train')
    # Get parameters for validation
    vl_metrics, vl_log_loss, vl_roc_vals = prepare_metrics(model_grid,
                                                           'cross_validate')
    # Combine log losses for training and validation
    log_loss_combined = pd.concat([tr_log_loss,vl_log_loss])
    # Create figure to plot log loss and ROC curve
    fig, axes = plt.subplots(1 , 2, figsize=(15,6))
    # Log loss for training and validation
    g1 = sns.barplot(x="dataset", y="value", hue="train_val",
                     data=log_loss_combined, ax=axes[0])
    # Format labels and title
    g1.set_xlabel('')
    g1.set_ylabel('Log Loss',fontsize=13)
    g1.set_title('Log Loss vs Dataset',fontsize=15)
    g1.legend(title='Fold')
    limits = (np.floor(min(log_loss_combined.value)*10)/10,
              np.ceil(max(log_loss_combined.value)*10)/10)
    g1.set_ylim(limits)

    # Plot mean ROC curve for training fold
    g2 = sns.lineplot(x=tr_roc_vals['fpr_mean'], y=tr_roc_vals['tpr_mean'],
                  label='train', ax=axes[1], color='tab:blue')
    # Plot the standard deviation for training ROC
    plt.fill_between(tr_roc_vals['fpr_mean'],
                     tr_roc_vals['tpr_mean'] - tr_roc_vals['tpr_std'],
                     tr_roc_vals['tpr_mean'] + tr_roc_vals['tpr_std'],
                     color='tab:blue', alpha=0.2)
    # Plot mean ROC curve for validation fold
    sns.lineplot(x=vl_roc_vals['fpr_mean'], y=vl_roc_vals['tpr_mean'],
                  label='cross_validate', ax=axes[1], color='tab:orange')
    # Plot the standard deviation for validation ROC
    plt.fill_between(vl_roc_vals['fpr_mean'],
                     vl_roc_vals['tpr_mean'] - vl_roc_vals['tpr_std'],
```

```
                     vl_roc_vals['tpr_mean'] + vl_roc_vals['tpr_std'],
                     color='tab:orange', alpha=0.2)

    # Format labels and title
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
    g2.set_xlabel('False Positve Rate', fontsize=13)
    g2.legend(title='Fold')
    g2.set_ylabel('True Positve Rate', fontsize=13)
    g2.set_title('ROC Curve',fontsize=15)

    # Plot metrics for training fold
    fig, axes = plt.subplots(2 , 1, figsize=(15,12))
    g3 = sns.barplot(x="dataset", y="value", hue="metric",
                     data=tr_metrics, ax=axes[0])
    # Format labels and title
    g3.set_xlabel('')
    g3.set_ylabel('Score', fontsize=13)
    g3.set_title('Training Scores vs Dataset',fontsize=15)
    g3.legend(title='Metric')
    limits = (np.floor(min(tr_metrics.value)*10)/10,
              np.ceil(max(tr_metrics.value)*10)/10)
    g3.set_ylim(limits)

    # Plot metrics for validation fold
    g4 = sns.barplot(x="dataset", y="value", hue="metric",
                     data=vl_metrics, ax=axes[1])
    # Format labels and title
    g4.set_xlabel('')
    g4.set_ylabel('Score',fontsize=13)
    g4.set_title('Cross Validation Scores vs Dataset',fontsize=15)
    g4.legend(title='Metric')
    limits = (np.floor(min(vl_metrics.value)*10)/10,
              np.ceil(max(vl_metrics.value)*10)/10)
    g4.set_ylim(limits)
```

The following function also does similar operations for training and validation datasets.

[28]:
```
def prepare_predictions(model_grid, train_test='test'):
    """
    This function plots metrics on train/test predictions
    model_grid: Custom_GridSearchCV object
    Run this code after fitting.
    """
    # Convert prediction from Custom_GrisSearchCV into dataframe
    # Select train or test
    tmp = model_grid.predictions.loc[model_grid.predictions.
 ↪train_test==train_test]
```

```python
# Initialize squeezed predictions
squeezed_preds = pd.DataFrame(columns=['metric','value','train_test'])
# Find metrics from 'cross_eval'
columns = model_grid.predictions.columns[3:]
# Iterate through 'predictions' columns
for col in columns:
    # Initialize a dummy dataframe for each column
    sq_preds = pd.DataFrame(columns=squeezed_preds.columns)
    # Assign values
    sq_preds.value = tmp[col]
    sq_preds.train_test = tmp['train_test']
    sq_preds.metric = col
    # Append values to 'squeezed_preds'
    squeezed_preds = pd.concat([squeezed_preds,sq_preds])
# Reset index
squeezed_preds = squeezed_preds.reset_index()
# Get log loss from 'squeezed_preds'
log_loss_vals = squeezed_preds.loc[squeezed_preds.metric=='log_loss_score']
squeezed_preds.drop(log_loss_vals.index, inplace=True)
# Get fpr and tpr from 'squeezed_preds'
fpr = squeezed_preds.loc[squeezed_preds.metric=='fpr']
tpr = squeezed_preds.loc[squeezed_preds.metric=='tpr']
# Drop 'fpr' and 'tpr' from 'squeezed_preds'
squeezed_preds.drop(fpr.index, inplace=True)
squeezed_preds.drop(tpr.index, inplace=True)
# Find the longest fpr/tpr
roc_max_len = fpr.value.apply(lambda x: len(x)).max()
# Reset indices for 'fpr' and 'tpr'
fpr = fpr.reset_index()
tpr = tpr.reset_index()
# Initialize 'fpr_mat' and 'tpr_mat'
fpr_mat = np.zeros((len(fpr), roc_max_len))
tpr_mat = np.zeros((len(tpr), roc_max_len))
# Iteratre through each fpr and tpr, and interpolate values
for i in range(len(fpr)):
    # Create a uniformly spaced 'fpr' values
    xvals = np.linspace(0, 1, roc_max_len)
    # Interpolate y values
    yinterp = np.interp(xvals, fpr.loc[i,'value'], tpr.loc[i,'value'])
    # Update fpr and tpr matrix
    fpr_mat[i,:] = xvals
    tpr_mat[i,:] = yinterp
# Create roc_vals dictionary
roc_vals = {}
# Instead of taking the entire matrices, the mean and std values are
# selected for 'fpr' and 'tpr'
roc_vals['fpr_mean'] = fpr_mat.mean(axis=0)
```

```
    roc_vals['tpr_mean'] = tpr_mat.mean(axis=0)
    roc_vals['fpr_std'] = fpr_mat.std(axis=0)
    roc_vals['tpr_std'] = tpr_mat.std(axis=0)
    # Return squeezed metrics, log loss and roc
    return squeezed_preds, log_loss_vals, roc_vals

def plot_predictions(model_grid, valid_test='test'):
    """
    This function plots predictions on different datasets
    model_grid: Custom_GridSearchCV object
    Run this code after fitting.
    """
    # Get parameters for training
    tr_preds, tr_log_loss, tr_roc_vals = prepare_predictions(model_grid,
                                                             'train')
    # Get parameters for validation
    ts_preds, ts_log_loss, ts_roc_vals = prepare_predictions(model_grid,
                                                             valid_test)
    # Combine log losses for training and validation
    log_loss_combined = pd.concat([tr_log_loss,ts_log_loss])
    # Create figure to plot log loss and ROC curve
    fig, axes = plt.subplots(1 , 2, figsize=(15,6))
    # Log loss for training and validation
    g1 = sns.barplot(x="metric", y="value", hue="train_test",
                     data=log_loss_combined, ax=axes[0])
    # Format labels and title
    g1.set_xlabel('')
    g1.set_ylabel('Log Loss',fontsize=13)
    g1.set_title('Log Loss vs Dataset',fontsize=15)
    g1.legend(title='Dataset')

    # Plot mean ROC curve for training fold
    g2 = sns.lineplot(x=tr_roc_vals['fpr_mean'], y=tr_roc_vals['tpr_mean'],
                  label='train', ax=axes[1], color='tab:blue')
    # Plot the standard deviation for training ROC
    plt.fill_between(tr_roc_vals['fpr_mean'],
                     tr_roc_vals['tpr_mean'] - tr_roc_vals['tpr_std'],
                     tr_roc_vals['tpr_mean'] + tr_roc_vals['tpr_std'],
                     color='tab:blue', alpha=0.2)
    # Plot mean ROC curve for validation fold
    sns.lineplot(x=ts_roc_vals['fpr_mean'], y=ts_roc_vals['tpr_mean'],
                  label=valid_test, ax=axes[1], color='tab:orange')
    # Plot the standard deviation for validation ROC
    plt.fill_between(ts_roc_vals['fpr_mean'],
                     ts_roc_vals['tpr_mean'] - ts_roc_vals['tpr_std'],
                     ts_roc_vals['tpr_mean'] + ts_roc_vals['tpr_std'],
                     color='tab:orange', alpha=0.2)
```

```
    # Format labels and title
    plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
    g2.set_xlabel('False Positve Rate', fontsize=13)
    g2.legend(title='Dataset')
    g2.set_ylabel('True Positve Rate', fontsize=13)
    g2.set_title('ROC Curve',fontsize=15)

    # Plot metrics for training data
    preds = pd.concat([tr_preds,ts_preds])
    fig, ax = plt.subplots(figsize=(15,6))
    g3 = sns.barplot(x="train_test", y="value", hue="metric",
                     data=preds, ax=ax)

    limits = (np.floor(min(preds.value)*10)/10,
              np.ceil(max(preds.value)*10)/10)

    # Format labels and title
    g3.set_ylim(limits)
    g3.set_xlabel('')
    g3.set_ylabel('Score', fontsize=13)
    g3.set_title('Scores vs Training and '+valid_test.title()+'␣
↪Datasets',fontsize=15)
    g3.legend(title='Metric')
```

To speed up plotting sklearn's confusion matrix plotter, a custom one is written that takes in only the true and estimated values.

[339]:
```
def plot_confusion_matrix(y_true, y_pred, normalize=None):
    '''
    Simplified confusion matrix plotter
    y_true: True y values
    y_pred: Predicted y values
    normalize: 'normalize' input used for confusion_matrix
    '''
    # Generate a square plot
    fig, ax = plt.subplots(figsize=(5,4))

    # Create a confusion matrix
    cm = confusion_matrix(y_true, y_pred, normalize=normalize)

    # Plot heatmap
    sns.heatmap(cm, annot=True, cmap='viridis', linecolor='black',
                linewidth=1, ax=ax)
    # Apply labels and limits
    plt.xlabel('Predicted label')
    plt.ylabel('True label')
```

```
    plt.xlim(2,0)
    plt.ylim(0,2)
```

Training the models take a long time. So, the models are saved as `dill` files that can be read from file.

Best performing models and their predictions will be stored in these variables.

CAUTION: running the entire notebook takes at least 24 hours.

The pretrained model will be available when ready.

[30]:
```
# Best models list
best_models = []

# Vectorization used in files
vectorization_type = []

# Define metrics by importance
metrics = ['accuracy','auc','recall']
```

4.4 Shallow Learning

4.4.1 Naive Bayes

The first model used is naive Bayes. Parameters `alpha` and `fit_prior` were used to create a grid search.

[31]:
```
# Check if the variable exists
if not exists('nb_gs.pickle'):

    # Define parameters ranges
    params = {'alpha':['0','1'],
              'fit_prior':['False','True']}

    # Create a Custom_GridSearchCV instance
    nb_gs = Custom_GridSearchCV('MultinomialNB', param_grid=params, cv=3)
else:
    # Load from file
    with open('nb_gs.pickle', 'rb') as f:
        nb_gs = pickle.load(f)
```

[32]:
```
# Run cross-validation with accuracy as the primary scoring
rprt, rp_df, _ = nb_gs.cross_validate(X_train_vec[:2], y_train,
                                      vectorization=vec_labels[:2])
```

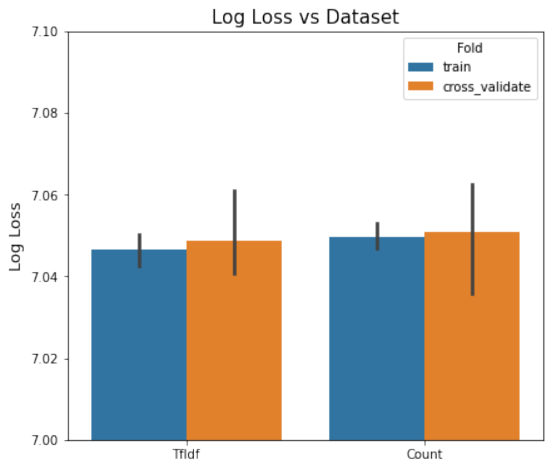
In orders to choose the best dataset to fit with the model, let's aggregate the metrics. Sorting the average accuracy, recall and AUC metrics yields:

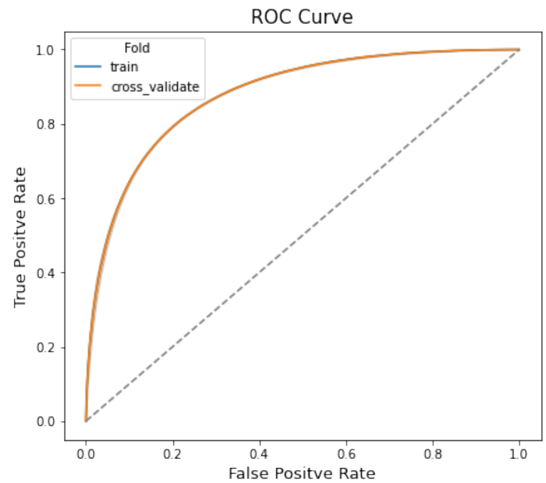
[33]:
```python
# Find training and validation metrics
nb_gs_metrics_train,_,_ = prepare_metrics(nb_gs, train_val='train')
nb_gs_metrics_valid,_,_ = prepare_metrics(nb_gs, train_val='cross_validate')

# Combine metrics
nb_gs_metrics = pd.concat([nb_gs_metrics_train,nb_gs_metrics_valid])

# Rename dataset as 'dataset_train/cross_validate'
nb_gs_metrics.dataset = nb_gs_metrics.dataset+'_'+nb_gs_metrics.train_val

# Create a placeholder dataframe to store the average values
nb_gs_metrics_mean = pd.DataFrame(columns=nb_gs_metrics.metric.unique(),
                                  index=nb_gs_metrics.dataset.unique())

# Iterate through each row and column, aggregate values and take the mean
for col in nb_gs_metrics_mean.columns:
    for idx in nb_gs_metrics_mean.index:
        avg = nb_gs_metrics.loc[(nb_gs_metrics.metric==col) & (nb_gs_metrics.
 ↪dataset==idx),'value']
        nb_gs_metrics_mean.loc[idx,col] = avg.mean()

# Sort average metrics by 'metrics'
nb_gs_metrics_mean.sort_values(by=metrics,ascending=False)
```

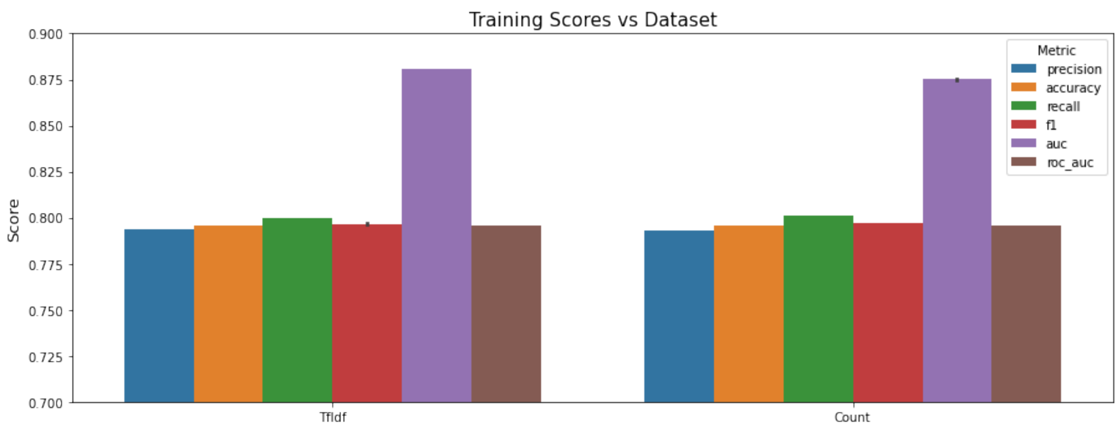
[33]:
```
                      precision  accuracy    recall        f1       auc  \
TfIdf_train            0.793827  0.795987  0.799663  0.796734  0.881023
TfIdf_cross_validate   0.793735  0.795919  0.799639  0.796675  0.880983
Count_train            0.792897    0.7959  0.801025   0.79694  0.875053
Count_cross_validate   0.792864  0.795862  0.800981  0.796901  0.875016

                        roc_auc
TfIdf_train            0.795987
TfIdf_cross_validate   0.795919
Count_train              0.7959
Count_cross_validate   0.795862
```

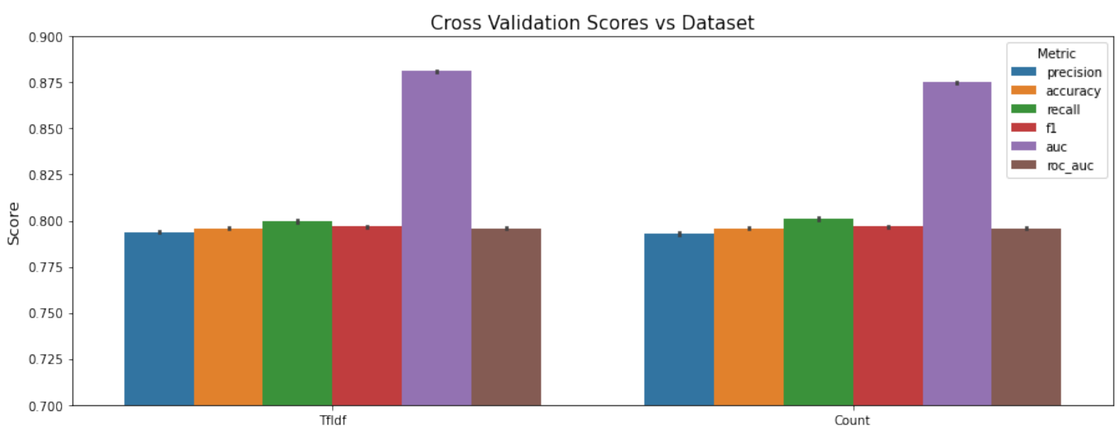
The performance metrics of the model are shown below.

[34]:
```python
# Plot the metrics for training and validation datasets
plot_metrics(nb_gs)
```









`TfIdf`showed significant metrics compared to `Count`.

[35]:
```python
# Fit grid search models with the best training dataset
# Specifying TfIdf to have better accuracy values
nb_gs.fit(X_train_vec[0], y_train)
```

Now, let's produce predictions based on the model grid.

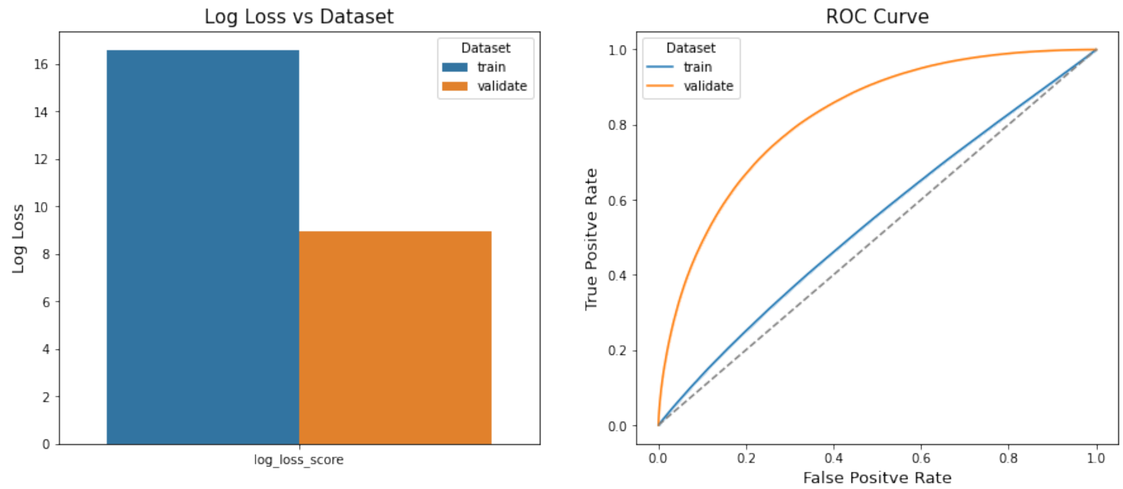
[36]:
```python
# Predict test and training datasets
# Also get the metrics of fit
# Check if the models have not been predicted yet
if not isinstance(nb_gs.predictions, pd.DataFrame):
    prep = Preprocess(transformer='tfidf',max_df=0.979,min_df=0.0201)
    nb_gs.predict(prep.transform(X_valid), y_valid, train_test='validate')
    nb_gs.predict(X_train_vec[-1], y_train, train_test='train')
nb_gs.predictions.head()
```

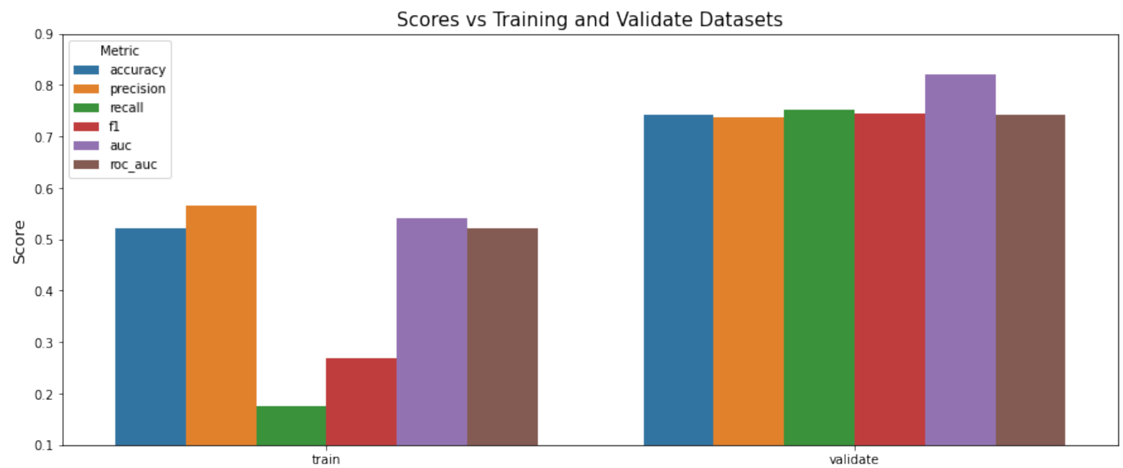
[36]:
```
  train_test                                             preds  \
0   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, …
1   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, …
2   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, …
3   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, …
0      train  [0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, …

                                          prob_preds  log_loss_score  \
0  [[0.3902222283229388, 0.6097777716770622], [0…        8.928094
1  [[0.3902222283229388, 0.60977777167706], [0.72…        8.928094
2  [[0.3902264776423026, 0.6097735223576966], [0…        8.928094
3  [[0.3902264776423026, 0.6097735223576966], [0…        8.928094
0  [[0.6285026028322631, 0.37149739716773683], [0…       16.562082

   accuracy  precision    recall        f1  \
0  0.741508   0.736084  0.752996  0.744444
1  0.741508   0.736084  0.752996  0.744444
2  0.741508   0.736081  0.753004  0.744446
3  0.741508   0.736081  0.753004  0.744446
0  0.520480   0.566003  0.175625  0.268071

                                                 fpr  \
0  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
1  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
2  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
3  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
0  [0.0, 7.936507936507937e-07, 7.936507936507937…

                                                 tpr       auc   roc_auc
0  [0.0, 1.8518518518518519e-06, 0.00014814814814…  0.821527  0.741508
1  [0.0, 1.8518518518518519e-06, 0.00014814814814…  0.821527  0.741508
2  [0.0, 1.8518518518518519e-06, 0.00014814814814…  0.821528  0.741508
3  [0.0, 1.8518518518518519e-06, 0.00014814814814…  0.821528  0.741508
```

```
0  [0.0, 0.0, 1.5873015873015873e-06, 1.587301587…  0.540398  0.520480
```

Plotting metrics over the validation dataset.

[37]:
```python
# Plot metrics for predicted values
plot_predictions(nb_gs, valid_test='validate')
```





Accuracy, recall and AUC are used to determine the best model.

[38]:
```python
# Find the best model and model metrics based on given metrics
best_nb_model, best_nb_model_metrics = nb_gs.best_model(metrics=metrics,
                                                        valid_test='validate')
# Add predictions of the best model
best_nb_model.predictions = nb_gs.predictions.
 ↪loc[best_nb_model_metrics['index'],:]
```

```python
# Store best model
best_models.append(best_nb_model)

# Store the type of vectorization used
vectorization_type.append('tfidf')

# Display best model parameters
best_nb_model.get_params
```

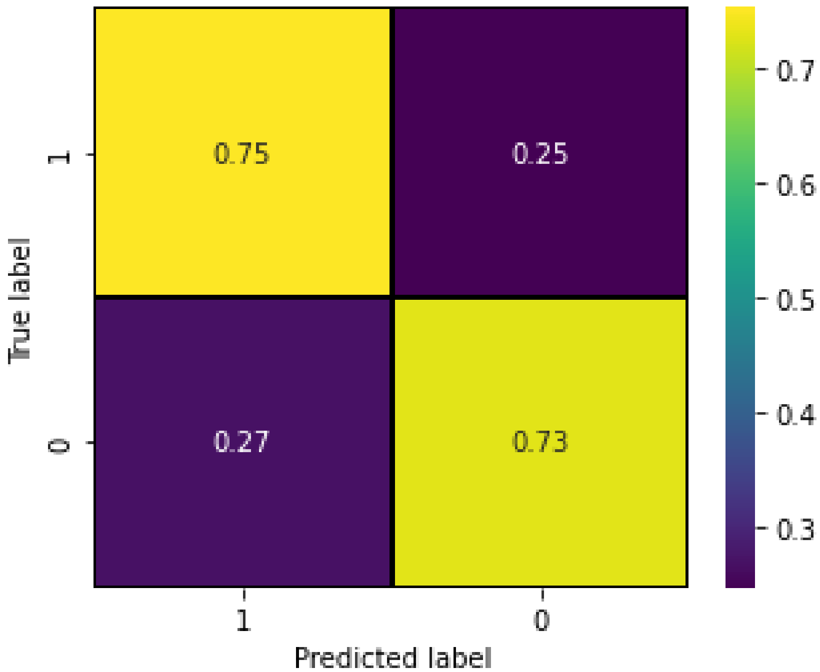
[38]: <bound method BaseEstimator.get_params of MultinomialNB(alpha=1,
fit_prior=False)>

[39]:
```python
# Best logreg model metrics
best_nb_model_metrics
```

[39]:
```
index                                                                2
train_test                                                    validate
preds              [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0, …
prob_preds         [[0.3902264776423026, 0.6097735223576966], [0…
log_loss_score                                                 8.92809
accuracy                                                      0.741508
precision                                                     0.736081
recall                                                        0.753004
f1                                                            0.744446
fpr                [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
tpr                [0.0, 1.8518518518518519e-06, 0.00014814814814…
auc                                                           0.821528
roc_auc                                                       0.741508
Name: 0, dtype: object
```

Displaying the metrics for the best performing model and plotting the confusion matrix.

[40]:
```python
# Confusion matrix
plot_confusion_matrix(y_valid, best_nb_model_metrics.preds,
                      normalize='true')
```



Model can now be saved to file.

[41]:
```
# Save the grid search model if it does not exist
if not exists('nb_gs.pickle'):
    with open('nb_gs.pickle', 'wb') as f:
        pickle.dump(nb_gs, f)
```

[42]:
```
# Delete 'nb_gs' for memory managment
del nb_gs
```

4.4.2 Logistic Regression

The first model used is logistic regression. Regularization factor, fit intercept, and L1 or L2 penalty were considered for grid search. `lbfgs` solver does not allow for L1 penalty. So, `liblinear` solver used instead. The downside is that `liblinear` does not allow for parallelized jobs, which is why `n_jobs` is missing as an input parameter.

[43]:
```
# Check if the variable exists
if not exists('logreg_gs.pickle'):
    # Define regularization range
    C = np.linspace(0.1, 1, 2)

    # Define parameters ranges
    params = {'C':[str(s) for s in C],
              'fit_intercept':['False','True'],
```

```
                'max_iter':['1e3'],
                'penalty':["'l1'","'l2'"],
                'solver':["'liblinear'"]}

    # Create a Custom_GridSearchCV instance
    logreg_gs = Custom_GridSearchCV('LogisticRegression',
                                    param_grid=params,
                                    cv=3)
else:
    with open('logreg_gs.pickle', 'rb') as f:
        logreg_gs = pickle.load(f)
```

[44]:
```
# Run cross-validation with accuracy as the primary scoring
rprt, rp_df, _ = logreg_gs.cross_validate(X_train_vec, y_train,
                                          vectorization=vec_labels)
```

In orders to choose the best dataset to fit with the model, let's aggregate the metrics. Sorting the average accuracy, recall and AUC metrics yields:

[45]:
```
# Find training and validation metrics
logreg_gs_metrics_train,_,_ = prepare_metrics(logreg_gs, train_val='train')
logreg_gs_metrics_valid,_,_ = prepare_metrics(logreg_gs,␣
 ↪train_val='cross_validate')

# Combine metrics
logreg_gs_metrics = pd.concat([logreg_gs_metrics_train,logreg_gs_metrics_valid])

# Rename dataset as 'dataset_train/cross_validate'
logreg_gs_metrics.dataset = logreg_gs_metrics.dataset+'_'+logreg_gs_metrics.
 ↪train_val

# Create a placeholder dataframe to store the average values
logreg_gs_metrics_mean = pd.DataFrame(columns=logreg_gs_metrics.metric.unique(),
                                  index=logreg_gs_metrics.dataset.unique())

# Iterate through each row and column, aggregate values and take the mean
for col in logreg_gs_metrics_mean.columns:
    for idx in logreg_gs_metrics_mean.index:
        avg = logreg_gs_metrics.loc[(logreg_gs_metrics.metric==col) &␣
 ↪(logreg_gs_metrics.dataset==idx),'value']
        logreg_gs_metrics_mean.loc[idx,col] = avg.mean()

# Sort average metrics by recall, AUC and accuracy
logreg_gs_metrics_mean.sort_values(by=metrics,ascending=False)
```

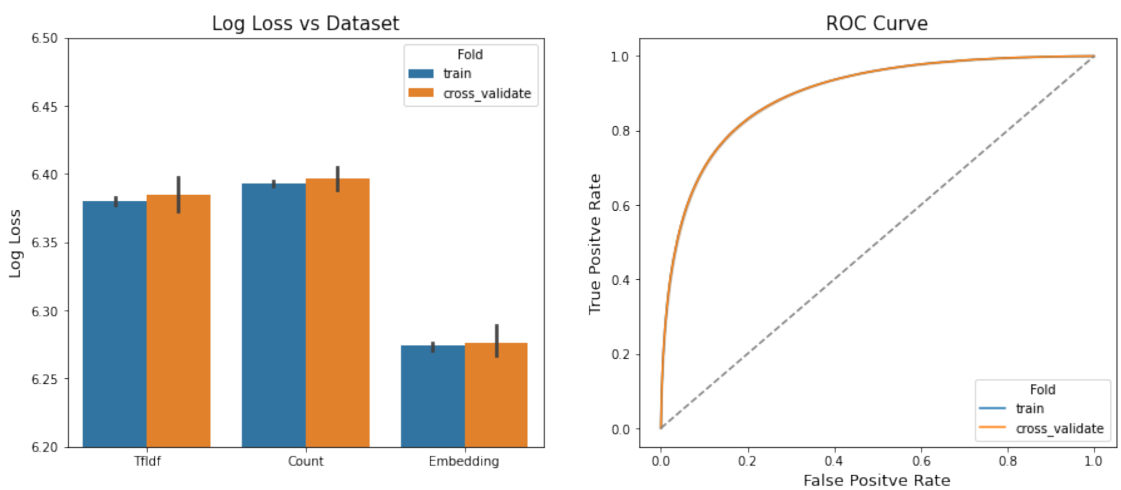
[45]:
```
                         precision  accuracy    recall        f1       auc  \
Embedding_train           0.820747  0.818354  0.814623  0.817673  0.898025
```

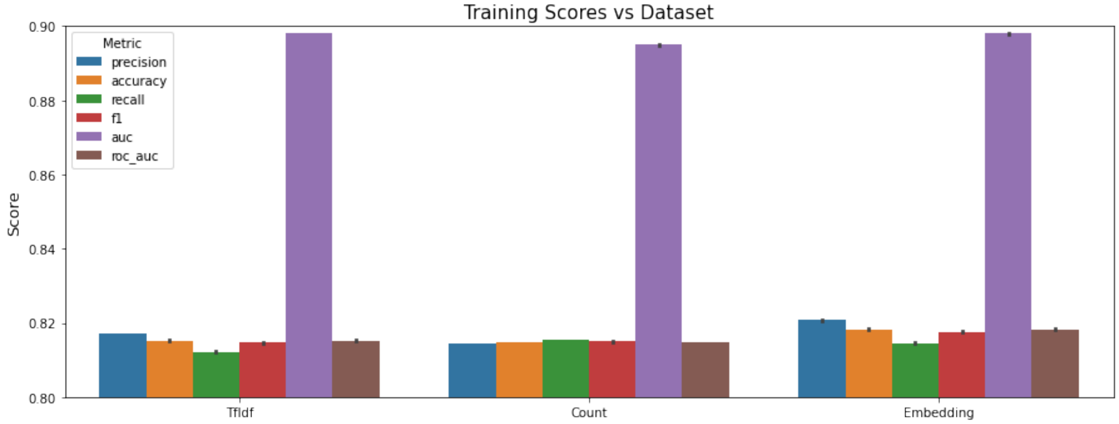
Embedding_cross_validate	0.820664	0.81828	0.814564	0.817602	0.897943
TfIdf_train	0.817185	0.815278	0.812272	0.814721	0.898081
TfIdf_cross_validate	0.817037	0.815151	0.812178	0.8146	0.897996
Count_train	0.81447	0.814901	0.815586	0.815028	0.894937
Count_cross_validate	0.814388	0.814796	0.815444	0.814916	0.894852

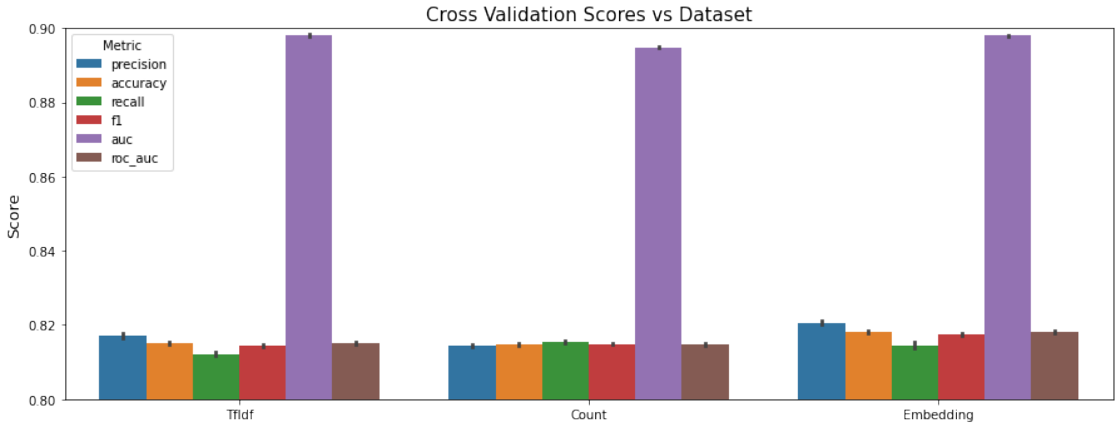
	roc_auc
Embedding_train	0.818354
Embedding_cross_validate	0.81828
TfIdf_train	0.815278
TfIdf_cross_validate	0.815151
Count_train	0.814901
Count_cross_validate	0.814796

The performance metrics of the model are shown below.

[46]:
```
# Plot the metrics for training and cross_validation datasets
plot_metrics(logreg_gs)
```







Word embedding had the highest performance.

[47]:
```
# Fit grid search models with the best training dataset
# Specifying embedding to have better accuracy values
logreg_gs.fit(X_train_vec[-1], y_train)
```

Now, let's produce predictions based on the model grid.

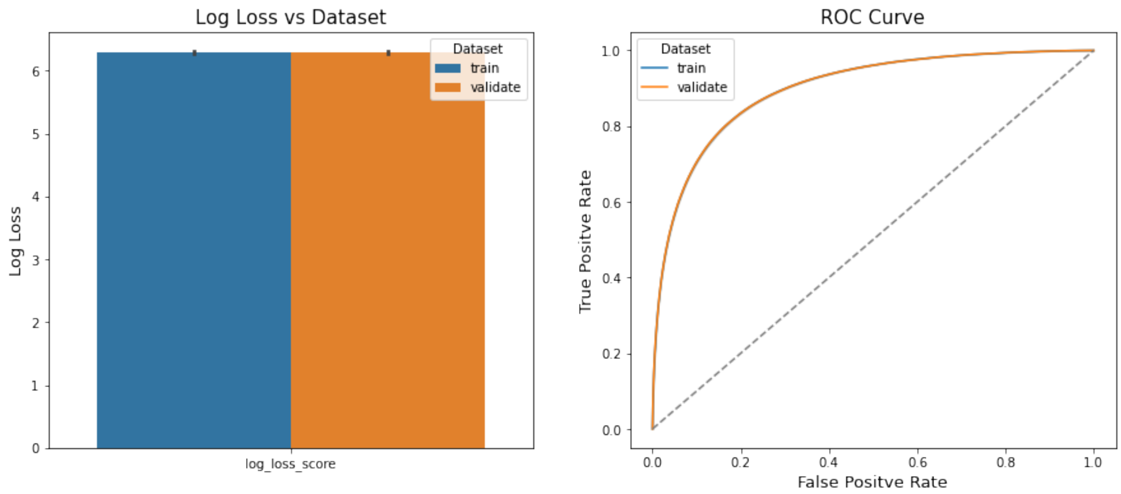
[48]:
```
# Predict test and training datasets
# Also get the metrics of fit
# Check if the models have not been predicted yet
if not isinstance(logreg_gs.predictions, pd.DataFrame):
    prep = Preprocess(transformer='embed')
    logreg_gs.predict(prep.transform(X_valid), y_valid, train_test='validate')
    logreg_gs.predict(X_train_vec[-1], y_train, train_test='train')
logreg_gs.predictions.head()
```

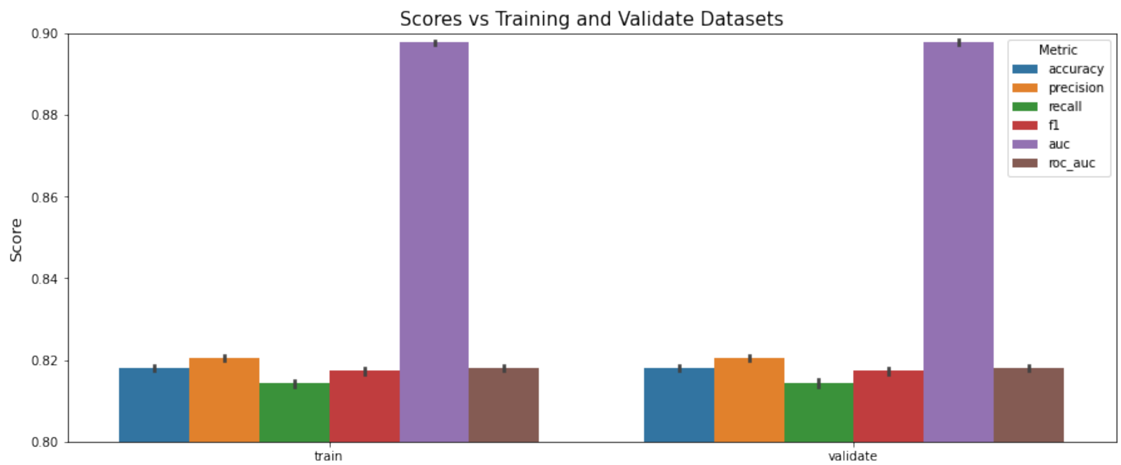
[48]:
```
  train_test                                              preds  \
0   validate  [1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, …
1   validate  [1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, …
2   validate  [1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, …
```

```
3   validate  [1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, …
4   validate  [1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, …

                                          prob_preds  log_loss_score  \
0  [[0.10269263594560363, 0.8973073640543964], [0…        6.279093
1  [[0.11333726717753934, 0.8866627328224607], [0…        6.341967
2  [[0.09999002092036968, 0.9000099790796303], [0…        6.276790
3  [[0.11008529675875522, 0.8899147032412448], [0…        6.338897
4  [[0.09411404120268296, 0.905885958797317], [0…        6.251685

   accuracy  precision    recall        f1  \
0  0.818204   0.820577  0.814502  0.817528
1  0.816383   0.819056  0.812194  0.815611
2  0.818270   0.820637  0.814580  0.817597
3  0.816472   0.819134  0.812302  0.815704
4  0.818997   0.821230  0.815522  0.818366

                                                 fpr  \
0  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
1  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
2  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
3  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
4  [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…

                                                 tpr       auc   roc_auc
0  [0.0, 1.8518518518518519e-06, 2.96296296296296…  0.897989  0.818204
1  [0.0, 1.8518518518518519e-06, 3.14814814814814…  0.896314  0.816383
2  [0.0, 1.8518518518518519e-06, 2.77777777777777…  0.898036  0.818270
3  [0.0, 1.8518518518518519e-06, 3.14814814814814…  0.896358  0.816472
4  [0.0, 1.8518518518518519e-06, 2.03703703703703…  0.898650  0.818997
```

Plotting metrics over the validation dataset.

[49]:
```
# Plot metrics for predicted values
plot_predictions(logreg_gs, valid_test='validate')
```





Accuracy, recall and AUC are used to determine the best model.

[50]:
```
# Find the best model and model metrics based on given metrics
best_logreg_model, best_logreg_model_metrics = logreg_gs.
 ↪best_model(metrics=metrics,
                                                                  ␣
 ↪valid_test='validate')

# Add predictions
best_logreg_model.predictions = logreg_gs.predictions.
 ↪loc[best_logreg_model_metrics['index'],:]

# Store best model
best_models.append(best_logreg_model)
```

```python
# Store the type of vectorization used
vectorization_type.append('embed')

# Display best model parameters
best_logreg_model.get_params
```

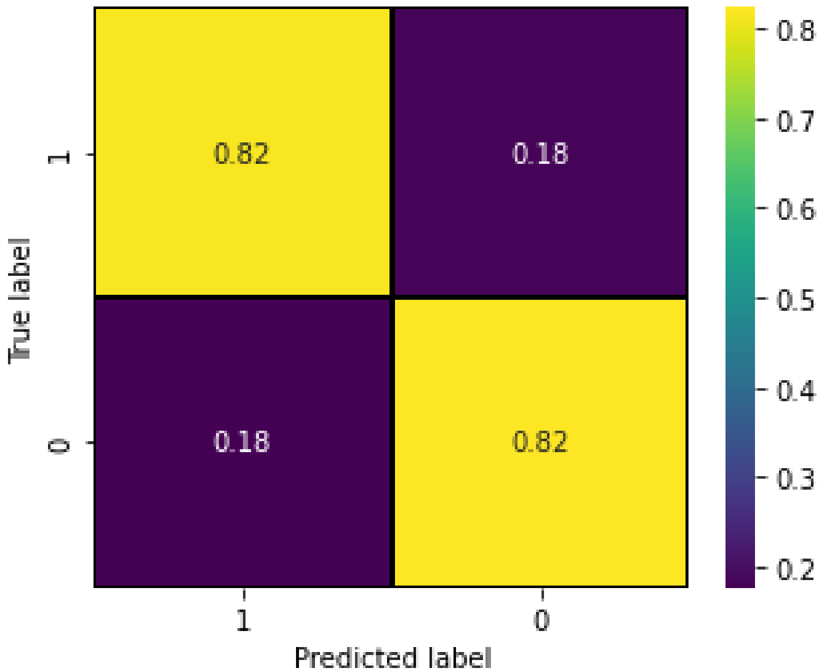
[50]:
```
<bound method BaseEstimator.get_params of LogisticRegression(max_iter=1000.0,
penalty='l1', solver='liblinear')>
```

Displaying the metrics for the best performing model and plotting the confusion matrix.

[51]:
```python
# Best logreg model metrics
best_logreg_model_metrics
```

[51]:
```
index                                                               6
train_test                                                   validate
preds                 [1, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, …
prob_preds            [[0.09158854373804315, 0.9084114562619569], [0…
log_loss_score                                                6.24957
accuracy                                                     0.819058
precision                                                    0.821295
recall                                                       0.815578
f1                                                           0.818426
fpr                   [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
tpr                   [0.0, 1.8518518518518519e-06, 2.2222222222222…
auc                                                            0.8987
roc_auc                                                      0.819058
Name: 0, dtype: object
```

[52]:
```python
# Confusion matrix
plot_confusion_matrix(y_valid, best_logreg_model_metrics.preds,
                      normalize='true')
```



Model can now be saved to file.

[53]:
```
# Save the grid search model if it does not exist
if not exists('logreg_gs.pickle'):
    with open('logreg_gs.pickle', 'wb') as f:
        pickle.dump(logreg_gs, f)
```

[54]:
```
# Delete 'logreg_gs' for memory managment
del logreg_gs
```

Surprisingly, the model did well.

4.4.3 Random Forest

Now, let us apply the same method using random forest. Fewer parameters are used in lieu of memory requirements is larger parameter space were to be used.

[55]:
```
# Check if the variable exists
if not exists('rf_gs.pickle'):
    # Define n_estimators range
    n_estimators = np.arange(30, 100, 30)

    # Define min_sample_split range
    min_samples_split = np.linspace(0.1, 1, 2, endpoint=True)

    # Define parameters ranges
```

```
    params = {'max_depth':['None']+[str(s) for s in np.arange(1, 51, 20)],
              'min_samples_split':['2']+[str(s) for s in min_samples_split],
              'n_estimators':[str(n) for n in n_estimators],
              'n_jobs':['n_cpu'],
              'random_state':['SEED']}

    # Create a Custom_GridSearchCV instance
    rf_gs = Custom_GridSearchCV('RandomForestClassifier', param_grid=params,␣
↪cv=3)
else:
    with open('rf_gs.pickle', 'rb') as f:
        rf_gs = pickle.load(f)
```

[56]:
```
# Run cross-validation with recall as the primary scoring
rprt, rp_df,_ = rf_gs.cross_validate(X_train_vec, y_train,
                                     vectorization=vec_labels)
```

In orders to choose the best dataset to fit with the model, let's aggregate the metrics. Sorting the average accuracy, recall and AUC metrics yields:

[57]:
```
# Find training and validation metrics
rf_gs_metrics_train,_,_ = prepare_metrics(rf_gs, train_val='train')
rf_gs_metrics_valid,_,_ = prepare_metrics(rf_gs, train_val='cross_validate')

# Combine metrics
rf_gs_metrics = pd.concat([rf_gs_metrics_train,rf_gs_metrics_valid])

# Rename dataset as 'dataset_train/validate'
rf_gs_metrics.dataset = rf_gs_metrics.dataset+'_'+rf_gs_metrics.train_val

# Create a placeholder dataframe to store the average values
rf_gs_metrics_mean = pd.DataFrame(columns=rf_gs_metrics.metric.unique(),
                                  index=rf_gs_metrics.dataset.unique())

# Iterate through each row and column, aggregate values and take the mean
for col in rf_gs_metrics_mean.columns:
    for idx in rf_gs_metrics_mean.index:
        avg = rf_gs_metrics.loc[(rf_gs_metrics.metric==col) & (rf_gs_metrics.
↪dataset==idx),'value']
        rf_gs_metrics_mean.loc[idx,col] = avg.mean()

# Sort average metrics by recall, AUC and accuracy
rf_gs_metrics_mean.sort_values(by=metrics,ascending=False)
```

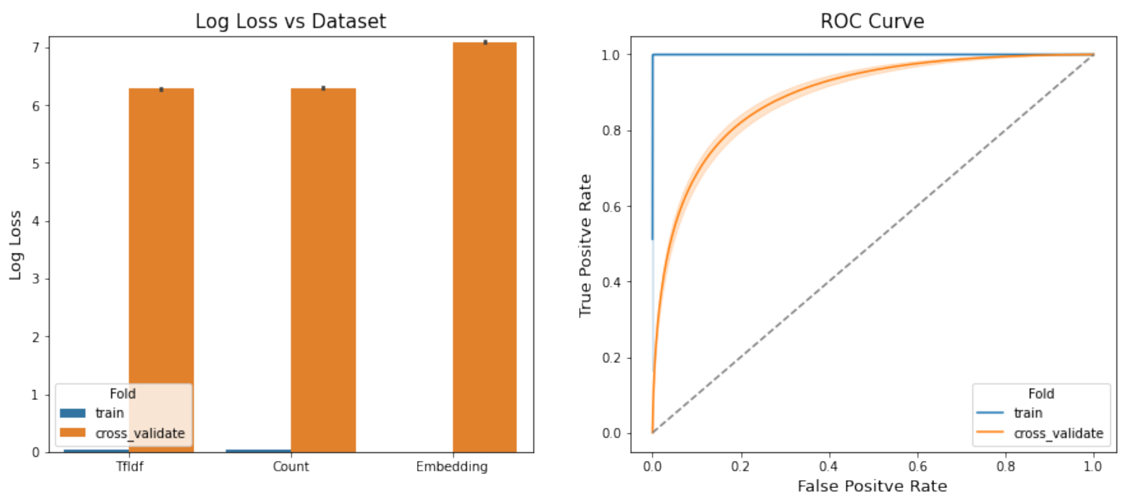
[57]:
```
                         precision  accuracy    recall        f1       auc  \
Embedding_train           0.999996  0.999997  0.999999  0.999997         1
Count_train               0.998743  0.998919  0.999095  0.998919  0.999957
```

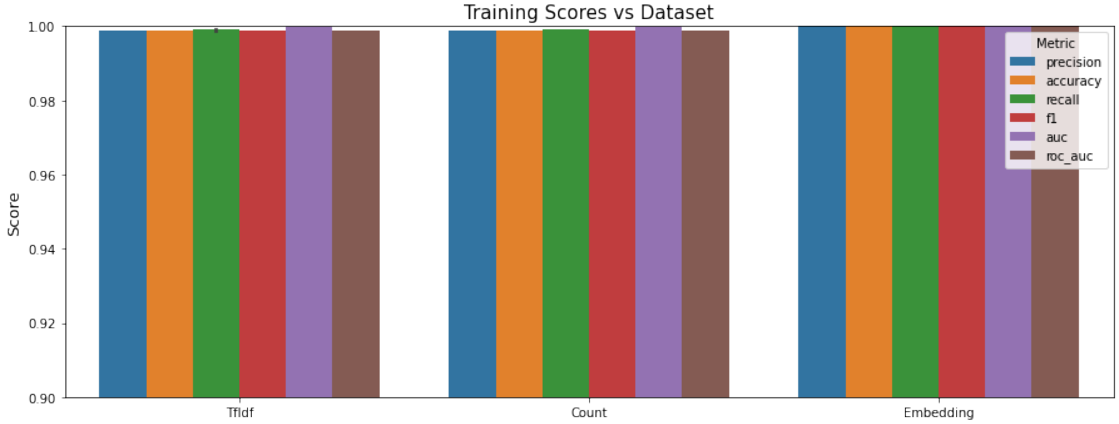
TfIdf_train	0.99873	0.998872	0.999014	0.998872	0.999951
TfIdf_cross_validate	0.821617	0.818173	0.81282	0.817195	0.900173
Count_cross_validate	0.82091	0.817752	0.812833	0.816851	0.898059
Embedding_cross_validate	0.802327	0.794856	0.782501	0.79229	0.875734

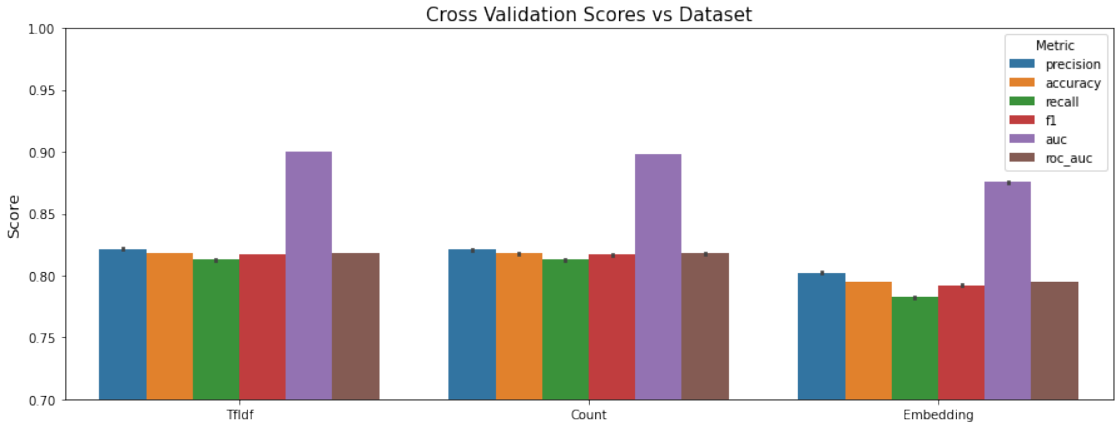
	roc_auc
Embedding_train	0.999997
Count_train	0.998919
TfIdf_train	0.998872
TfIdf_cross_validate	0.818173
Count_cross_validate	0.817752
Embedding_cross_validate	0.794856

The performance metrics of the model are shown below.

[58]:
```
# Plot the metrics for training and validation datasets
plot_metrics(rf_gs)
```







Clearly, there is an overfitting of data here. That will be further investigated after fitting validation dataset.

[59]:
```
# Fit grid search models with the best training dataset
# Specifying count to have better accuracy values
rf_gs.fit(X_train_vec[1], y_train)
```

Now, let's produce predictions based on the model grid.

[60]:
```
# Predict test and training datasets
# Also get the metrics of fit
# Check if the models have not been predicted yet
if not isinstance(rf_gs.predictions, pd.DataFrame):
    prep = Preprocess(transformer='count',max_df=0.979,min_df=0.0201)
    rf_gs.predict(prep.transform(X_valid), y_valid, train_test='validate')
    rf_gs.predict(X_train_vec[1], y_train, train_test='train')
rf_gs.predictions.head()
```

[60]:
```
  train_test                                             preds  \
0   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, …
1   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, …
```

```
2   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, …
3   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, …
4   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0, …

                                          prob_preds  log_loss_score  \
0  [[0.4, 0.6], [0.9333333333333333, 0.0666666666…        9.092399
1  [[0.4166666666666667, 0.5833333333333334], [0…       8.929812
2  [[0.45555555555555555, 0.5444444444444444], [0…        8.869370
3  [[0.41687433882421165, 0.5831256611757883], [0…        9.860414
4  [[0.39586407192093537, 0.6041359280790645], [0…        9.908514

   accuracy  precision    recall        f1  \
0  0.736751   0.745597  0.718741  0.731923
1  0.741458   0.746196  0.731837  0.738947
2  0.743208   0.746700  0.736131  0.741378
3  0.714515   0.725155  0.690885  0.707606
4  0.713122   0.722352  0.692367  0.707042

                                                 fpr  \
0  [0.0, 0.0035703703703703705, 0.003570370370370…
1  [0.0, 0.00135, 0.00135, 0.001351851851851852, …
2  [0.0, 0.000787037037037037, 0.0007888888888888…
3  [0.0, 0.0, 0.0, 0.0, 0.0, 1.8518518518518519e-…
4  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …

                                                 tpr       auc   roc_auc
0  [0.0, 0.041570370370370037, 0.0415722222222222…  0.814314  0.736751
1  [0.0, 0.018962962962962963, 0.0189648148148148…  0.819023  0.741458
2  [0.0, 0.0119, 0.011901851851851853, 0.01190555…  0.820621  0.743208
3  [0.0, 1.8518518518518519e-06, 7.40740740740740…  0.793539  0.714515
4  [0.0, 3.7037037037037037e-06, 1.11111111111111…  0.790615  0.713122
```

Some of the parameters used in random forest caused zero division error when thrown into `recall_score` function. That is why the standard deviation of the ROC curve is larger towards the center. Therefore, all recall values equal to 0 are removed.

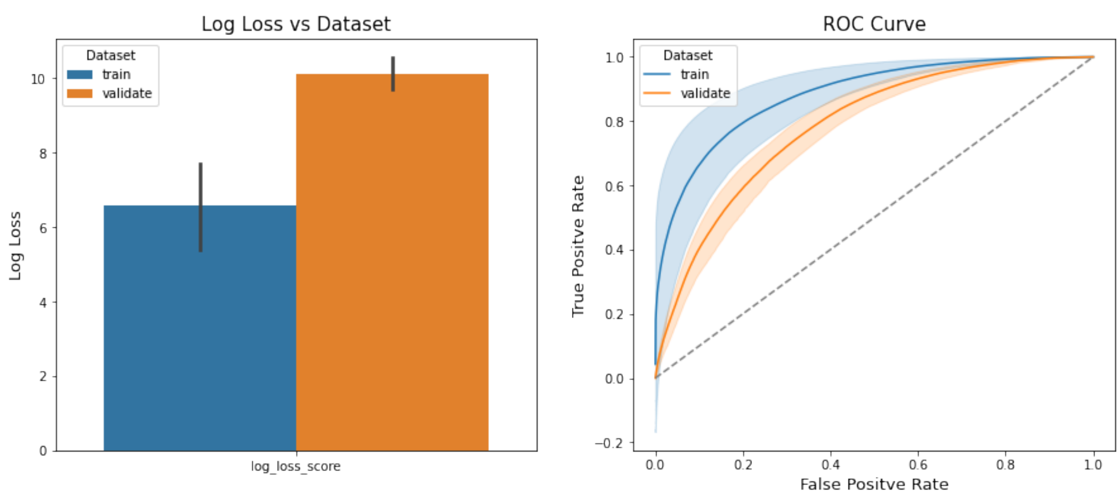
[61]:
```python
# Remove models with recall=0
rf_gs.predictions = rf_gs.predictions.loc[rf_gs.predictions.recall>0]
rf_gs.predictions.sort_values(by=['accuracy'], ascending=False).head()
```

[61]:
```
   train_test                                              preds  \
2       train  [1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, …
1       train  [1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, …
0       train  [1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, …
29      train  [1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, …
28      train  [1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, …

                                          prob_preds  log_loss_score  \
```

```
2   [[0.022222222222222223, 0.9777777777777777], […        0.039981
1   [[0.03333333333333333, 0.9666666666666667], [0…        0.042544
0   [[0.03333333333333333, 0.9666666666666667], [0…        0.067886
29  [[0.18577950943446003, 0.8142204905655398], [0…        4.326794
28  [[0.19003493807956573, 0.8099650619204344], [0…        4.339609

    accuracy  precision    recall        f1  \
2   0.998842   0.998688  0.998998  0.998843
1   0.998768   0.998650  0.998887  0.998768
0   0.998035   0.998124  0.997944  0.998034
29  0.874728   0.885868  0.860293  0.872893
28  0.874357   0.885540  0.859853  0.872508

                                                   fpr  \
2   [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
1   [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
0   [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
29  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
28  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …

                                                   tpr       auc   roc_auc
2   [0.0, 0.09147222222222222, 0.09147460317460318…  0.999952  0.998842
1   [0.0, 0.12794761904761906, 0.12794920634920634…  0.999948  0.998768
0   [0.0, 0.2186142857142857, 0.21861666666666665,…  0.999931  0.998035
29  [0.0, 7.936507936507937e-07, 0.00054523809523 8…  0.952465  0.874728
28  [0.0, 7.936507936507937e-07, 0.0008, 0.0008015…  0.952079  0.874357
```

Plotting metrics over the validation dataset.

[62]:
```python
# Plot metrics for predicted values
plot_predictions(rf_gs, valid_test='validate')
```



[63]:
```
# Find the best model and model metrics based on given metrics
best_rf_model, best_rf_model_metrics = rf_gs.best_model(metrics=metrics,
                                                        valid_test='validate')
# Add predictions
best_rf_model.predictions = rf_gs.predictions.
 ↪loc[best_rf_model_metrics['index'],:]

# Store best model
best_models.append(best_rf_model)

# Store the type of vectorization used
vectorization_type.append('count')

# Display best model parameters
best_rf_model.get_params
```

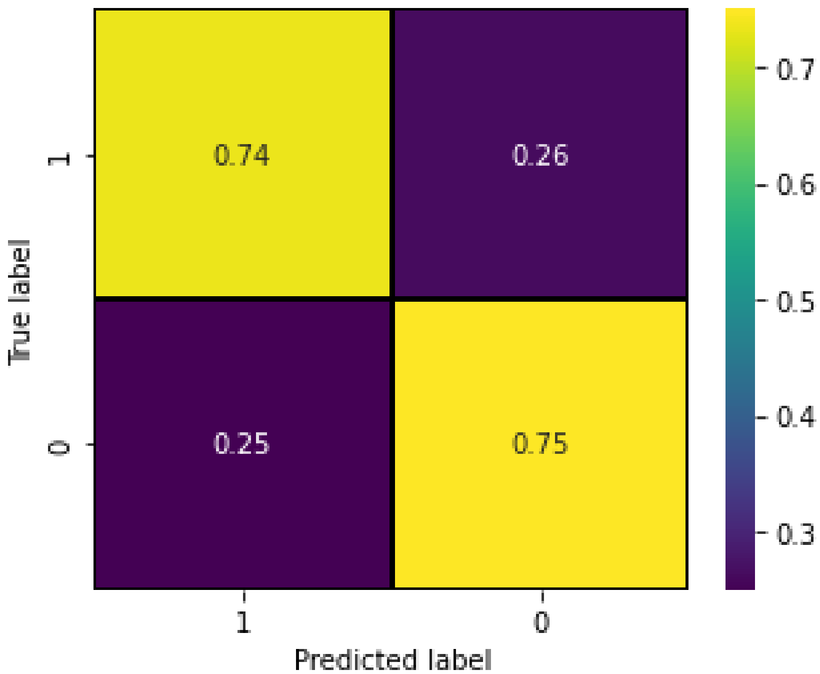
[63]:
```
<bound method BaseEstimator.get_params of
RandomForestClassifier(n_estimators=90, n_jobs=7, random_state=123)>
```

[64]:
```
# Best rf model metrics
best_rf_model_metrics
```

[64]:
```
index                                                                    2
train_test                                                        validate
preds                [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, …
prob_preds           [[0.45555555555555555, 0.5444444444444444], [0…
log_loss_score                                                     8.86937
accuracy                                                          0.743208
precision                                                           0.7467
recall                                                            0.736131
f1                                                                0.741378
```

```
fpr                [0.0, 0.0007870370370370, 0.0007888888888888…
tpr                [0.0, 0.0119, 0.011901851851851853, 0.01190555…
auc                                                         0.820621
roc_auc                                                     0.743208
Name: 0, dtype: object
```

[65]:
```python
# Confusion matrix
plot_confusion_matrix(y_valid, best_rf_model_metrics.preds,
                      normalize='true');
```



[66]:
```python
# Save model
if not exists('rf_gs.pickle'):
    with open('rf_gs.pickle', 'wb') as f:
        pickle.dump(rf_gs, f)
```

[67]:
```python
# Delete 'rf_gs' for memory managment
del rf_gs
```

4.5 Gradient Boosting

4.5.1 XGBoost

In addition to the parameters used for random forest, learning rate is added as a parameter for XGBoost. Also notice that GPU is enabled for XGBoost.

[68]:
```
# Check if the variable exists
if not exists('xgb_gs.pickle'):

    # Define learning rate range
    learning_rate = [0.001,0.01]

    # Define min_child_weight range
    min_child_weight = np.arange(1, 5, 2)

    # Define max_depth range
    max_depth = np.arange(5, 10, 2)

    # Define parameters ranges
    params = {'learning_rate': [str(l) for l in learning_rate],
              'max_depth': ['None']+[str(m) for m in max_depth],
              'min_child_weight': ['None']+[str(m) for m in min_child_weight],
              'random_state':['SEED'],
              'tree_method':["'gpu_hist'"]}

    # Create a Custom_GridSearchCV instance
    xgb_gs = Custom_GridSearchCV('XGBClassifier', param_grid=params, cv=3)
else:
    # Replace xgb_gs by model_cv[5]
    with open('xgb_gs.pickle', 'rb') as f:
        xgb_gs = pickle.load(f)
```

[69]:
```
# Run cross-validation with accuracy as the primary scoring
rprt, rp_df,_ = xgb_gs.cross_validate(X_train_vec, y_train,
                                      vectorization=vec_labels)
```

[70]:
```
# Find training and validation metrics
xgb_gs_metrics_train,_,_ = prepare_metrics(xgb_gs, train_val='train')
xgb_gs_metrics_valid,_,_ = prepare_metrics(xgb_gs, train_val='cross_validate')

# Combine metrics
xgb_gs_metrics = pd.concat([xgb_gs_metrics_train,xgb_gs_metrics_valid])

# Rename dataset as 'dataset_train/validate'
xgb_gs_metrics.dataset = xgb_gs_metrics.dataset+'_'+xgb_gs_metrics.train_val

# Create a placeholder dataframe to store the average values
xgb_gs_metrics_mean = pd.DataFrame(columns=xgb_gs_metrics.metric.unique(),
                                   index=xgb_gs_metrics.dataset.unique())

# Iterate through each row and column, aggregate values and take the mean
for col in xgb_gs_metrics_mean.columns:
    for idx in xgb_gs_metrics_mean.index:
```

```
        avg = xgb_gs_metrics.loc[(xgb_gs_metrics.metric==col) & (xgb_gs_metrics.
↪dataset==idx),'value']
        xgb_gs_metrics_mean.loc[idx,col] = avg.mean()

# Sort average metrics by accuracy, recall, and AUC
xgb_gs_metrics_mean.sort_values(by=metrics, ascending=False)
```

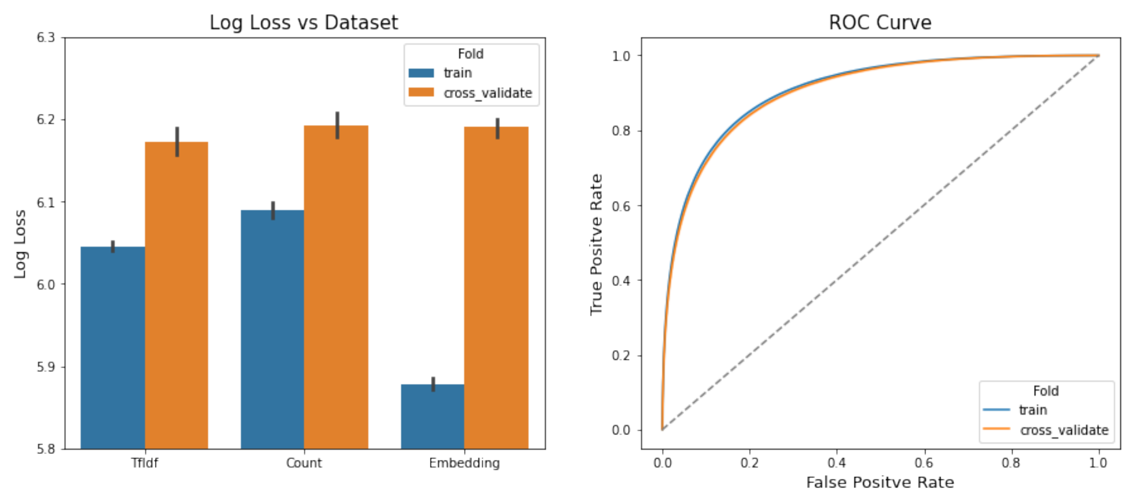
[70]:

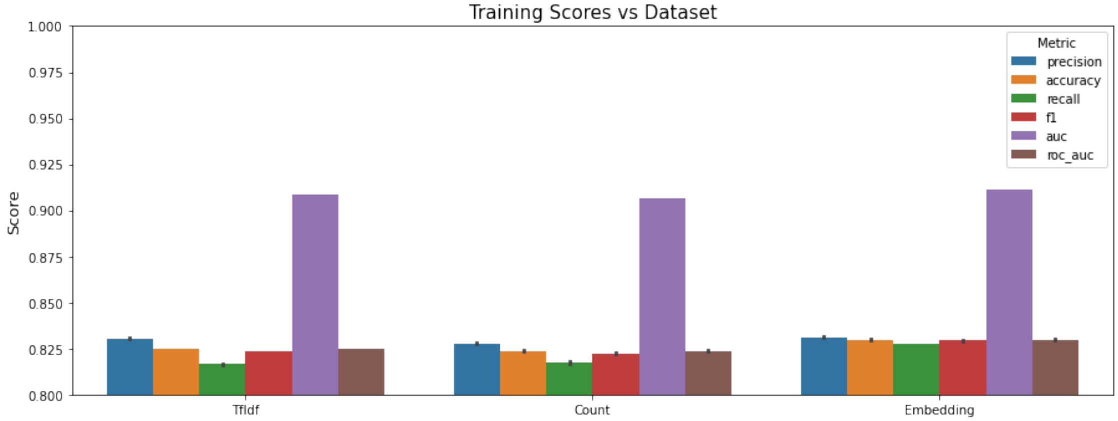
```
                          precision  accuracy    recall        f1       auc  \
Embedding_train            0.831275  0.829816  0.827613   0.82944  0.911312
TfIdf_train                0.830578  0.824984  0.816523   0.82349  0.908613
Count_train                0.827883  0.823702  0.817327  0.822571  0.906611
TfIdf_cross_validate       0.826826  0.821295  0.812835  0.819771  0.905168
Embedding_cross_validate   0.822104  0.820751  0.818652  0.820374  0.903046
Count_cross_validate       0.824881  0.820721  0.814321  0.819566  0.903706

                           roc_auc
Embedding_train           0.829816
TfIdf_train               0.824984
Count_train               0.823702
TfIdf_cross_validate      0.821295
Embedding_cross_validate  0.820751
Count_cross_validate      0.820721
```

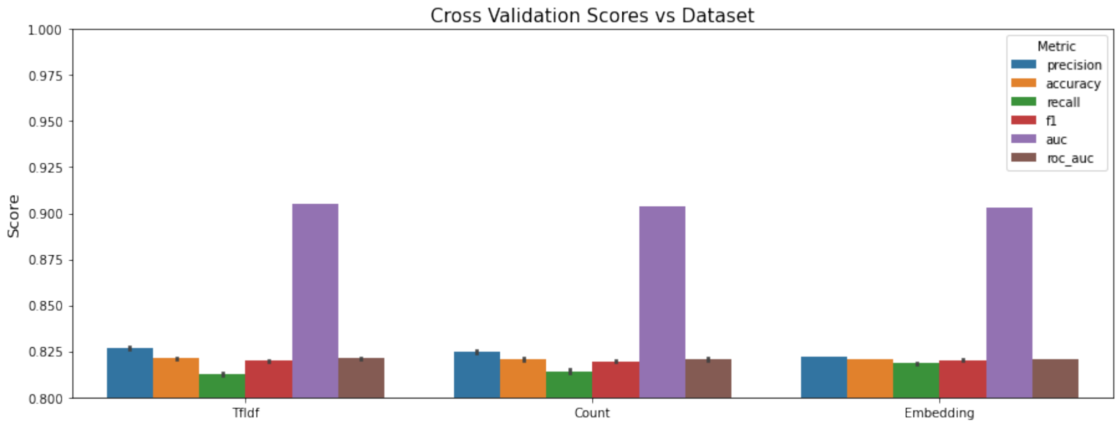
Clearly TfIdf vectorization is preferable over the others.

[71]:

```
# Plot the metrics for training and validation datasets
plot_metrics(xgb_gs)
```







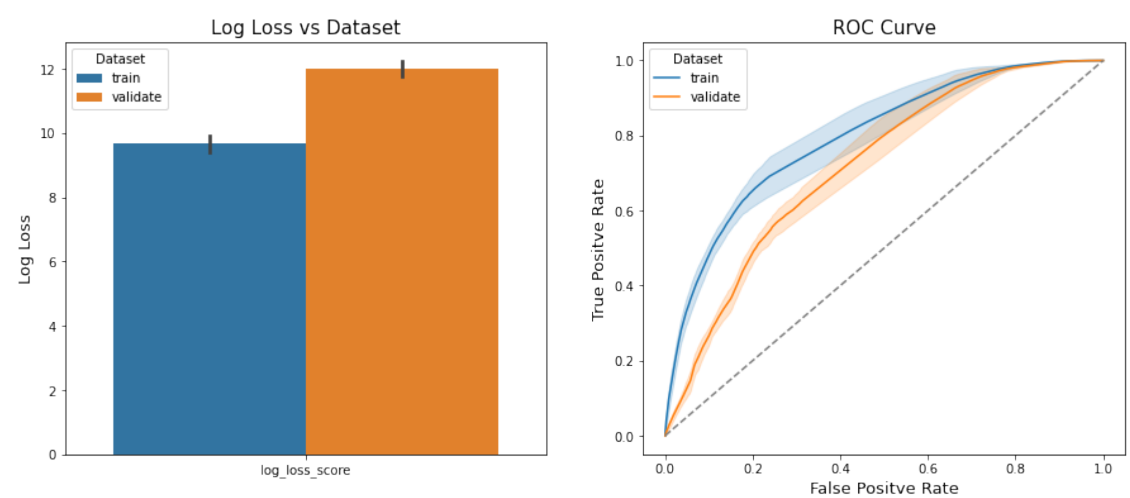
[72]:
```
# Fit grid search models with the best training dataset
# TfIdf has consistent predictions
xgb_gs.fit(X_train_vec[0], y_train)
```

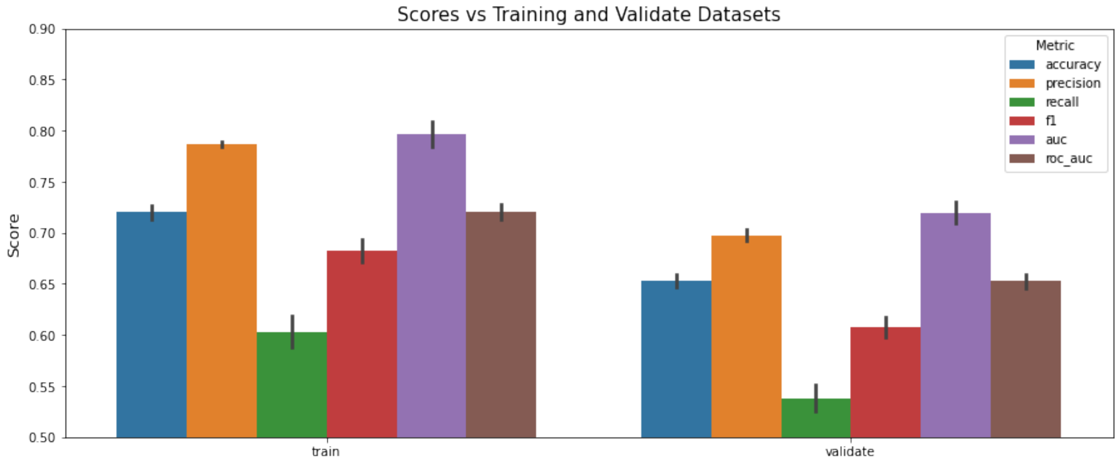
[73]:
```
# Predict test and training datasets
# Also get the metrics of fit
if not isinstance(xgb_gs.predictions, pd.DataFrame):
    prep = Preprocess(transformer='tfidf',max_df=0.979, min_df=0.0201)
    tmp = pd.DataFrame(prep.transform(X_valid), columns=xgb_gs.models[0].
 ↪get_booster().feature_names)
    xgb_gs.predict(tmp, y_valid, train_test='validate')
    xgb_gs.predict(X_train_vec[0], y_train, train_test='train')
xgb_gs.predictions.head()
```

[73]:
```
  train_test                                              preds  \
0   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, …
1   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, …
2   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, …
3   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, …
4   validate  [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 0, 0, 0, …
```

```
                                          prob_preds  log_loss_score  \
0  [[0.48048568, 0.5195143], [0.52673846, 0.47326…       12.576460
1  [[0.48048097, 0.51951903], [0.52706206, 0.4729…       12.576875
2  [[0.4804814, 0.5195186], [0.5270652, 0.4729347…       12.576843
3  [[0.4918313, 0.5081687], [0.52714515, 0.472854…       12.680655
4  [[0.4918313, 0.5081687], [0.52714515, 0.472854…       12.680655

   accuracy  precision    recall        f1  \
0  0.635877   0.686039  0.501061  0.579138
1  0.635865   0.686044  0.501007  0.579104
2  0.635866   0.686038  0.501022  0.579112
3  0.632860   0.679577  0.502785  0.577964
4  0.632860   0.679577  0.502785  0.577964

                                                 fpr  \
0  [0.0, 0.04490740740740741, 0.05688148148148148…
1  [0.0, 0.04490740740740741, 0.05687962962962963…
2  [0.0, 0.04490740740740741, 0.05688333333333333…
3  [0.0, 0.011975925925925926, 0.0587759259259259…
4  [0.0, 0.011975925925925926, 0.0587759259259259…

                                                 tpr       auc   roc_auc
0  [0.0, 0.10247592592592593, 0.11983518518518518…  0.686112  0.635877
1  [0.0, 0.10247592592592593, 0.11983518518518518…  0.686117  0.635865
2  [0.0, 0.10247407407407408, 0.11983333333333333…  0.686094  0.635866
3  [0.0, 0.01735925925925926, 0.12049814814814815…  0.679663  0.632860
4  [0.0, 0.01735925925925926, 0.12049814814814815…  0.679663  0.632860
```

[74]:
```python
# Plot metrics for predicted values
plot_predictions(xgb_gs, valid_test='validate')
```





[75]:
```
# Find the best model and model metrics based on given metrics
best_xgb_model, best_xgb_model_metrics = xgb_gs.best_model(metrics=metrics,
                                                                     ␣
 ↪valid_test='validate')

# Add predictions
best_xgb_model.predictions = xgb_gs.predictions.
 ↪loc[best_xgb_model_metrics['index'],:]

# # Store best model
best_models.append(best_xgb_model)

# Store the type of vectorization used
vectorization_type.append('tfidf')

# Display best model parameters
best_xgb_model.get_params
```

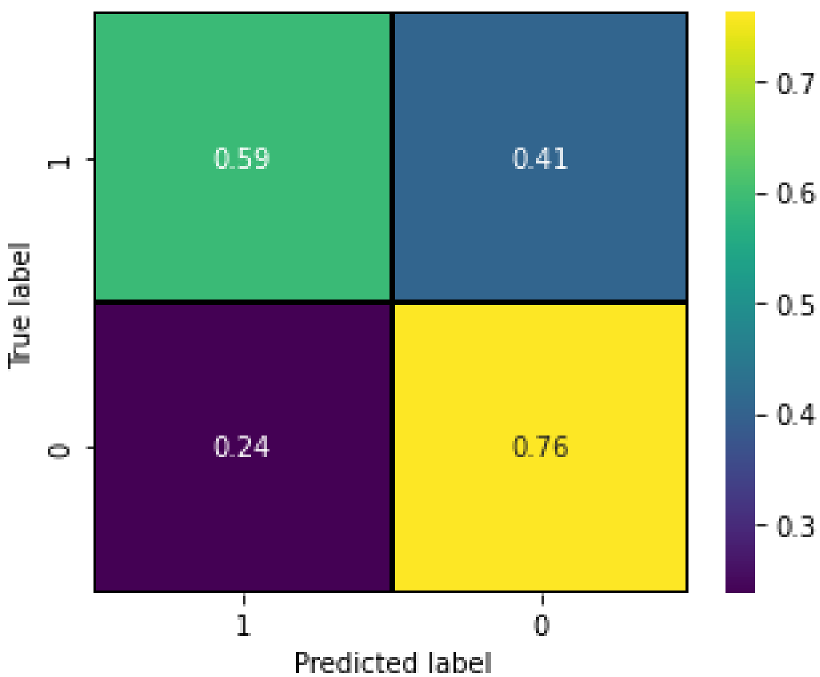
[75]:
```
<bound method XGBModel.get_params of XGBClassifier(base_score=0.5,
booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=0,
              importance_type='gain', interaction_constraints='',
              learning_rate=0.01, max_delta_step=0, max_depth=9,
              min_child_weight=1, missing=nan,
              monotone_constraints='(0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0
,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0…,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,
0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0)',
              n_estimators=100, n_jobs=0, num_parallel_tree=1, random_state=123,
```

```
                 reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1,
                 tree_method='gpu_hist', validate_parameters=1, verbosity=None)>
```

[76]:
```
# Best DT model metrics
best_xgb_model_metrics
```

[76]:
```
index                                                                21
train_test                                                     validate
preds                [1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, …
prob_preds           [[0.4159636, 0.5840364], [0.6635467, 0.3364533…
log_loss_score                                                  11.1318
accuracy                                                       0.677706
precision                                                      0.713767
recall                                                         0.593357
f1                                                             0.648016
fpr                  [0.0, 0.0, 0.0, 0.0, 0.0, 7.222222222222222e-0…
tpr                  [0.0, 5.555555555555556e-06, 1.481481481481481…
auc                                                            0.758295
roc_auc                                                        0.677706
Name: 0, dtype: object
```

[77]:
```
# Confusion matrix
plot_confusion_matrix(y_valid, best_xgb_model_metrics.preds,
                      normalize='true');
```



[78]:
```
# Save model to file
if not exists('xgb_gs.pickle'):
    with open('xgb_gs.pickle', 'wb') as f:
        pickle.dump(xgb_gs, f)
```

[79]:
```
# Delete 'xgb_gs' for memory managment
del xgb_gs
```

XGBoost did not perform as anticipated.

4.5.2 CatBoost

For CatBoost, border count, depth, iterations, l2 leaf regularization and learning rate were used as grid parameters. Similar to XGBoost, `GPU` are also enabled. Class weights were rejected by the model as those parameters needed to be defined along with `fit` function, which were not implemented in the `Custom_GridSearchCV` class.

[80]:
```
# Check if the variable exists
if not exists('cb_gs.pickle'):

    # Define parameters ranges
    params = {'border_count':[100,200],
              'depth':np.arange(1,11,5),
              'iterations':[500,1000],
              'l2_leaf_reg':[10,100],
              'learning_rate':[0.001,0.01],
              'logging_level':["'Silent'"],
              'random_state':['SEED'],
              'task_type':["'GPU'"],
              'thread_count':['n_cpu']}

    # Convert parameters to string
    for key in params.keys():
        params[key] = [str(p) for p in params[key]]

    # Create a Custom_GridSearchCV instance
    cb_gs = Custom_GridSearchCV('CatBoostClassifier', param_grid=params, cv=3)
else:
    # Replace xgb_gs by model_cv[5]
    with open('cb_gs.pickle', 'rb') as f:
        cb_gs = pickle.load(f)
```

[81]:
```
# Run cross-validation with accuracy as the primary scoring
rprt, rp_df,_ = cb_gs.cross_validate(X_train_vec, y_train,
                                     vectorization=vec_labels)
```

[82]:
```
# Find training and validation metrics
cb_gs_metrics_train,_,_ = prepare_metrics(cb_gs, train_val='train')
```

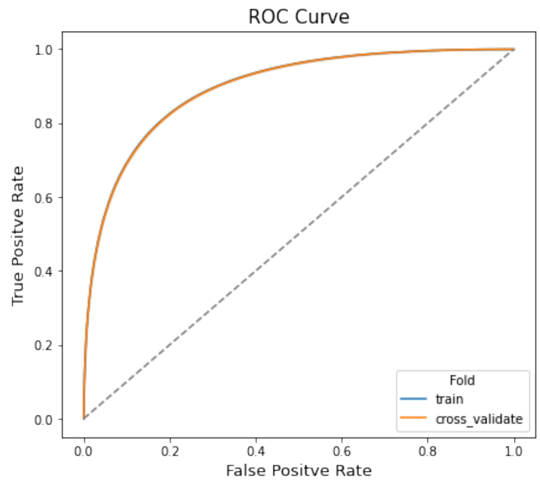
```
cb_gs_metrics_valid,_,_ = prepare_metrics(cb_gs, train_val='cross_validate')

# Combine metrics
cb_gs_metrics = pd.concat([cb_gs_metrics_train,cb_gs_metrics_valid])

# Rename dataset as 'dataset_train/validate'
cb_gs_metrics.dataset = cb_gs_metrics.dataset+'_'+cb_gs_metrics.train_val

# Create a placeholder dataframe to store the average values
cb_gs_metrics_mean = pd.DataFrame(columns=cb_gs_metrics.metric.unique(),
                                  index=cb_gs_metrics.dataset.unique())

# Iterate through each row and column, aggregate values and take the mean
for col in cb_gs_metrics_mean.columns:
    for idx in cb_gs_metrics_mean.index:
        avg = cb_gs_metrics.loc[(cb_gs_metrics.metric==col) & (cb_gs_metrics.
 ↪dataset==idx),'value']
        cb_gs_metrics_mean.loc[idx,col] = avg.mean()

# Sort average metrics by recall, AUC and accuracy
cb_gs_metrics_mean.sort_values(by=metrics,ascending=False)
```

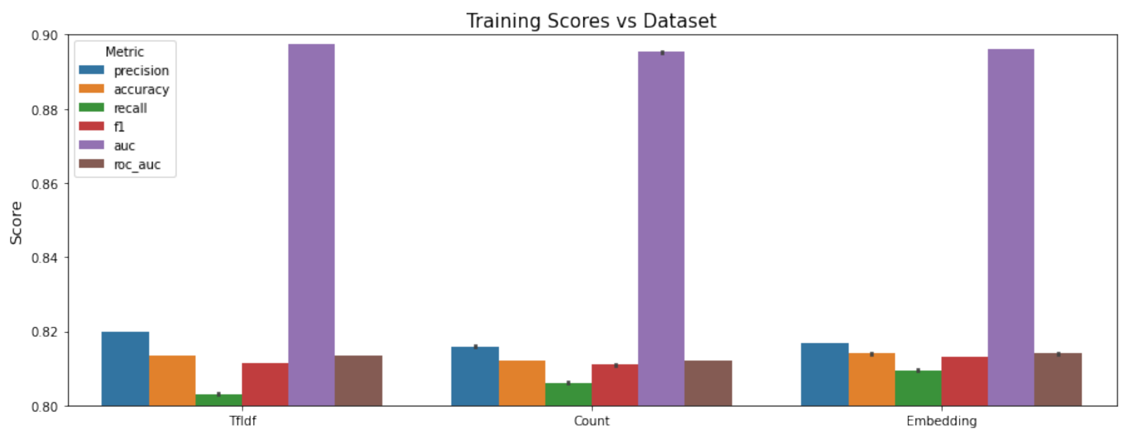
[82]:

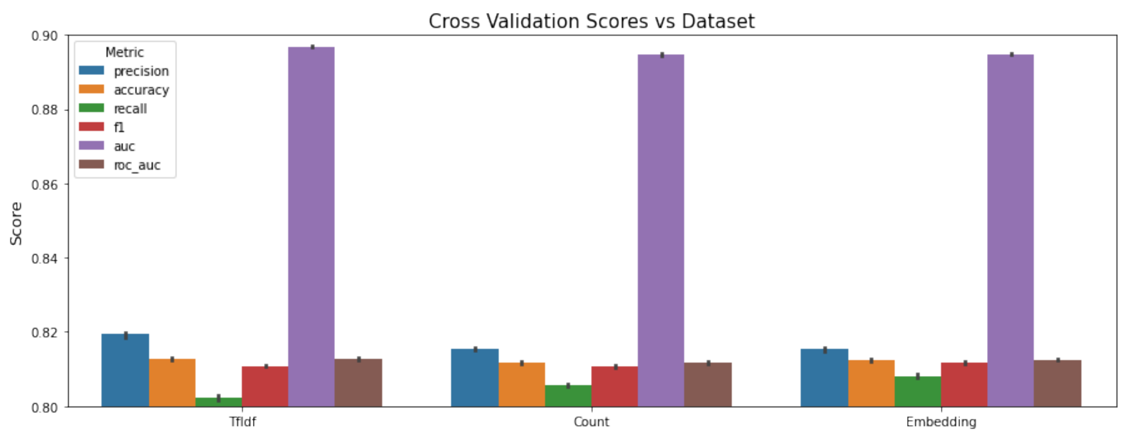
```
                         precision  accuracy    recall        f1       auc  \
Embedding_train           0.816862     0.814  0.809484  0.813156  0.896173
TfIdf_train               0.820011  0.813416  0.803112  0.811473  0.897557
TfIdf_cross_validate       0.81939  0.812773  0.802416  0.810813  0.896874
Embedding_cross_validate  0.815313   0.81255  0.808169  0.811725  0.894864
Count_train               0.815936   0.81212  0.806082  0.810979  0.895285
Count_cross_validate      0.815531  0.811728  0.805701  0.810586  0.894833

                           roc_auc
Embedding_train              0.814
TfIdf_train               0.813416
TfIdf_cross_validate      0.812773
Embedding_cross_validate   0.81255
Count_train                0.81212
Count_cross_validate      0.811728
```

[83]:

```
# Plot the metrics for training and validation datasets
plot_metrics(cb_gs)
```







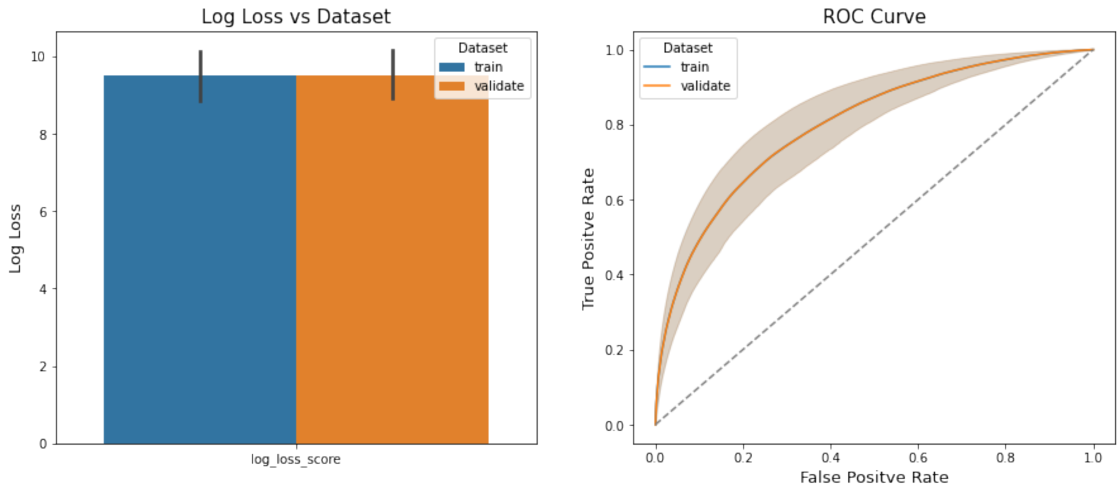
Embedding has the largest good tradeoff between accuracy and recall for the validation dataset.

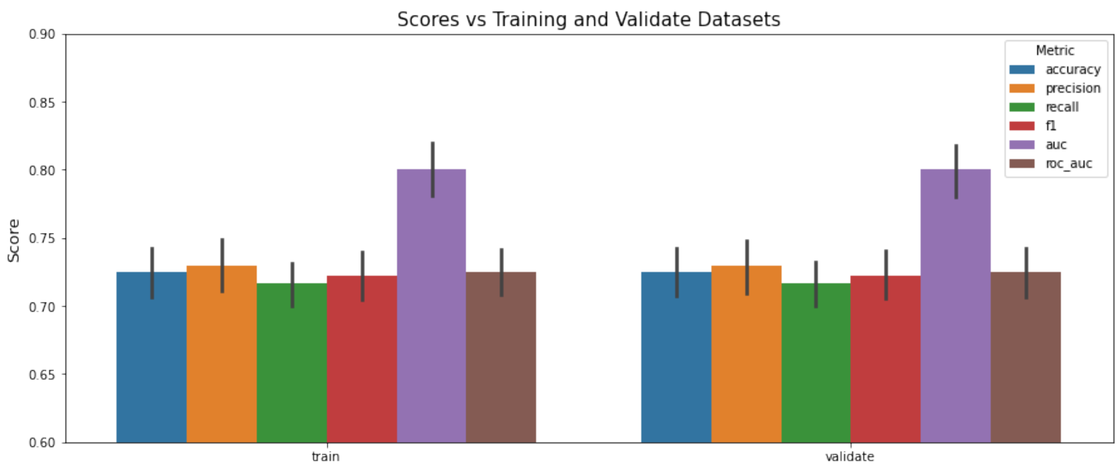
[84]:
```python
# Fit grid search models with the best training dataset
# SMOTE has better accuracy and recall values
# Therefore, 'class_weight' is disabled
cb_gs.fit(X_train_vec[-1], y_train)
```

[85]:
```python
# Predict test and training datasets
# Also get the metrics of fit
if not isinstance(cb_gs.predictions, pd.DataFrame):
    prep = Preprocess(transformer='embed')
    cb_gs.predict(prep.transform(X_valid), y_valid, train_test='validate')
    cb_gs.predict(X_train_vec[-1], y_train, train_test='train')
cb_gs.predictions.head()
```

[85]:
```
  train_test                                              preds  \
0   validate  [0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, …
1   validate  [0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, …
2   validate  [0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, …
3   validate  [0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, …
4   validate  [0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 0, …

                                          prob_preds  log_loss_score  \
0  [[0.5397395104078336, 0.46026048959216637], [0…       12.535583
1  [[0.5536506883079098, 0.44634931169209024], [0…        9.620915
2  [[0.539739470548865 4, 0.4602605294511346], [0…       12.535583
3  [[0.5536514013698142, 0.4463485986301858], [0…        9.620723
4  [[0.5588194018766796, 0.44118059812332044], [0…       11.576508

   accuracy  precision    recall        f1  \
0  0.637062   0.633671  0.649746  0.641608
1  0.721449   0.726587  0.710111  0.718255
2  0.637062   0.633671  0.649746  0.641608
3  0.721455   0.726590  0.710122  0.718262
4  0.664830   0.664822  0.664852  0.664837

                                                 fpr  \
0  [0.0, 0.010840740740740741, 0.0112962962962962…
1  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
2  [0.0, 0.010840740740740741, 0.0112962962962962…
3  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
4  [0.0, 0.0005925925925925926, 0.000618518518518…

                                                 tpr       auc   roc_auc
0  [0.0, 0.08546666666666666, 0.08802037037037037…  0.703734  0.637062
1  [0.0, 5.555555555555556e-05, 0.000120370370370…  0.796411  0.721449
2  [0.0, 0.08546666666666666, 0.08802037037037037…  0.703734  0.637062
3  [0.0, 5.555555555555556e-05, 0.000120370370370…  0.796411  0.721455
4  [0.0, 0.013351851851851853, 0.0138074074074074…  0.733144  0.664830
```

[86]:
```python
# Plot metrics for predicted values
plot_predictions(cb_gs, valid_test='validate')
```





CatBoost appears to have close prediction for training and validation test compared to the other models. This will be quantified later.

[87]:
```python
# Find the best model and model metrics based on given metrics
best_cb_model, best_cb_model_metrics = cb_gs.best_model(metrics=metrics,
                                                        valid_test='validate')
# Add predictions
best_cb_model.predictions = cb_gs.predictions.
↪loc[best_cb_model_metrics['index'],:]

# # Store best model
```

```python
best_models.append(best_cb_model)

# Store the type of vectorization used
vectorization_type.append('embed')

# Display best model parameters
best_cb_model.get_params
```

[87]:

```
<bound method CatBoost.get_params of <catboost.core.CatBoostClassifier object at
0x000001C52F3808B0>>
```

[88]:

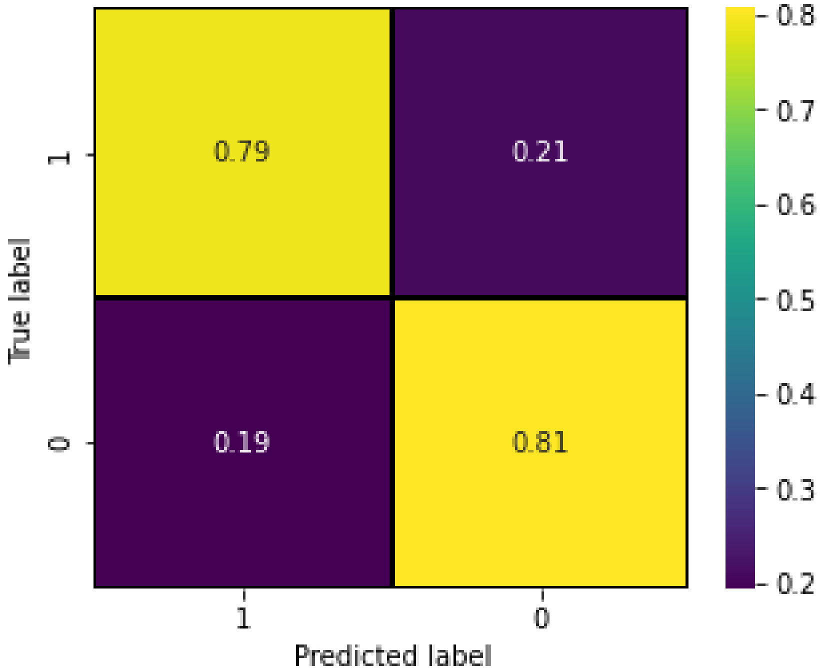
```python
# Best DT model metrics
best_cb_model_metrics
```

[88]:

```
index                                                                 29
train_test                                                      validate
preds               [1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 0, 0, …
prob_preds          [[0.27241187914142595, 0.727588120858574], [0…
log_loss_score                                                   6.96102
accuracy                                                         0.79846
precision                                                       0.803139
recall                                                          0.790743
f1                                                              0.796893
fpr                 [0.0, 0.0, 0.0, 1.8518518518518519e-06, 1.8518…
tpr                 [0.0, 1.8518518518518519e-06, 2.96296296296296…
auc                                                             0.881108
roc_auc                                                          0.79846
Name: 0, dtype: object
```

[89]:

```python
# Confusion matrix
plot_confusion_matrix(y_valid, best_cb_model_metrics.preds,
                      normalize='true');
```



The models can now be saved to file.

[90]:
```
if not exists('cb_gs.pickle'):
    with open('cb_gs.pickle', 'wb') as f:
        pickle.dump(cb_gs, f)
```

[91]:
```
# Delete 'cb_gs' for memory managment
del cb_gs, X_train_vec
```

4.6 Sequence Models

Sequence models are general representations of deep neural networks that specialize in natural language processing. Some of these methods include: recurrent neural networks (RNN), gated recurrent units (GRU) and long short term memory (LSTM). For most cases, LSTM delivers good accuracy compared to the other methods, which is why it has been selected as a primary mode for building deep neural networks. Adam optimizer was chosen by default, which has strong performance compared to stochastic gradient descent.

4.6.1 Long Short Term Memory

To use the same kind of reporting for the previous models, the predicted probabilities should be used to compute various metrics. The following function simply does that.

[92]:
```
def dnn_res_to_pd(y, prob_preds, train_test):
    # Empty dataframe to store results
    tmp = {}
```

```
    # Populate 'tmp' with values
    # Calculate predictions
    preds = 1*(prob_preds>0.5)
    # Compute fpr and tpr
    fpr, tpr, threshold = roc_curve(y, prob_preds)
    # Store metrics
    tmp['train_test'] = train_test
    tmp['preds'] = [preds.T]
    tmp['prob_preds'] = [prob_preds.T]
    tmp['log_loss_score'] = log_loss(y, preds)
    tmp['accuracy'] = accuracy_score(y, preds)
    tmp['precision'] = precision_score(y, preds)
    tmp['recall'] = recall_score(y, preds)
    tmp['f1'] = f1_score(y, preds)
    tmp['fpr'] = [fpr]
    tmp['tpr'] = [tpr]
    tmp['auc'] = auc(fpr, tpr)
    tmp['roc_auc'] = roc_auc_score(y, preds)
    # Return dataframe
    return pd.DataFrame(tmp)
```

There are two variations of LSMT used in this project. The first one is without GloVe embedding, and the second, with GloVe embedding. The following function facilitates a predefined word embedding matrix if provided. Also notice that, CuDNNLSTM is used instead of simple LSTM layer to expedite model fitting.

[93]:
```
def build_lstm_model(embedding=None, MAX_LENGTH=None, MAX_FEATURES=None):
    '''
    Function to build an LSTM model
    embedding: Embedding matrix. default=None
    MAX_LENGTH: Maximum length of the input layer
    MAX_FEATURES: Maximum features in the embedding layer
    '''
    # If embedding not specified, specify input and embedding layers,
    # based on MAX_LENGTH and MAX_FEATURES
    if embedding is None:
        sequences = layers.Input(shape=(MAX_LENGTH,))
        embedded = layers.Embedding(MAX_FEATURES, 64)(sequences)
    # Else use defined, untrainable embedding matrix
    else:
        sequences = layers.Input(shape=(embedding.shape[1],))
        embedded = layers.Embedding(embedding.shape[0],embedding.shape[1],
                                    weights=[embedding_matrix],
                                    trainable=False)(sequences)
    # LSTM layers
    # CuDNNLSTM runs much faster than LSTM model
    x = layers.CuDNNLSTM(128, return_sequences=True)(embedded)
```

```
    # Specify dropout
    x = layers.Dropout(0.2)(x)
    x = layers.CuDNNLSTM(128)(x)
    x = layers.Dropout(0.2)(x)
    x = layers.Dense(100, activation='relu')(x)
    x = layers.Dense(32, activation='relu')(x)
    # Apply sigmoid for output layer
    predictions = layers.Dense(1, activation='sigmoid')(x)
    # Create model instance
    model = models.Model(inputs=sequences, outputs=predictions)
    # Use Adam optimizer, binary cross entropy and accuracy metric
    model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model
```

For the deep neural network models, the data needed to be tokenized differently. Because Keras also allows for token padding.

[94]:
```
if not exists('lstm_model_no_weight.pickle'):
    # If pickled file not found, set fitted to False
    fitted = False
    # Maximum features for LSTM model input
    max_features = 20000
    # Initiallize tokenizer with max_features
    tokenizer = Tokenizer(num_words=max_features)
    # Fit tokenizer to training data
    tokenizer.fit_on_texts(X_train)
    # Convert text to sequences for both training and validation dataset
    train_texts = tokenizer.texts_to_sequences(X_train)
    val_texts = tokenizer.texts_to_sequences(X_valid)
    # Apply padding based on the maximum training token
    max_length = max(len(train_ex) for train_ex in train_texts)
    train_texts = pad_sequences(train_texts, maxlen=max_length)
    val_texts = pad_sequences(val_texts, maxlen=max_length)
    # Build LSTM model
    lstm_model_no_weight = build_lstm_model(MAX_FEATURES=max_features,
                                            MAX_LENGTH=max_length)
    # Save input parameters to file
    f = open('lstm_model_no_weight.pickle', 'wb')
    pickle.dump(tokenizer, f)
    pickle.dump(train_texts, f)
    pickle.dump(val_texts, f)
else:
    with open('lstm_model_no_weight.pickle', 'rb') as f:
        # Skip 'tokenizer'
        _ = pickle.load(f)
```

```
        # Skip 'train_texts'
        _ = pickle.load(f)
        # Skip 'val_texts'
        _ = pickle.load(f)
        # Load model predictions on training data
        train_preds = pickle.load(f)
        # Load model predictions on validation data
        val_preds = pickle.load(f)
    # Load pretrained model
    lstm_model_no_weight = keras.models.load_model('models/lstm_model_no_weight.
↪h5')
    fitted = True
```

The model layers are displayed below.

[95]:
```
# Display model summary
lstm_model_no_weight.summary()
```

```
Model: "functional_15"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_9 (InputLayer)        [(None, 167)]             0

 embedding_7 (Embedding)     (None, 167, 64)           1280000

 cu_dnnlstm_12 (CuDNNLSTM)   (None, 167, 128)          99328

 dropout_10 (Dropout)        (None, 167, 128)          0

 cu_dnnlstm_13 (CuDNNLSTM)   (None, 128)               132096

 dropout_11 (Dropout)        (None, 128)               0

 dense_21 (Dense)            (None, 100)               12900

 dense_22 (Dense)            (None, 32)                3232

 dense_23 (Dense)            (None, 1)                 33

=================================================================
Total params: 1,527,589
Trainable params: 1,527,589
Non-trainable params: 0
_________________________________________________________________
```

If the model is not fitted, the following code performs that and saves the model to file.

[96]:
```
# Fit the data if not fitted
if not fitted:
    # Run model for a single epoch
    lstm_model_no_weight.fit(
            train_texts,
            y_train,
            batch_size=128,
            epochs=1,
            validation_data=(val_texts, y_valid));
    # Save fitted model to file
    lstm_model_no_weight.save('models/lstm_model_no_weight.h5',␣
 ↪save_format='tf')
```

Predictions are also saved to file.

[97]:
```
# Predict training and validation, and save to file
if not fitted:
    train_preds = lstm_model_no_weight.predict(train_texts)
    val_preds = lstm_model_no_weight.predict(val_texts)
    # Save predictions to file
    pickle.dump(train_preds, f)
    pickle.dump(val_preds, f)
    f.close()
```

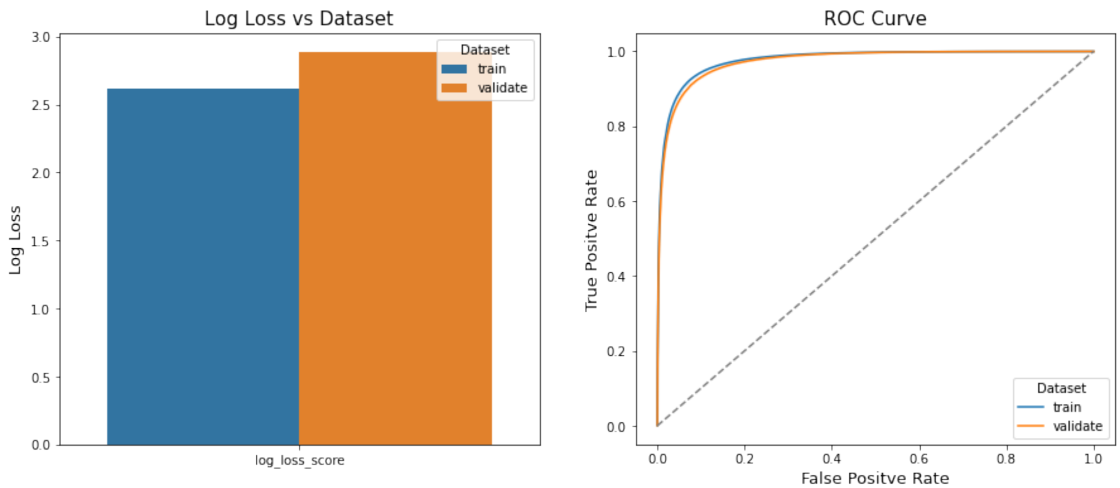
On a single epoch, our LSTM model has much higher performance than the other models.

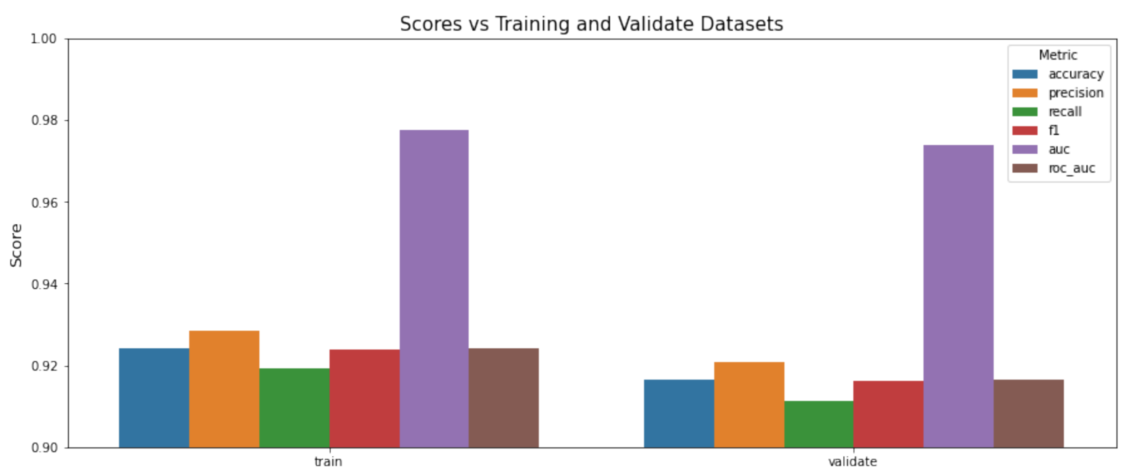
[98]:
```
# Convert predictions to dataframe
predictions = pd.concat([dnn_res_to_pd(y_valid, val_preds,'validate'),
                         dnn_res_to_pd(y_train, train_preds,'train')])
# Add predictions to the model
lstm_model_no_weight.predictions = predictions
lstm_model_no_weight.predictions
```

[98]:
```
  train_test                                             preds  \
0   validate  [[1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0,…
0      train  [[1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1,…

                                          prob_preds  log_loss_score  \
0  [[0.9910585, 0.028316455, 0.0017643009, 0.8170…        2.884851
0  [[0.8621141, 0.004045642, 0.17851877, 0.127429…        2.616820

   accuracy  precision    recall        f1  \
0  0.916476   0.920733  0.911417  0.916051
0  0.924236   0.928546  0.919207  0.923853

                                                 fpr  \
0  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
0  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
```

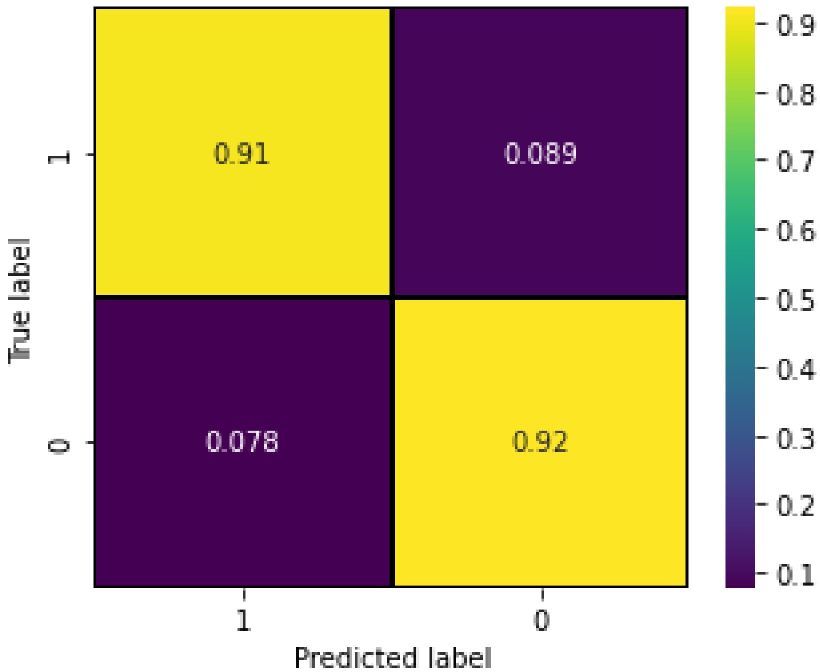
```
                                                tpr       auc   roc_auc
0  [0.0, 1.8518518518518519e-06, 5.92592592592592…  0.973753  0.916476
0  [0.0, 7.936507936507937e-07, 4.444444444444444…  0.977506  0.924236
```

[99]:
```python
# Plot model performance on training and validation datasets
plot_predictions(lstm_model_no_weight, valid_test='validate')
```





[100]:
```python
# Show the onfusion matrix
plot_confusion_matrix(y_valid, 1*(val_preds>0.5), normalize='true')
```



[101]:
```
# # Store best model
best_models.append(lstm_model_no_weight)

# Store the type of vectorization used
vectorization_type.append('tokenized-no-weight')
```

[102]:
```
# Delete unused variables
del train_preds, val_preds
```

Now, let us use GloVe word embedding and retrain the model. First, the embedding matrix must be computed based on how many words have been tokenized.

[103]:
```
if not exists('lstm_model_glove.pickle'):
    fitted = False
    # With embedding matrix, the length is defined by the number of columns
    max_length = len(embeddings_index[next(iter(embeddings_index))])
    # Use another tokenizer with no maximum features
    tokenizer = Tokenizer()
    # Fit to the training data
    tokenizer.fit_on_texts(X_train)
    # Tokenize and change words to sequences for training and validation␣
↪datasets
    train_texts = tokenizer.texts_to_sequences(X_train)
    val_texts = tokenizer.texts_to_sequences(X_valid)
    # Apply padding
```

```
    train_texts = pad_sequences(train_texts, maxlen=max_length)
    val_texts = pad_sequences(val_texts, maxlen=max_length)
    # Choose words existing only in the tokenized training dataset
    word_index = tokenizer.word_index
    # Instatiate an embedding matrix
    embedding_matrix = np.zeros((len(word_index)+1, max_length))
    for word, i in word_index.items():
        embedding_vector = embeddings_index.get(word)
        # If word exists in the dictionary, replace values
        if embedding_vector is not None:
            embedding_matrix[i] = embedding_vector
    # Build glove LSTM model
    lstm_model_glove = build_lstm_model(embedding=embedding_matrix)
    # Save values to file
    f = open('lstm_model_glove.pickle','wb')
    pickle.dump(tokenizer, f)
    pickle.dump(train_texts, f)
    pickle.dump(val_texts, f)
else:
    with open('lstm_model_glove.pickle','rb') as f:
        # Skip 'tokenizer'
        _ = pickle.load(f)
        # Skip 'train_texts'
        _ = pickle.load(f)
        # Skip 'val_texts'
        _ = pickle.load(f)
        # Load model predictions on training data
        train_preds = pickle.load(f)
        # Load model predictions on validation data
        val_preds = pickle.load(f)
    # Load pretrained model
    lstm_model_glove = keras.models.load_model('models/lstm_model_glove.h5')
    fitted = True
```

[104]:
```
# Display model summary
lstm_model_glove.summary()
```

```
Model: "functional_17"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_10 (InputLayer)       [(None, 300)]             0

 embedding_8 (Embedding)     (None, 300, 300)          90908400

 cu_dnnlstm_14 (CuDNNLSTM)   (None, 300, 128)          220160

 dropout_12 (Dropout)        (None, 300, 128)          0
```

```
 cu_dnnlstm_15 (CuDNNLSTM)   (None, 128)               132096

 dropout_13 (Dropout)        (None, 128)               0

 dense_24 (Dense)            (None, 100)               12900

 dense_25 (Dense)            (None, 32)                3232

 dense_26 (Dense)            (None, 1)                 33

=================================================================
Total params: 91,276,821
Trainable params: 368,421
Non-trainable params: 90,908,400
_________________________________________________________________
```

Clearly, using word embedding is going to exponentially increase our computation. But for the most part, the embedding layer is set to non-trainable.

[105]:
```python
# Fit the data if not fitted
if not fitted:
    # Run model for a single epoch
    lstm_model_glove.fit(train_texts,
                         y_train,
                         batch_size=128,
                         epochs=1,
                         validation_data=(val_texts, y_valid));
    lstm_model_glove.save('models/lstm_model_glove.h5', save_format='tf')
```

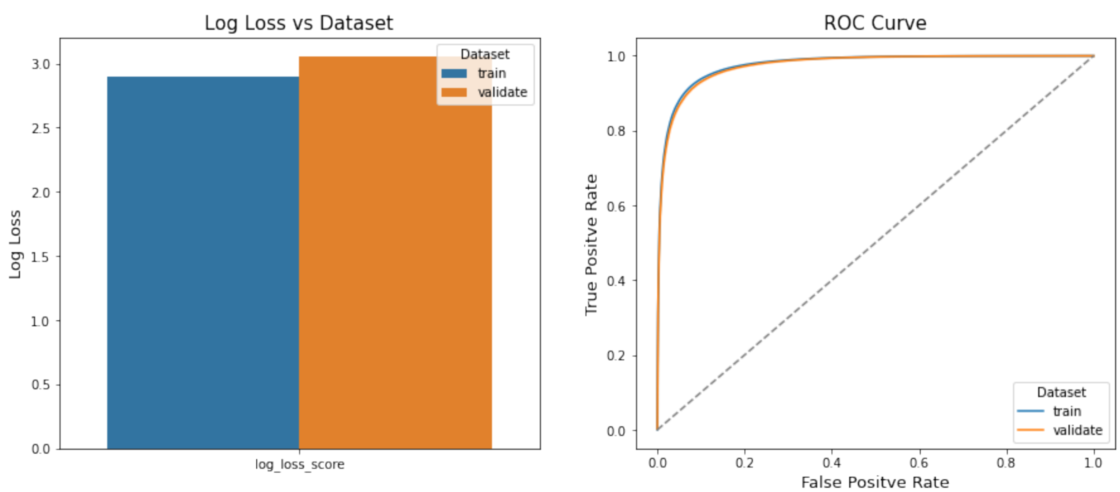
[106]:
```python
# Predict training and validation, and save to file
if not fitted:
    train_preds = lstm_model_glove.predict(train_texts)
    val_preds = lstm_model_glove.predict(val_texts)
    # Save predicitions to file
    pickle.dump(train_preds, f)
    pickle.dump(val_preds, f)
    f.close()
```

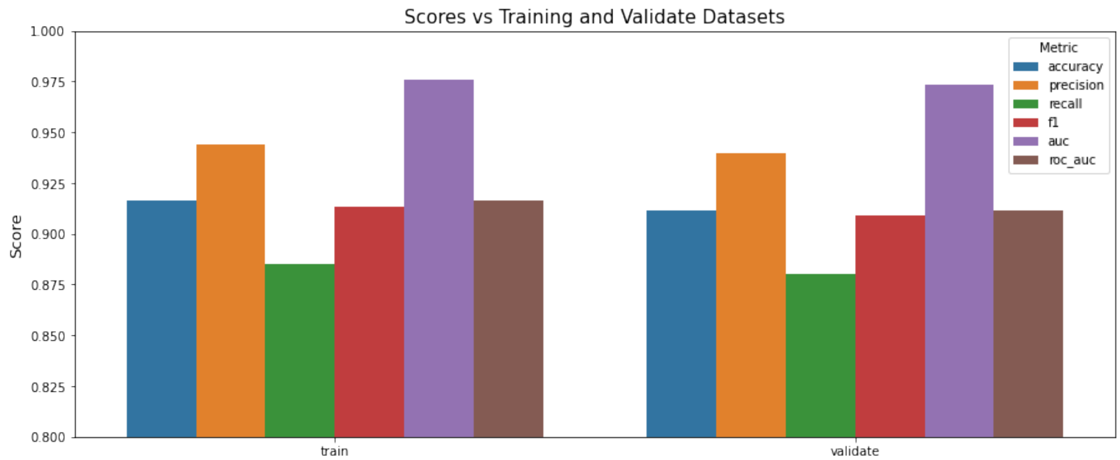
[107]:
```python
# Convert predictions to dataframe
predictions = pd.concat([dnn_res_to_pd(y_valid, val_preds,'validate'),
                         dnn_res_to_pd(y_train, train_preds,'train')])
# Add predictions to the model
lstm_model_glove.predictions = predictions
lstm_model_glove.predictions
```

[107]:
```
  train_test                                              preds  \
0   validate  [[1, 0, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0,…
```

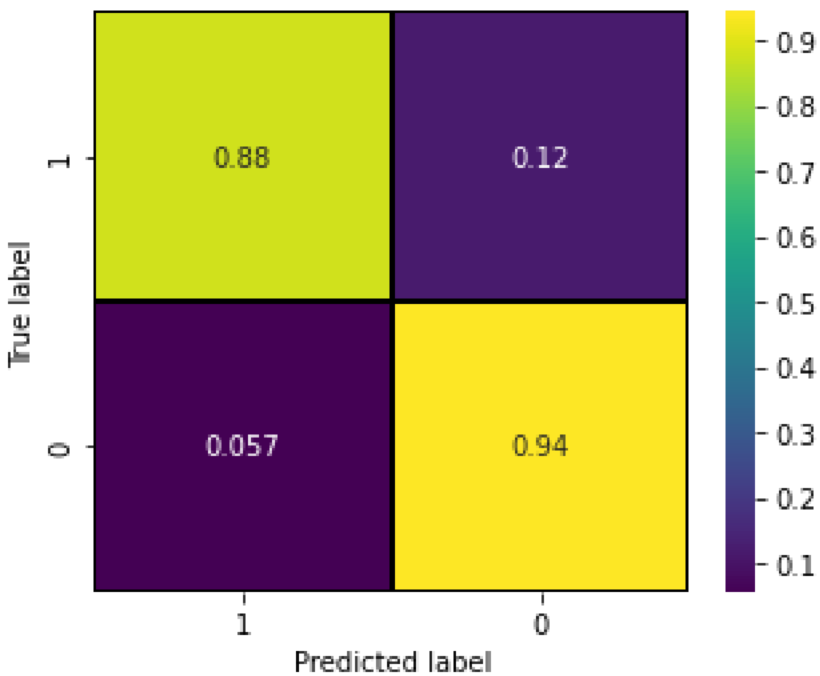
```
0      train  [[1, 0, 0, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1,…

                                          prob_preds  log_loss_score  \
0  [[0.99480337, 0.014124167, 0.0027095953, 0.409…        3.052675
0  [[0.96191967, 0.010168016, 0.11027366, 0.14406…        2.895960

   accuracy  precision    recall        f1  \
0  0.911617   0.939485  0.879911  0.908723
0  0.916154   0.943840  0.884964  0.913455

                                                 fpr  \
0  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
0  [0.0, 0.0, 0.0, 0.0, 0.0, 7.936507936507937e-0…

                                                 tpr       auc   roc_auc
0  [0.0, 1.8518518518518519e-06, 3.51851851851851…  0.973686  0.911617
0  [0.0, 7.936507936507937e-07, 1.587301587301587…  0.976052  0.916154
```

[108]:
```python
# Plot model performance
plot_predictions(lstm_model_glove, valid_test='validate')
```





[109]:
```
# Plot the confusion matrix
plot_confusion_matrix(y_valid, 1*(val_preds>0.5), normalize='true')
```



This variation of LSTM performed less than the previous model. One possible explanation is that since the embedding layer is untrainable, that limited the number of parameters.

[110]:
```
# # Store best model
best_models.append(lstm_model_glove)
```

```
# Store the type of vectorization used
vectorization_type.append('tokenized-glove')
```

[111]:
```
# Delete unused variables
del train_preds, val_preds
```

4.7 Transformer Models

4.7.1 Bidirectional Encoder Representations from Transformers

Here is another implementation of BERT using DistelBERT. Technically, this is not a transformer model. But uses DistilBERT embedding. For this case, 1D CNN layers with max pooling were used instead of LSTM as it is a common practice to include elements of CNN with transformer models. Implementing transformer models takes a lot of computational resources which is why the were skipped from this project.

[112]:
```
def build_bert_text_model(MAX_LENGTH=None, MAX_FEATURES=None):
    # Define input layer
    sequences = layers.Input(shape=(MAX_LENGTH,))
    # Embedding layer
    embedded = layers.Embedding(MAX_FEATURES, 128)(sequences)
    # First 1D CNN layer
    x = layers.Conv1D(filters=100,
                      kernel_size=2,
                      padding="valid",
                      activation="relu")(embedded)
    # Second 1D CNN layer
    x = layers.Conv1D(filters=100,
                      kernel_size=3,
                      padding="valid",
                      activation="relu")(x)
    # Third 1D CNN layer
    x = layers.Conv1D(filters=50,
                      kernel_size=4,
                      padding="valid",
                      activation="relu")(x)
    # Global max pooling
    x = layers.GlobalMaxPool1D()(x)
    # Dense layer with dropout
    x = layers.Dense(512, activation='relu')(x)
    x = layers.Dropout(rate=0.2)(x)
    # Output layer
    predictions = layers.Dense(1, activation='sigmoid')(x)
    model = models.Model(inputs=sequences, outputs=predictions)
    model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model
```

Here is a helper function that performs DistilBERT tokenization and id conversion.

[113]:
```
def tokenize_reviews(text_reviews):
    '''
    Function that tokenizes based on DistilBERT
    text_reviews: Input string
    '''
    return tokenizer.convert_tokens_to_ids(tokenizer.tokenize(text_reviews))
```

[114]:
```
MODEL_NAME = 'distilbert-base-uncased-finetuned-sst-2-english'
tokenizer = DistilBertTokenizer.from_pretrained(MODEL_NAME)
if not exists('bert_tokenized.pickle'):
    fitted = False
    # Use DistilBert tokenizer
    train_tokenized = [tokenize_reviews(review) for review in tqdm(X_train.
 ↪to_list())]
    val_tokenized = [tokenize_reviews(review) for review in tqdm(X_valid.
 ↪to_list())]
    # Define max length based on training data
    max_length = max(len(tokens) for tokens in train_tokenized)
    # Apply padding
    train_texts = pad_sequences(train_tokenized, maxlen=max_length)
    val_texts = pad_sequences(val_tokenized, maxlen=max_length)
    # Build BERT model
    bert_model = build_bert_text_model(MAX_LENGTH=max_length,
                                       MAX_FEATURES=len(tokenizer.vocab))
    # Save tokens to file
    f = open('bert_tokenized.pickle','wb')
    pickle.dump(train_texts, f)
    pickle.dump(val_texts, f)
else:
    with open('bert_tokenized.pickle','rb') as f:
        # Skip 'train_texts'
        _ = pickle.load(f)
        # Skip 'val_texts'
        _ = pickle.load(f)
        # Load model predictions for training
        train_preds = pickle.load(f)
        # Load model predictions for validation
        val_preds = pickle.load(f)
    # Load pretrained model
    bert_model = keras.models.load_model('models/bert_tokenized_model.h5')
    fitted = True
```

[115]:
```
# Show summary
bert_model.summary()
```

```
Model: "model"
```

```
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_1 (InputLayer)        [(None, 392)]             0

 embedding (Embedding)       (None, 392, 128)          3906816

 conv1d (Conv1D)             (None, 391, 100)          25700

 conv1d_1 (Conv1D)           (None, 389, 100)          30100

 conv1d_2 (Conv1D)           (None, 386, 50)           20050

 global_max_pooling1d (Globa  (None, 50)               0
 lMaxPooling1D)

 dense (Dense)               (None, 512)               26112

 dropout (Dropout)           (None, 512)               0

 dense_1 (Dense)             (None, 1)                 513

=================================================================
Total params: 4,009,291
Trainable params: 4,009,291
Non-trainable params: 0
_________________________________________________________________
```

[116]:

```
# Run if not fitted
if not fitted:
    bert_model.fit(train_texts,
                   y_train,
                   batch_size=128,
                   epochs=1,
                   validation_data=(val_texts, y_valid));
    bert_model.save('models/bert_tokenized_model.h5', save_format='tf')
```

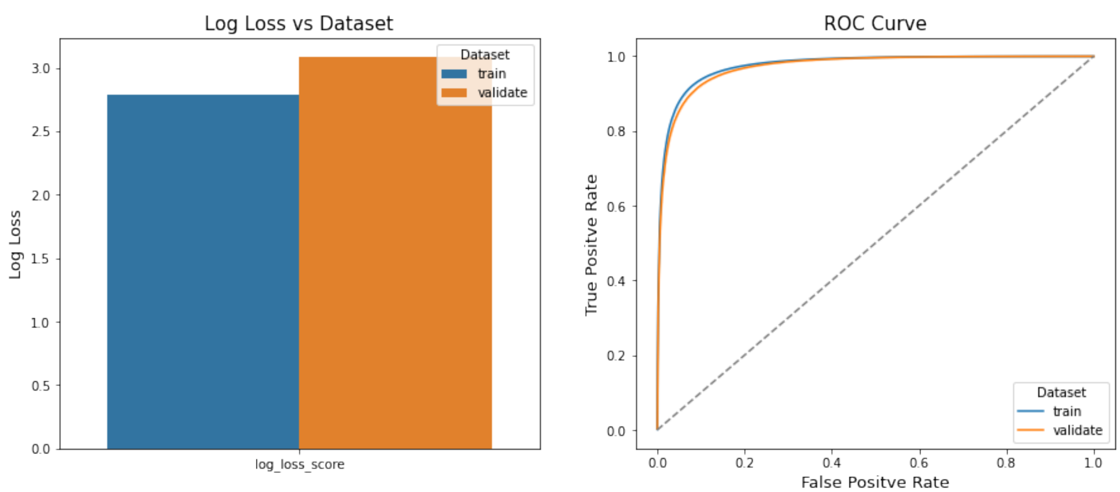
[117]:

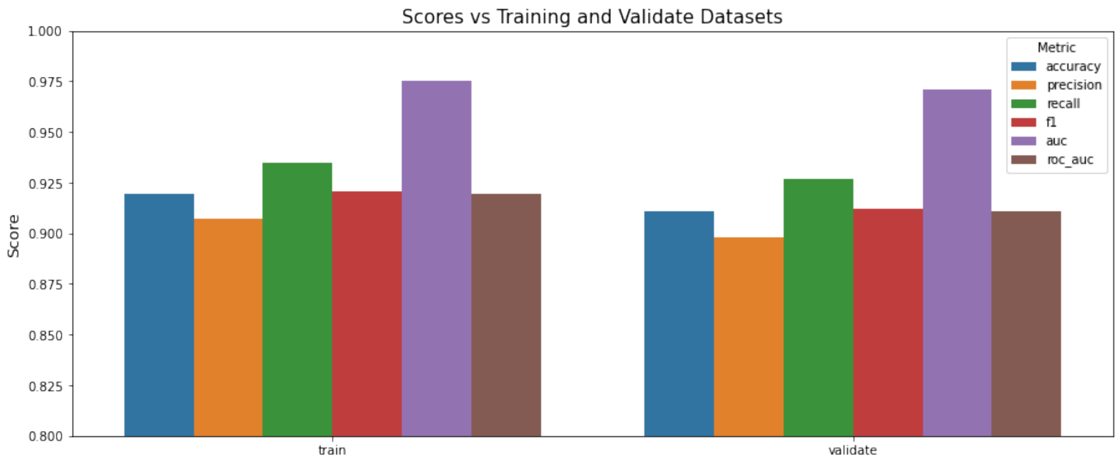
```
# Run predictions is not fitted
if not fitted:
    train_preds = bert_model.predict(train_texts)
    val_preds = bert_model.predict(val_texts)
    # Save predictions to file
    pickle.dump(train_preds, f)
    pickle.dump(val_preds, f)
    f.close()
```

[118]:
```
# Convert predictions to dataframe
predictions = pd.concat([dnn_res_to_pd(y_valid, val_preds,'validate'),
                         dnn_res_to_pd(y_train, train_preds,'train')])
# Add predictions to the model
bert_model.predictions = predictions
bert_model.predictions
```

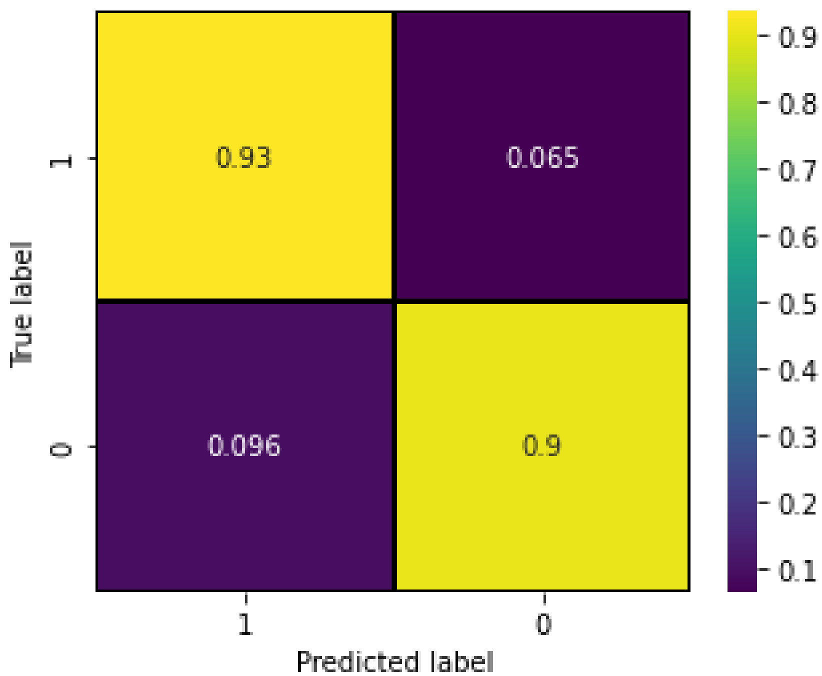
[118]:
```
  train_test                                              preds  \
0   validate  [[1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0,…
0      train  [[1, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1,…

                                          prob_preds  log_loss_score  \
0  [[0.99894893, 0.051377565, 0.0034568012, 0.788…        3.082980
0  [[0.96683025, 0.01142404, 0.74035144, 0.453830…        2.782287

   accuracy  precision    recall        f1  \
0  0.910740   0.898169  0.926526  0.912127
0  0.919446   0.907125  0.934577  0.920646

                                                 fpr  \
0  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …
0  [0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, …

                                                 tpr       auc   roc_auc
0  [0.0, 1.8518518518518519e-06, 0.00012777777777…  0.970848  0.910740
0  [0.0, 7.936507936507937e-07, 3.968253968253968…  0.975247  0.919446
```

[119]:
```
# Display metrics
plot_predictions(bert_model, valid_test='validate')
```





[120]:
```
# Show confusion matrix
plot_confusion_matrix(y_train, 1*(train_preds>0.5), normalize='true')
```



[121]:
```
# # Store best model
best_models.append(bert_model)

# Store the type of vectorization used
vectorization_type.append('tokenized-bert')
```

[122]:
```
# Delete unused variables
del train_preds, val_preds, X_train
```

5 Evaluation

Now that all models have been fitted with training dataset and tested on validation. We can now import the test dataset and make predictions with the best performing models from each model.

5.1 Model Performances

First we need to check if test dataset is preprocessed.

[157]:
```
# Check if test.zip exists
if exists('data/test.zip'):
    # Load using pandas
    test_df = pd.read_csv('data/test.zip', compression='gzip')
    # Apply string cleaner (remove square bracets from each side)
    def str_cleaner(line):
        return line[1:-1].replace("'",'').replace(' ','').replace(',',' ')
    # Apply str_cleaner function
    test_df.statements = test_df.statements.apply(str_cleaner)
else:
    # Else load the B2Z file
    test_file_lines = load_data('data/test.ft.txt.bz2')
    # Clean it and save it to file
    test_df = save_to_file(test_file_lines, 'train')
    del train_file_lines
```

Lets split the test dataset to features and labels.

[158]:
```
X_test, y_test = test_df.statements, test_df.labels
del test_df
```

For smoother operation, different tokenizations of the test files are stored in a dictionary.

[125]:
```
if not exists('test_dataset_dict.pickle'):
    # If file doesn't exist
    MODEL_NAME = 'distilbert-base-uncased-finetuned-sst-2-english'
    # Initiallize dicionary
    test_dataset_dict = {}
    # Perform TfIdf
    prep = Preprocess(transformer='tfidf',max_df=0.98083,min_df=0.01917)
    test_dataset_dict['tfidf'] = prep.transform(X_test, return_vectorizer=False)
    # Apply count
    prep = Preprocess(transformer='count',max_df=0.98083,min_df=0.01917)
    test_dataset_dict['count'] = prep.transform(X_test, return_vectorizer=False)
    # Apply word embedding
    prep = Preprocess(transformer='embed')
```

```
    test_dataset_dict['embed'] = prep.transform(X_test)
    # Load tokenizer for the first LSTM model
    with open('lstm_model_no_weight.pickle', 'rb') as f:
        tokenizer = pickle.load(f)
        train_texts = pickle.load(f)
    # Apply tokenization and padding
    test_texts = tokenizer.texts_to_sequences(X_test)
    test_dataset_dict['tokenized-no-weight'] = pad_sequences(test_texts,
                                                      maxlen=train_texts.
 ↪shape[1])
    # Load tokenizer for the second LSTM model (with word embedding)
    with open('lstm_model_glove.pickle', 'rb') as f:
        tokenizer = pickle.load(f)
        train_texts = pickle.load(f)
    # Apply tokenization and padding
    test_texts = tokenizer.texts_to_sequences(X_test)
    test_dataset_dict['tokenized-glove'] = pad_sequences(test_texts,
                                                      maxlen=train_texts.
 ↪shape[1])
    # Load padded train data for the last model
    with open('bert_tokenized.pickle', 'rb') as f:
        train_texts = pickle.load(f)
    # Apply DistilBert tokenizer and padding
    tokenizer = DistilBertTokenizer.from_pretrained(MODEL_NAME)
    test_tokenized = [tokenize_reviews(review) for review in tqdm(X_test.
 ↪to_list())]
    test_dataset_dict['tokenized-bert'] = pad_sequences(test_tokenized,
                                                  maxlen=train_texts.shape[1])
    # Save the dictionary to file
    with open('test_dataset_dict.pickle', 'wb') as f:
        pickle.dump(test_dataset_dict, f)
else:
    # Load processed testing data from file
    with open('test_dataset_dict.pickle', 'rb') as f:
        test_dataset_dict = pickle.load(f)
```

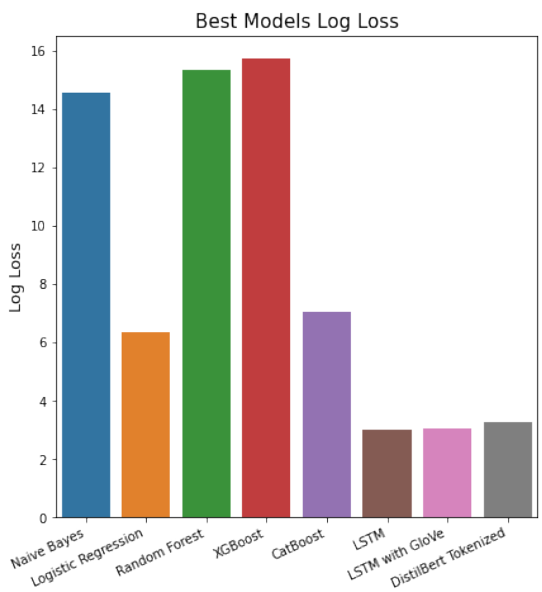
Now, we can iterate through the best models and make test predictions.

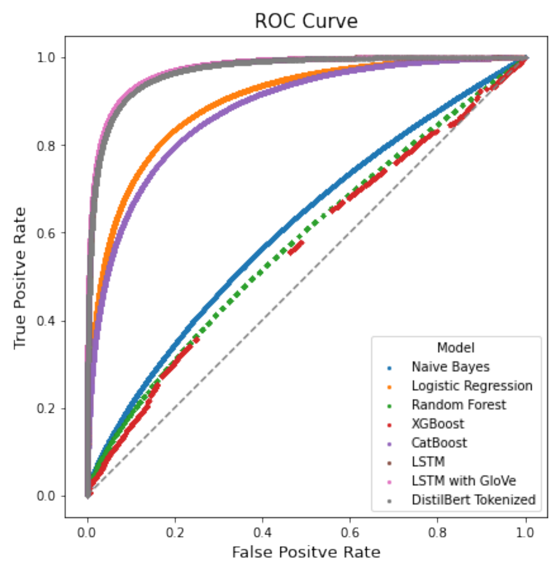
[127]:
```
for model, vec in zip(best_models, vectorization_type):
    try:
        test_preds_prob = model.predict_proba(test_dataset_dict[vec])
        tmp_df = dnn_res_to_pd(y_test, test_preds_prob[:,1], 'test')
    except:
        test_preds_prob = model.predict(test_dataset_dict[vec])
        tmp_df = dnn_res_to_pd(y_test, test_preds_prob, 'test')
    model.predictions = pd.concat([model.predictions, tmp_df])
```

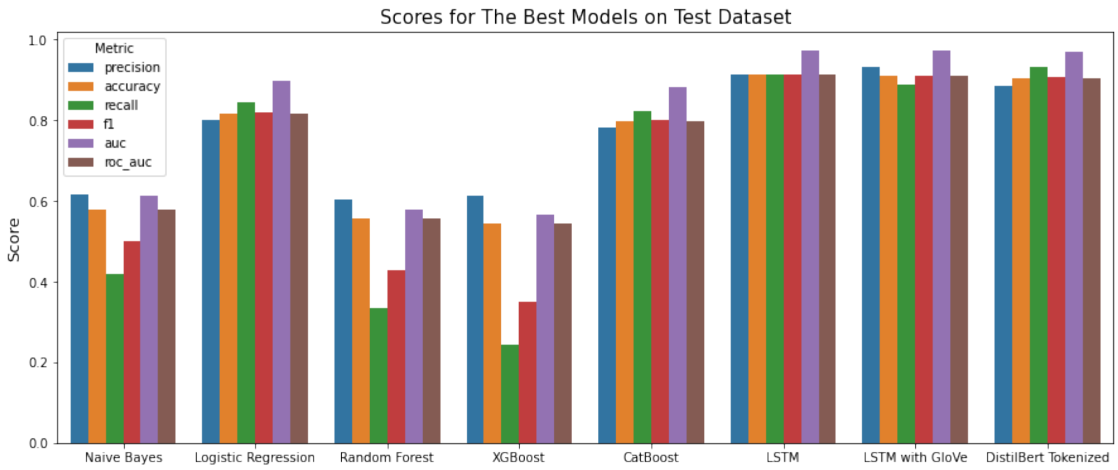
The performance summary of the best models selected are summarized in the figures plotted below.

[128]:
```python
# Set columns
columns = cb_gs_metrics_mean.columns

# Find the labels from the name of the models
labels = ['Naive Bayes','Logistic Regression', 'Random Forest',
          'XGBoost', 'CatBoost', 'LSTM', 'LSTM with GloVe',
          'DistilBert Tokenized']

# Iterate through each models
best_models_metrics = best_models[0].predictions.loc[best_models[0].predictions.
 ↪train_test=='test']
for model in best_models[1:]:
    # Find test predictions in each model
    tmp = model.predictions.loc[model.predictions.train_test=='test']
    best_models_metrics = pd.concat([best_models_metrics,tmp])

# Set labels as indices
best_models_metrics.index = labels

# Create figure to plot log loss and ROC curve
fig, axes = plt.subplots(1 , 2, figsize=(15,7))

# Log loss for the models
g1 = sns.barplot(x=labels, y=best_models_metrics['log_loss_score'], ax=axes[0])

# Format labels and title
g1.set_xlabel('')
g1.set_ylabel('Log Loss',fontsize=13)
g1.set_title('Best Models Log Loss',fontsize=15)
g1.set_xticklabels(g1.get_xticklabels(), rotation=25,
                   horizontalalignment='right')

# Plot mean ROC curve for the best models
for idx in labels:
    g2 = sns.scatterplot(x=best_models_metrics.loc[idx,'fpr'],
                         y=best_models_metrics.loc[idx,'tpr'],
                         label=idx, ax=axes[1], linewidth=0, s=10)

# Format labels and title
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
g2.set_xlabel('False Positve Rate', fontsize=13)
g2.legend(title='Model')
g2.set_ylabel('True Positve Rate', fontsize=13)
g2.set_title('ROC Curve',fontsize=15)

# Save figure
plt.savefig('images/best_model_log_and_roc.jpg');
```

```
# Plot metrics for the models
report_df = pd.DataFrame(columns=['model','value','metric'])
for col in columns:
    tmp_df = pd.DataFrame(columns=report_df.columns)
    tmp_df.value = best_models_metrics.loc[:, col]
    tmp_df.model = best_models_metrics.index
    tmp_df.metric = col
    report_df = pd.concat([report_df, tmp_df], ignore_index=True)
fig, ax = plt.subplots(figsize=(15,6))
g3 = sns.barplot(x="model", y="value", hue="metric",
                     data=report_df, ax=ax)

# Format labels and title
g3.set_xlabel('')
g3.set_ylabel('Score', fontsize=13)
g3.set_title('Scores for The Best Models on Test Dataset',fontsize=15)
g3.legend(title='Metric');

# Save figure
plt.savefig('images/best_model_performance.jpg');
```







5.2 Final Model

As expected, the first LSTM model gave the highest accuracy on the test dataset.

[129]:
```python
# Copy best_models_metrics
tmp_df = best_models_metrics.copy()

# Reset index
tmp_df = tmp_df.reset_index().reset_index()

# Sort values by difference between accuracy and recall
tmp_df = tmp_df.sort_values(by='accuracy', ascending=False)

# Select the index of the first in the table
idx = tmp_df.level_0.iloc[0]

# Final model
final_model =  best_models[idx]

# Print final model name and get parameters
print(labels[idx])
final_model.summary()
```

```
LSTM
Model: "functional_15"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_9 (InputLayer)        [(None, 167)]             0


 embedding_7 (Embedding)     (None, 167, 64)           1280000
```

```
 cu_dnnlstm_12 (CuDNNLSTM)   (None, 167, 128)          99328

 dropout_10 (Dropout)        (None, 167, 128)          0

 cu_dnnlstm_13 (CuDNNLSTM)   (None, 128)               132096

 dropout_11 (Dropout)        (None, 128)               0

 dense_21 (Dense)            (None, 100)               12900

 dense_22 (Dense)            (None, 32)                3232

 dense_23 (Dense)            (None, 1)                 33

=================================================================
Total params: 1,527,589
Trainable params: 1,527,589
Non-trainable params: 0
_________________________________________________________________
```

Now we can retrain the model for larger epochs to refine the performance. Results are saved to file.

[131]:
```
if not exists('final_model_results.pickle')
    with open('lstm_model_no_weight.pickle', 'rb') as f:
        # Load 'tokenizer'
        tokenizer = pickle.load(f)
        # Load 'train_texts'
        train_texts = pickle.load(f)
        # Load 'val_texts'
        val_texts = pickle.load(f)

    # Retrain model with more epochs
    history = final_model.fit(train_texts,
                              y_train,
                              batch_size=128,
                              epochs=4,
                              validation_data=(val_texts, y_valid));
    # Save final model for deployement
    final_model.save('models/final_model.h5', save_format='tf')
    # Save fit results to file
    with open('final_model_results.pickle','wb') as f:
        pickle.dump(history.history, f)
else:
    # Save final model for deployement
    final_model = keras.models.load_model('models/final_model.h5')

    # Fetch tokenizer from file
    with open('lstm_model_no_weight.pickle', 'rb') as f:
```

```
        # Get 'tokenizer'
        tokenizer = pickle.load(f)

    # Load fit results from file
    with open('final_model_results.pickle','rb') as f:
        history = pickle.load(f)
```

```
Epoch 1/4
19688/19688 [==============================] - 1049s 53ms/step - loss: 0.1929 -
accuracy: 0.9234 - val_loss: 0.1958 - val_accuracy: 0.9220
Epoch 2/4
19688/19688 [==============================] - 1042s 53ms/step - loss: 0.1713 -
accuracy: 0.9333 - val_loss: 0.1909 - val_accuracy: 0.9241
Epoch 3/4
19688/19688 [==============================] - 1042s 53ms/step - loss: 0.1540 -
accuracy: 0.9410 - val_loss: 0.1951 - val_accuracy: 0.9240
Epoch 4/4
19688/19688 [==============================] - 1041s 53ms/step - loss: 0.1382 -
accuracy: 0.9480 - val_loss: 0.2002 - val_accuracy: 0.9228
```

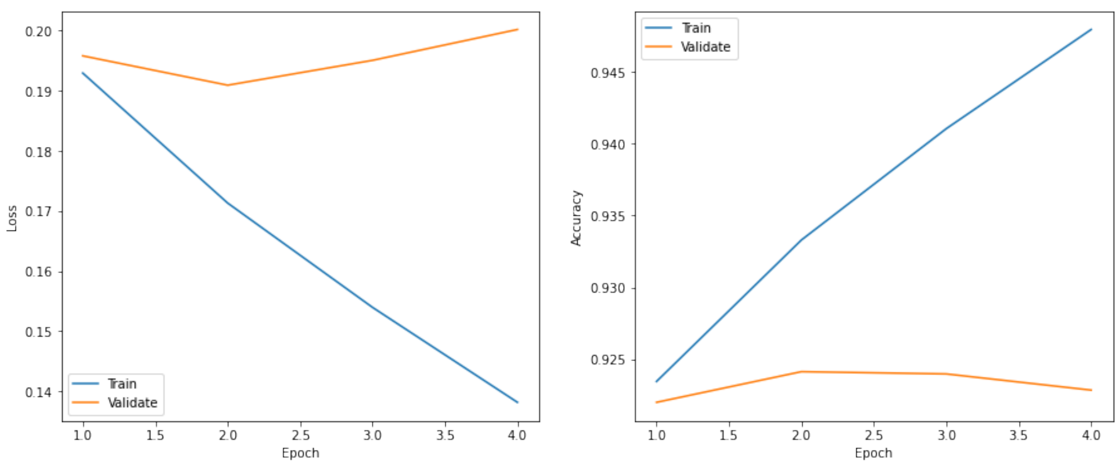
Choosing larger epochs usually results in overfitting, which is undesirable. We can now plot the model performance over the training epochs.

[150]:
```
def plot_history(history):
    # Metrics for plotting
    metrics = ['loss', 'accuracy']
    # Set epoch lengths as x-values
    epochs = list(range(1, len(history['loss'])+1))
    # Plot metrics
    fig, axes = plt.subplots(1, 2, figsize=(15,6))
    # Iterate through each metrics
    for metric, ax in zip(metrics, axes.flatten()):
        # Plot training metrics
        sns.lineplot(epochs, history[metric], label='Train', ax=ax)
        # Plot validation metrics
        sns.lineplot(epochs, history['val_'+metric], label='Validate', ax=ax)
        # Set axis labels
        ax.set_xlabel('Epoch')
        ax.set_ylabel(metric.title())
        ax.legend();
```

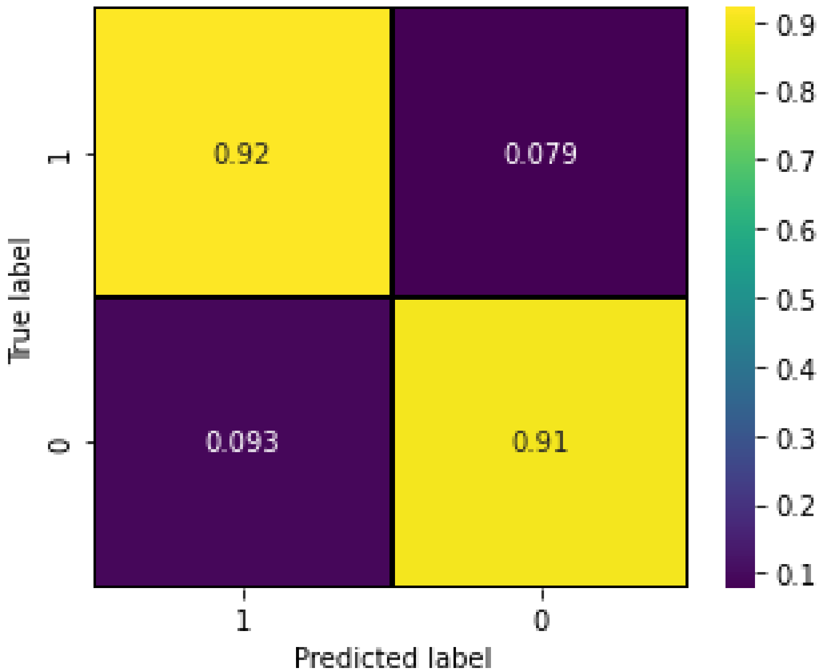
Plotting the model performances, we can see that validation suffers a bit at higher epochs.

[328]:
```
# Plot history
try:
    plot_history(history.history)
except:
    plot_history(history)
plt.savefig('images/epochs.jpg');
```

```
C:\Users\zeaps\Anaconda3\envs\learn-env\lib\site-
packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
C:\Users\zeaps\Anaconda3\envs\learn-env\lib\site-
packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
C:\Users\zeaps\Anaconda3\envs\learn-env\lib\site-
packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
C:\Users\zeaps\Anaconda3\envs\learn-env\lib\site-
packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variables
as keyword args: x, y. From version 0.12, the only valid positional argument
will be `data`, and passing other arguments without an explicit keyword will
result in an error or misinterpretation.
  warnings.warn(
```



[340]:
```python
# Confusion matrix for test prediction
test_preds = final_model.predict(test_dataset_dict['tokenized-no-weight'])
plot_confusion_matrix(y_test, 1*(test_preds>0.5), normalize='true')
```



These are the metrics of the final model. It is considerably better than the other modes.

[152]:
```
# Metrics of the final model
dnn_res_to_pd(y_test, test_preds, 'test')[columns]
```

[152]:

	precision	accuracy	recall	f1	auc	roc_auc
0	0.908266	0.91399	0.921	0.914589	0.970818	0.91399

5.3 Model Interpretation

Now that our model has been selected, it is time to explain the significance of each variable used to make the prediction. For this project, LIME is used as way to demonstrate model performance. A great thing about this library is that it can show us which parts of the statement can be attributed to making a positive or negative predictions with probability. By following those steps, we can learn more about the features that can actively influence our predictions.

[200]:
```
# Class names used for interpretation
class_names=['negative','positive']
# Initialize LIME explaniner
explainer= LimeTextExplainer(class_names=class_names)
```

The following function predicts the probability of a statement to either being positive or negative based on the final model.

[229]:
```
# Function to predict probabilities of an input text
def predict_proba(statements):
```

```
    # Store processed strings
    processed_str = []
    # Iterate through each sentiment and clean data
    for statment in statements:
        # data_cleaner returns the lemmed statement and label, if specified
        cleaned_str, _ = data_cleaner(statment, labeled=False,␣
 ↪spell_check=False)
        # Append cleaned data
        processed_str.append(cleaned_str)
    # Tokenize word using tokenizer for the final model
    tokenized = tokenizer.texts_to_sequences(processed_str)
    # Apply padding
    input_data = pad_sequences(tokenized,
                               maxlen=test_dataset_dict['tokenized-no-weight'].shape[1])
    # Predict the sentiment of the statement
    pred = final_model.predict(input_data)
    # Return the binary probabilities
    return np.array([[1-i[0],i[0]] for i in pred])
```

Now let's choose a random statement from the test file and test the performance.

[324]:
```
# Randomly choose comment from the test dataset
idx = 0
print('Actual sentiment for this review is', class_names[y_test[idx]])
explainer.explain_instance(X_test[0], predict_proba).show_in_notebook(text=True)
```

```
Actual sentiment for this review is positive
```

```
<IPython.core.display.HTML object>
```

[239]:
```
# Randomly choose comment from the test dataset
idx = 512
print('Actual sentiment for this review is', class_names[y_test[idx]])
explainer.explain_instance(X_test[512], predict_proba).
 ↪show_in_notebook(text=True)
```

```
Actual sentiment for this review is negative
```

```
<IPython.core.display.HTML object>
```

So far so good. We can now use comments pulled from random product on Amazon and see how the prediction is going to fair.

[322]:
```
# Test on a custom positive review
```

```
custom_review = "Gildan Men's Crew T-Shirts are very comfortable very well made␣
↪and I would highly recommend them I wear a lot of white shirts and comfort␣
↪bility and the style and fabric of the shirt is very important to me I Used␣
↪to always Hans but they've got to be very expensive and I don't mind the␣
↪price but the quality has also been reduced but Gildan Men's Crew T-Shirts␣
↪Suppress my expectations and if I could give them a 10 star I would I would␣
↪highly recommend "
explainer.explain_instance(custom_review, predict_proba).
↪show_in_notebook(text=True)
```

<IPython.core.display.HTML object>

[323]:
```
# Test on a custom negative review
custom_review = "The shirts say they are 100% Cotten but I don’t believe I have␣
↪ever felt such rough scratchy cotton. I have had these shirts for a few␣
↪weeks now and they have been washed multiple times and are still scratchy. I␣
↪also put one on this morning and it has a hole in the arm pit. I would not␣
↪suggest buying these and I will not buy them again."
explainer.explain_instance(custom_review, predict_proba).
↪show_in_notebook(text=True)
```

<IPython.core.display.HTML object>

Excellent! Although deep neural networks make it difficult to show the effect of each word towards making a sentiment prediction, the most frequent words in correctly and incorrectly predicting values can be displayed. The function below identifies true/false positives/negatives and gives the frequencies of the top 50 words from each category.

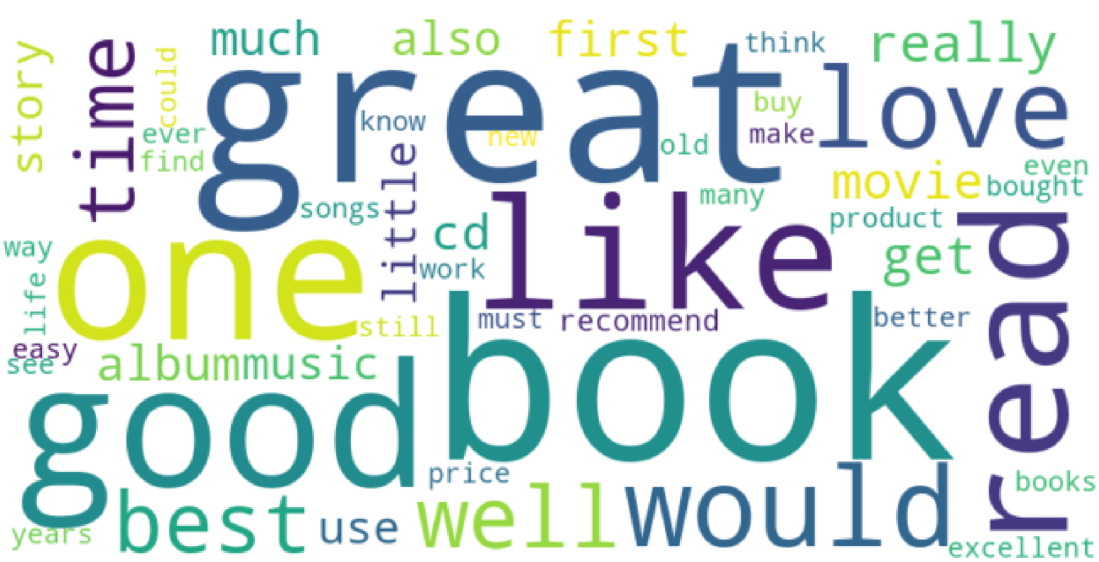
[275]:
```
def word_collection(dataset, y_true, y_pred, pred_type, top_num=10):
    '''
    Function that returns the top n words that are correctly
    or incorrectly classifed.
    dataset: Pandas Series file
    y_true: True y values
    y_pred: Predicted y values
    pred_type: Prediction type true or false positives/negatives
        True positve: 'tp'
        True negative: 'tn'
        False positive: 'fp'
        False negative: 'fn'
    '''
    if len(np.unique(y_pred))>2:
        y_pred = 1*(y_pred>0.5)
    # Take difference between true and predicted values
    diff =  [int(np.round(y_true[i]-y_pred[i])) for i in range(len(y_true))]
    # Set difference dictionary
    diff_d = {'tp':0, 'tn':0, 'fp':-1, 'fn':1}
    # Set pred_type dictionary
```

```
    pred_d = {'tp':1, 'tn':0, 'fp':1, 'fn':0}
    # Find indices with matching criteria
    idx = [i for i in range(len(y_pred)) if (diff[i]==diff_d[pred_type] and\
                                         y_pred[i] == pred_d[pred_type])]
    # Select a subset from the dataset with computed indices
    data = ' '.join(dataset[idx].to_list()).split()
    # Get frequency distribution of text
    data = FreqDist(data).most_common(top_num)
    # Return a dictionary of top_num words
    return dict(data)
```

Display the top 50 true positive words

[281]:
```
# Top 50 words in true positive comments
top_50_tp = word_collection(X_test, y_test, test_preds, 'tp', top_num=50)
```

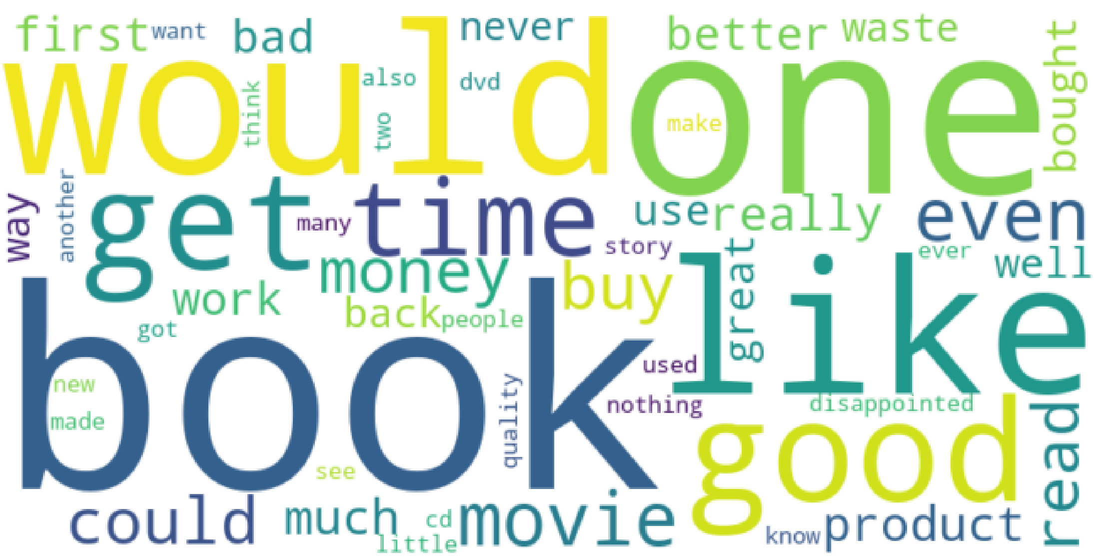
[296]:
```
# Define a wordcloud
wordcloud = WordCloud(width=800, height=400, background_color='white')
# Generate from word frequency
wordcloud.generate_from_frequencies(top_50_tp)
# Plot wordcloud
plt.figure(figsize=(12,6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off");
# Save figure
plt.savefig('images/true_pos.jpg');
```



Display the top 50 true negative words

```
[282]: # Top 50 words in true negative comments
top_50_tn = word_collection(X_test, y_test, test_preds, 'tn', top_num=50)
```

```
[297]: # Generate from word frequency
wordcloud.generate_from_frequencies(top_50_tn)
# Plot wordcloud
plt.figure(figsize=(12,6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off");
# Save figure
plt.savefig('images/true_neg.jpg');
```



Display the top 50 false positive words

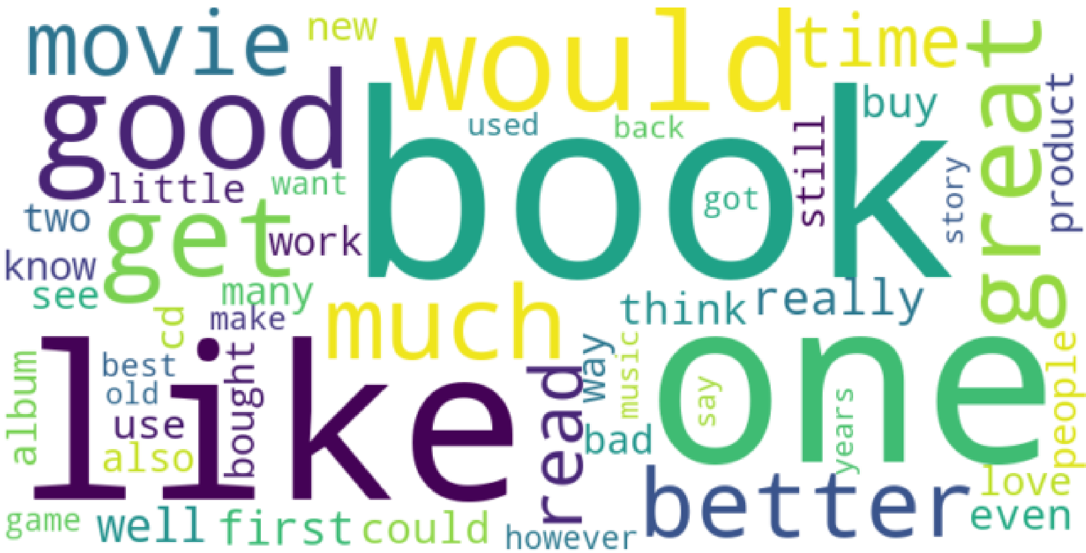
```
[285]: # Top 50 words in false positive comments
top_50_fp = word_collection(X_test, y_test, test_preds, 'fp', top_num=50)
```

```
[298]: # Generate from word frequency
wordcloud.generate_from_frequencies(top_50_fp)
# Plot wordcloud
plt.figure(figsize=(12,6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off");
# Save figure
plt.savefig('images/false_pos.jpg');
```

Display the top 50 false negative words

[287]:
```
# Top 50 words in false negtive comments
top_50_fn = word_collection(X_test, y_test, test_preds, 'fn', top_num=50)
```

[299]:
```
# Generate from word frequency
wordcloud.generate_from_frequencies(top_50_fn)
# Plot wordcloud
plt.figure(figsize=(12,6))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off");
# Save figure
plt.savefig('images/false_neg.jpg');
```



6 Conclusion

We built a binary text classification model LSTM that is able to perform Amazon reviews sentiment analysis with 91.4% accuracy. Our model was also able to assign probabilistic ratio for each word used from a completely unseen review. Word Clouds were generated to show which words are the appear the most in both true positive and negative reviews. It was also observed that LSTM with GloVe and BERT tokenized models also performed strongly. More deep learning architectures could be considered to improve the accuracy of test data.

7 Next Steps

he next steps include considering more robust models (layers with larger nodes) for an improved performance. Also, in this project I was aspired to implement transformer models which have significantly higher performance compared to the traditional LSTM model. The dataset used in this project have binary classes. It would be interesting to test the model performance on a star-based rating, instead of positive or negative reviews. Furthermore, creating a web deployable application for an interactive feedback is the next step.