case_study_1_1

March 28, 2020

Description

The Conversation AI team, a research initiative founded by Jigsaw and Google (both part of Alphabet), builds technology to protect voices in conversation. A main area of focus is machine learning models that can identify toxicity in online conversations, where toxicity is defined as anything rude, disrespectful or otherwise likely to make someone leave a discussion.

In year 2018, in the Toxic Comment Classification Challenge, you built multi-headed models to recognize toxicity and several subtypes of toxicity. This year's competition is a related challenge: building toxicity models that operate fairly across a diverse range of conversations.

Here's the background: When the Conversation AI team first built toxicity models, they found that the models incorrectly learned to associate the names of frequently attacked identities with toxicity. Models predicted a high likelihood of toxicity for comments containing those identities (e.g. "gay"), even when those comments were not actually toxic (such as "I am a gay woman"). This happens because training data was pulled from available sources where unfortunately, certain identities are overwhelmingly referred to in offensive ways. Training a model from data with these imbalances risks simply mirroring those biases back to users.

In this competition, you're challenged to build a model that recognizes toxicity and minimizes this type of unintended bias with respect to mentions of identities. You'll be using a dataset labeled for identity mentions and optimizing a metric designed to measure unintended bias. Develop strategies to reduce unintended bias in machine learning models, and you'll help the Conversation AI team, and the entire industry, build models that work well for a wide range of conversations.

Disclaimer: The dataset for this competition contains text that may be considered profane, vulgar, or offensive.

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Evaluation Metric

Competition Evaluation

This competition will use a newly developed metric that combines several submetrics to balance overall performance with various aspects of unintended bias.

First, we'll define each submetric.

Overall AUC

This is the ROC-AUC for the full evaluation set.

Bias AUCs

To measure unintended bias, we again calculate the ROC-AUC, this time on three specific subsets of the test set for each identity, each capturing a different aspect of unintended bias. You can learn more about these metrics in Conversation AI's recent paper Nuanced Metrics for Measuring Unintended Bias with Real Data in Text Classification.

Subgroup AUC: Here, we restrict the data set to only the examples that mention the specific identity subgroup. A low value in this metric means the model does a poor job of distinguishing between toxic and non-toxic comments that mention the identity.

BPSN (Background Positive, Subgroup Negative) AUC: Here, we restrict the test set to the non-toxic examples that mention the identity and the toxic examples that do not. A low value in this metric means that the model confuses non-toxic examples that mention the identity with toxic examples that do not, likely meaning that the model predicts higher toxicity scores than it should for non-toxic examples mentioning the identity.

BNSP (Background Negative, Subgroup Positive) AUC: Here, we restrict the test set to the toxic examples that mention the identity and the non-toxic examples that do not. A low value here means that the model confuses toxic examples that mention the identity with non-toxic examples that do not, likely meaning that the model predicts lower toxicity scores than it should for toxic examples mentioning the identity.

Generalized Mean of Bias AUCs

To combine the per-identity Bias AUCs into one overall measure, we calculate their generalized mean as defined below:

Mp(ms)=(1N s=1Nmps)1pMp(ms)=(1N s=1Nmsp)1p

where:

MpMp

= the pp

th power-mean function msms

= the bias metric mm

calulated for subgroup ss

NN

= number of identity subgroups

For this competition, we use a pp

value of -5 to encourage competitors to improve the model for the identity subgroups with the lowest model performance.

Final Metric

We combine the overall AUC with the generalized mean of the Bias AUCs to calculate the final model score:

score=w0AUCoverall+ a=1AwaMp(ms,a)score=w0AUCoverall+ a=1AwaMp(ms,a)

where:

A = number of submetrics (3) ms,ams,a

= bias metric for identity subgroup ss

using submetric aa

wawa

= a weighting for the relative importance of each submetric; all four ww

values set to 0.25

While the leaderboard will be determined by this single number, we highly recommend looking at the individual submetric results, as shown in this kernel, to guide you as you develop your models.

Submission File

Data Overview

Background

At the end of 2017 the Civil Comments platform shut down and chose make their ~2m public comments from their platform available in a lasting open archive so that researchers could understand and improve civility in online conversations for years to come. Jigsaw sponsored this effort and extended annotation of this data by human raters for various toxic conversational attributes.

In the data supplied for this competition, the text of the individual comment is found in the comment_text column. Each comment in Train has a toxicity label (target), and models should predict the target toxicity for the Test data. This attribute (and all others) are fractional values which represent the fraction of human raters who believed the attribute applied to the given comment. For evaluation, test set examples with target >= 0.5 will be considered to be in the positive class (toxic).

The data also has several additional toxicity subtype attributes. Models do not need to predict these attributes for the competition, they are included as an additional avenue for research. Subtype attributes are:

severe_toxicity

obscene

threat

insult

identity_attack

sexual_explicit

Additionally, a subset of comments have been labelled with a variety of identity attributes, representing the identities that are mentioned in the comment. The columns corresponding to identity attributes are listed below. Only identities with more than 500 examples in the test set (combined public and private) will be included in the evaluation calculation. These identities are shown in bold.

male

female

transgender

other_gender

heterosexual

homosexual_gay_or_lesbian

bisexual

other_sexual_orientation

christian

jewish

muslim

hindu

buddhist

atheist

other_religion

black

white

asian

latino

other_race_or_ethnicity

physical_disability

intellectual_or_learning_disability

psychiatric_or_mental_illness

other_disability

Note that the data contains different comments that can have the exact same text. Different comments that have the same text may have been labeled with different targets or subgroups.

Examples

Here are a few examples of comments and their associated toxicity and identity labels. Label values range from 0.0 - 1.0 represented the fraction of raters who believed the label fit the comment.

Comment: i'm a white woman in my late 60's and believe me, they are not too crazy about me either!!

Toxicity Labels: All 0.0

Identity Mention Labels: female: 1.0, white: 1.0 (all others 0.0)

Comment: Why would you assume that the nurses in this story were women?

Toxicity Labels: All 0.0

Identity Mention Labels: female: 0.8 (all others 0.0)

Comment: Continue to stand strong LGBT community. Yes, indeed, you'll overcome and you have.

Toxicity Labels: All 0.0

Identity Mention Labels: homosexual_gay_or_lesbian: 0.8, bisexual: 0.6, transgender: 0.3 (all others 0.0)

In addition to the labels described above, the dataset also provides metadata from Jigsaw's annotation: toxicity_annotator_count and identity_annotator_count, and metadata from Civil Comments: created_date, publication_id, parent_id, article_id, rating, funny, wow, sad, likes, disagree. Civil Comments' label rating is the civility rating Civil Comments users gave the comment.

Labelling Schema

To obtain the toxicity labels, each comment was shown to up to 10 annotators*. Annotators were asked to: "Rate the toxicity of this comment"

Very Toxic (a very hateful, aggressive, or disrespectful comment that is very likely to make you leave a discussion or give up on sharing your perspective)

Toxic (a rude, disrespectful, or unreasonable comment that is somewhat likely to make you leave a discussion or give up on sharing your perspective)

Hard to Say

Not Toxic

These ratings were then aggregated with the target value representing the fraction of annotations that annotations fell within the former two categories.

To collect the identity labels, annotators were asked to indicate all identities that were mentioned in the comment. An example question that was asked as part of this annotation effort was: "What genders are mentioned in the comment?"

Male

Female

Transgender

Other gender

No gender mentioned

Again, these were aggregated into fractional values representing the fraction of raters who said the identity was mentioned in the comment.

The distributions of labels and subgroup between Train and Test can be assumed to be similar, but not exact.

*Note: Some comments were seen by many more than 10 annotators (up to thousands), due to sampling and strategies used to enforce rater accuracy.

File descriptions

train.csv - the training set, which includes toxicity labels and subgroups test.csv - the test set, which does not include toxicity labels or subgroups

sample_submission.csv - a sample submission file in the correct format

Usage

This dataset is released under CC0, as is the underlying comment text.

[1]:
```
import pandas as pd
```

[2]:
```
train_data = pd.read_csv('train/train.csv')
test_data = pd.read_csv('test/test.csv')
print(train_data.shape)
print(test_data.shape)
```

```
(1804874, 45)
(97320, 2)
```

[9]:
```
print(train_data.columns)
print(test_data.columns)
```

```
Index(['id', 'target', 'comment_text', 'severe_toxicity', 'obscene',
       'identity_attack', 'insult', 'threat', 'asian', 'atheist', 'bisexual',
       'black', 'buddhist', 'christian', 'female', 'heterosexual', 'hindu',
       'homosexual_gay_or_lesbian', 'intellectual_or_learning_disability',
       'jewish', 'latino', 'male', 'muslim', 'other_disability',
       'other_gender', 'other_race_or_ethnicity', 'other_religion',
       'other_sexual_orientation', 'physical_disability',
       'psychiatric_or_mental_illness', 'transgender', 'white', 'created_date',
       'publication_id', 'parent_id', 'article_id', 'rating', 'funny', 'wow',
       'sad', 'likes', 'disagree', 'sexual_explicit',
       'identity_annotator_count', 'toxicity_annotator_count'],
      dtype='object')
Index(['id', 'comment_text'], dtype='object')
```

There are more than 1 million records and 45 columns and among 45 columns following columns are important including target and comment text :

identity attributes, representing the identities that are mentioned in the comment
male

female

transgender

other_gender

heterosexual

homosexual_gay_or_lesbian

bisexual

other_sexual_orientation

christian

jewish

muslim

hindu

buddhist

atheist

other_religion

black

white

asian

latino

other_race_or_ethnicity

physical_disability

intellectual_or_learning_disability

psychiatric_or_mental_illness

other_disability

import plotly.graph_objects as go import warnings

warnings.filterwarnings('ignore')We need to consider itentities mentioned in bold

[8]:
```
train_data.dtypes
```

[8]:
```
id                                    int64
target                              float64
comment_text                         object
severe_toxicity                     float64
obscene                             float64
identity_attack                     float64
insult                              float64
threat                              float64
asian                               float64
atheist                             float64
bisexual                            float64
black                               float64
buddhist                            float64
christian                           float64
female                              float64
```

```
heterosexual                              float64
hindu                                     float64
homosexual_gay_or_lesbian                 float64
intellectual_or_learning_disability       float64
jewish                                    float64
latino                                    float64
male                                      float64
muslim                                    float64
other_disability                          float64
other_gender                              float64
other_race_or_ethnicity                   float64
other_religion                            float64
other_sexual_orientation                  float64
physical_disability                       float64
psychiatric_or_mental_illness             float64
transgender                               float64
white                                     float64
created_date                               object
publication_id                              int64
parent_id                                 float64
article_id                                  int64
rating                                     object
funny                                       int64
wow                                         int64
sad                                         int64
likes                                       int64
disagree                                    int64
sexual_explicit                           float64
identity_annotator_count                    int64
toxicity_annotator_count                    int64
dtype: object
```

[5]:
```
train_data.comment_text.describe()
```

[5]:
```
count         1804874
unique        1780823
top        Well said.
freq              184
Name: comment_text, dtype: object
```

[39]:
```
def printCommentText(index):
    print(train_data_after_EDA.comment_text.values[index])
    print('#'*100)
```

[43]:
```
printCommentText(2000)
printCommentText(20000)
printCommentText(200000)
```

```
printCommentText(206353)
printCommentText(22342)
printCommentText(1)
```

```
I equally love men. leafy i love you. hugs and kisses.
################################################################################
####################
I agree with you Mr. Elrey.  People should be required to take a class in order
to publicly carry firearms.  These are serious tools and have to be treated
seriously. There are many people I would be comfortable around who carry weapons
but God help us if it becomes too "cool" to be seen with a weapon and people
start carrying as a fashion statement.
################################################################################
####################
Goodbye Norma Jean…
################################################################################
####################
Oh, you mean when Trump lied about his income tax returns and support for the
Iraq war and Holt didn't docile accept his lies?  Or are you upset at the other
lies he told, like the birther lies long after he knew Obama was born an
American citizen ?  Analysis after analysis has shown conclusively that Trump
lies constantly.  Ignore them at your peril.
################################################################################
####################
Great season ladies your helping to make this a BASKETBALL TOWN! It was good to
see all the community support. Our coach is also a keeper.
################################################################################
####################
Thank you!! This would make my life a lot less anxiety-inducing. Keep it up, and
don't let anyone get in your way!
################################################################################
####################
```

Some capital letters are there

Punchuations are there

Unwanted spaces are there

Stop words are there

[2]:
```
import plotly.graph_objects as go

import re
import nltk
nltk.download('punkt')
nltk.download('wordnet')
from nltk.stem.wordnet import WordNetLemmatizer
from nltk import word_tokenize
```

```
from nltk.stem import PorterStemmer

from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
import pickle
from sklearn.metrics import␣
↪roc_auc_score,roc_curve,auc,confusion_matrix,classification_report
%matplotlib inline

import pandas as pd
import numpy as np
import scipy
import matplotlib.pyplot as plt
import plotly.graph_objects as go
import pickle
from tqdm import tqdm
import seaborn as sns
# import logging
# logger = logging.getLogger("distributed.worker")
# logger1 = logging.getLogger("distributed.utils_perf")
# logger.setLevel(logging.ERROR)
# logger1.setLevel(logging.ERROR)
import seaborn as sns
import time
import gc
import itertools

from tqdm import tqdm
from nltk import FreqDist
from nltk.corpus import stopwords
from wordcloud import WordCloud
from multiprocessing import Pool

plt.style.use('ggplot')
tqdm.pandas()

from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB, GaussianNB
from sklearn.linear_model import LogisticRegression, SGDClassifier
from sklearn.calibration import CalibratedClassifierCV
from xgboost import XGBClassifier
from sklearn.pipeline import make_pipeline
from sklearn.ensemble import StackingClassifier, RandomForestClassifier

from sklearn import metrics
import joblib
```

```
import warnings
warnings.filterwarnings('ignore')
```

```
[nltk_data] Downloading package punkt to /home/user/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /home/user/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
/home/user/anaconda3/lib/python3.7/site-packages/tqdm/std.py:658: FutureWarning:

The Panel class is removed from pandas. Accessing it from the top-level
namespace will also be removed in the next version
```

1 Exploratory Data Analysis

[3]:

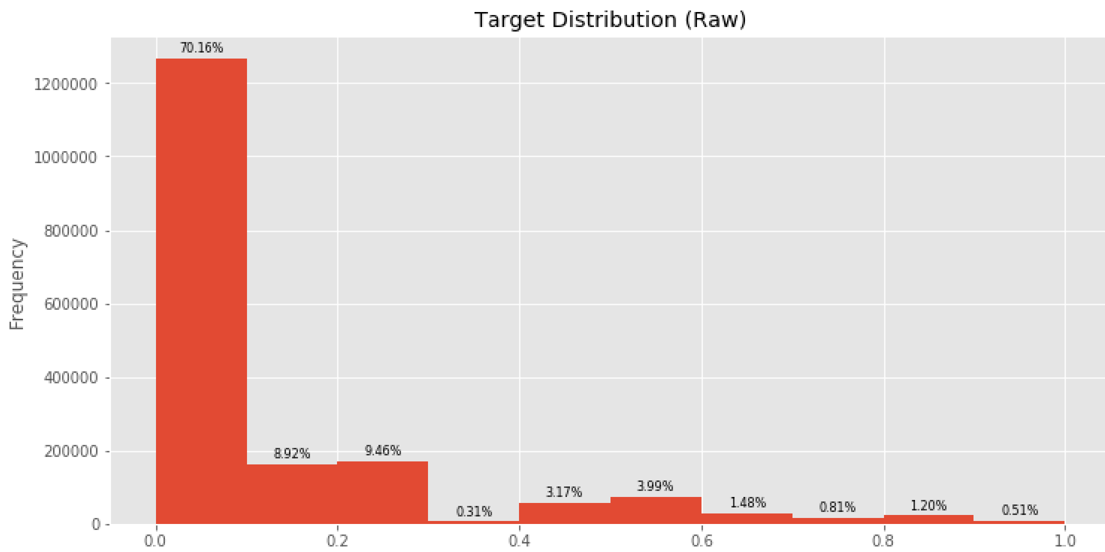
```
# https://gist.github.com/sebleier/554280
# we are removing the words from the stop words list: 'no', 'nor', 'not'
stopwords= ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you',␣
↪"you're", "you've",\
            "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he',␣
↪'him', 'his', 'himself', \
            'she', "she's", 'her', 'hers', 'herself', 'it', "it's", 'its',␣
↪'itself', 'they', 'them', 'their',\
            'theirs', 'themselves', 'what', 'which', 'who', 'whom', 'this',␣
↪'that', "that'll", 'these', 'those', \
            'am', 'is', 'are', 'was', 'were', 'be', 'been', 'being', 'have',␣
↪'has', 'had', 'having', 'do', 'does', \
            'did', 'doing', 'a', 'an', 'the', 'and', 'but', 'if', 'or',␣
↪'because', 'as', 'until', 'while', 'of', \
            'at', 'by', 'for', 'with', 'about', 'into', 'through', 'during',␣
↪'before', 'after',\
            'above', 'below', 'to', 'from', 'up', 'down', 'in', 'out', 'on',␣
↪'off', 'over', 'under', 'again', 'further',\
            'then', 'once', 'here', 'there', 'when', 'where', 'why', 'how',␣
↪'all', 'any', 'both', 'each', 'few', 'more',\
            'most', 'other', 'some', 'such', 'only', 'own', 'same', 'so',␣
↪'than', 'too', 'very', \
            's', 't', 'can', 'will', 'just', 'don', "don't", 'should',␣
↪"should've", 'now', 'd', 'll', 'm', 'o', 're', \
            've', 'y', 'ain', 'aren', "aren't", 'couldn', "couldn't", 'didn',␣
↪"didn't", 'doesn', "doesn't", 'hadn',\
            "hadn't", 'hasn', "hasn't", 'haven', "haven't", 'isn', "isn't",␣
↪'ma', 'mightn', "mightn't", 'mustn',\
```

```
            "mustn't", 'needn', "needn't", 'shan', "shan't", 'shouldn',␣
↪"shouldn't", 'wasn', "wasn't", 'weren', "weren't", \
            'won', "won't", 'wouldn', "wouldn't"]
```

[4]:
```
toxic_subtypes = ['severe_toxicity', 'obscene', 'identity_attack', 'insult',␣
↪'threat', 'sexual_explicit']
identities = ['asian', 'atheist', 'bisexual',
       'black', 'buddhist', 'christian', 'female', 'heterosexual', 'hindu',
       'homosexual_gay_or_lesbian', 'intellectual_or_learning_disability',
       'jewish', 'latino', 'male', 'muslim', 'other_disability',
       'other_gender', 'other_race_or_ethnicity', 'other_religion',
       'other_sexual_orientation', 'physical_disability',
       'psychiatric_or_mental_illness', 'transgender', 'white']

selected_identities = [
    'male', 'female', 'homosexual_gay_or_lesbian', 'christian', 'jewish',
    'muslim', 'black', 'white', 'psychiatric_or_mental_illness']
```

1.1 Target Distribution

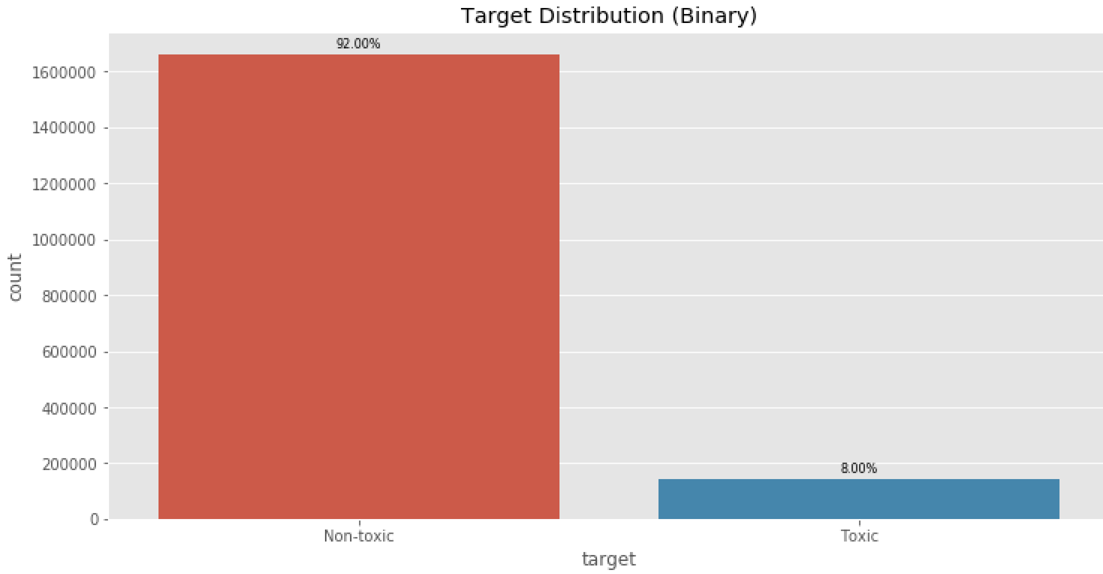
[13]:
```
plt.figure(figsize=(12,6))

plot = train_data.target.plot(kind='hist', bins=10)

ax = plot.axes

for p in ax.patches:
    ax.annotate(f'{p.get_height() * 100 / train_data.shape[0]:.2f}%',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center',
                va='center',
                fontsize=8,
                color='black',
                xytext=(0,7),
                textcoords='offset points')
plt.title('Target Distribution (Raw)')
plt.show()
```



[6]:
```
def convert_to_bool(df, col_name):
    df[col_name] = np.where(df[col_name] >= 0.5, True, False)

def convert_dataframe_to_bool(df):
    bool_df = df.copy()
    for col in ['target'] + selected_identities:
        convert_to_bool(bool_df, col)
    return bool_df

train_data = convert_dataframe_to_bool(train_data)
```

[16]:
```
plt.figure(figsize=(12,6))
plot = sns.countplot(x='target', data=pd.DataFrame(train_data['target'].
 ↪map({True:'Toxic', False:'Non-toxic'}), columns=['target']))

ax = plot.axes

for p in ax.patches:
    ax.annotate(f'{p.get_height() * 100 / train_data.shape[0]:.2f}%',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center',
                va='center',
                fontsize=8,
                color='black',
                xytext=(0,7),
                textcoords='offset points')

plt.title('Target Distribution (Binary)')
```

```
plt.show()
```



1.1.1 key Takeaways

Before Binarization

- Around 70% of data is having target value < 0.1 i.e non-toxic
- But there are 30 % of data having target value > 0.1
- Of all the 10 bins the most interesting bins to notice are 0.1 to 0.5 as annotators seems to be confused if those comments are toxic or not and hence our model may also be confused for those comments. #### After Binarization
- It is a highly imbalanced dataset having only 8% toxic data

1.2 Comment Length

[31]:
```
def decontracted(phrase):
    phrase = re.sub(r"won\'t", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)
    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)
```

```
    phrase = phrase.replace('\\r', ' ')
    phrase = phrase.replace('\\n', ' ')
    phrase = phrase.replace('\\"', ' ')
    phrase = re.sub('[^A-Za-z0-9]+', ' ', phrase)
    return phrase
```

[15]:
```
def cleanComments(text):
    sent = decontracted(text)
    sent = ' '.join(e for e in sent.split() if e.lower() not in stopwords).
↪lower().strip()
    return sent
```

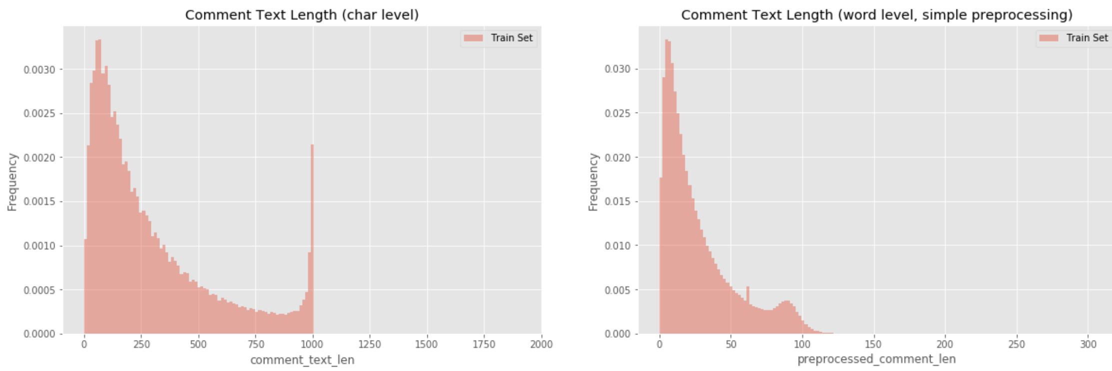
[16]:
```
def preprocessing(titles_array, return_len = False):

    processed_array = []

    for title in tqdm(titles_array):

        # remove other non-alphabets symbols with space (i.e. keep only␣
↪alphabets and whitespaces).
        processed = cleanComments(title)

        words = processed.split()

        if return_len:
            processed_array.append(len([word for word in words if word not in␣
↪stopwords]))
        else:
            processed_array.append(' '.join([word for word in words if word not␣
↪in stopwords]))

    return processed_array
```

[17]:
```
train_data['comment_text_len'] = train_data['comment_text'].progress_apply(len)

train_data['preprocessed_comment_len'] =␣
↪preprocessing(train_data['comment_text'], return_len=True)
```

```
100%|          | 1804874/1804874 [00:01<00:00, 1215870.78it/s]
100%|          | 1804874/1804874 [04:04<00:00, 7392.51it/s]
```

[18]:
```
plt.figure(figsize=(20,6))
plt.subplot(121)
sns.distplot(train_data['comment_text_len'], kde=False, bins=150, label='Train␣
↪Set', norm_hist=True)
plt.legend()
plt.ylabel('Frequency')
```

```
plt.title('Comment Text Length (char level)')

plt.subplot(122)
sns.distplot(train_data['preprocessed_comment_len'], kde=False, bins=150,␣
↪label='Train Set', norm_hist=True)
plt.legend()
plt.ylabel('Frequency')
plt.title('Comment Text Length (word level, simple preprocessing)')
plt.show()
```



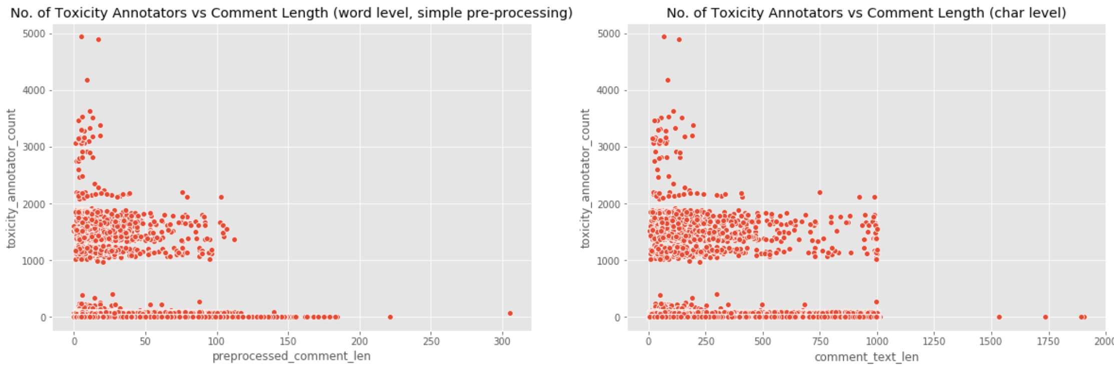
1.2.1 Key Takeaways

- Majority of comments have charecter lenght < 1000 but there are few comments with charecter length > 1000. This may be due to some special charecters or stopwords that we removed while cleaning comments.
- The maximum word length of comment text is around 130 after cleaning the comment text. That is a reasonable length.

1.3 No. of Toxicity Annotators vs Comment Length

[19]:
```
plt.figure(figsize=(20,6))
plt.subplot(121)
sns.scatterplot(x='preprocessed_comment_len',␣
↪y='toxicity_annotator_count',data=train_data)
plt.title('No. of Toxicity Annotators vs Comment Length (word level, simple␣
↪pre-processing)')

plt.subplot(122)
sns.scatterplot(x='comment_text_len',␣
↪y='toxicity_annotator_count',data=train_data)
plt.title('No. of Toxicity Annotators vs Comment Length (char level)')
```

```
plt.show()
```



1.3.1 Key Takeaways

- As we can see in both word level and charecter level, as length increases no of annotators for that comment decreases.

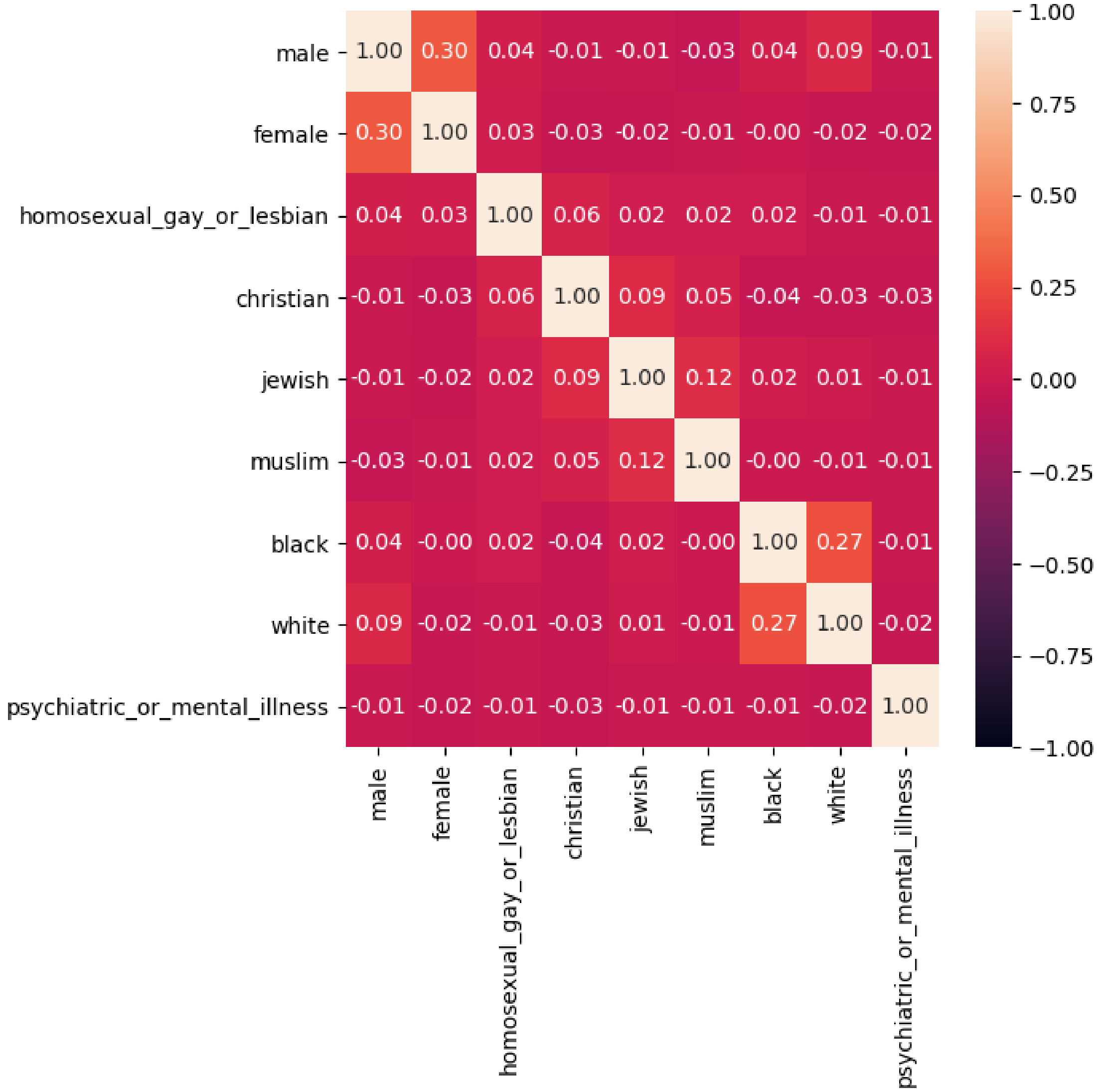
1.4 Identity Distribution

[35]:
```
for identity in selected_identities:
    counts = train_data[identity].sum()
    percentage = train_data[identity].sum() / train_data[identity].count() * 100
    print(f'{identity:<30}: {percentage:.2f}% , {counts}')
```

```
male                           : 2.46% , 44484
female                         : 2.96% , 53429
homosexual_gay_or_lesbian      : 0.61% , 10997
christian                      : 2.24% , 40423
jewish                         : 0.42% , 7651
muslim                         : 1.16% , 21006
black                          : 0.83% , 14901
white                          : 1.39% , 25082
psychiatric_or_mental_illness : 0.27% , 4889
```

[36]:
```
train['non_zero_selected_identity_counts'] = np.
 ↪count_nonzero(train_data[selected_identities], axis=1)
train.loc[train['identity_annotator_count'] == 0,␣
 ↪'non_zero_selected_identity_counts'] = np.NaN
selected_identity_corr = train_data.
 ↪loc[~train['non_zero_selected_identity_counts'].isna(), selected_identities].
 ↪corr()
```

[37]:
```
plt.style.use('default')

plt.figure(figsize=(6,6))
sns.heatmap(selected_identity_corr,
            vmin=-1, vmax=1, annot=True, fmt='.2f')
plt.show()
```

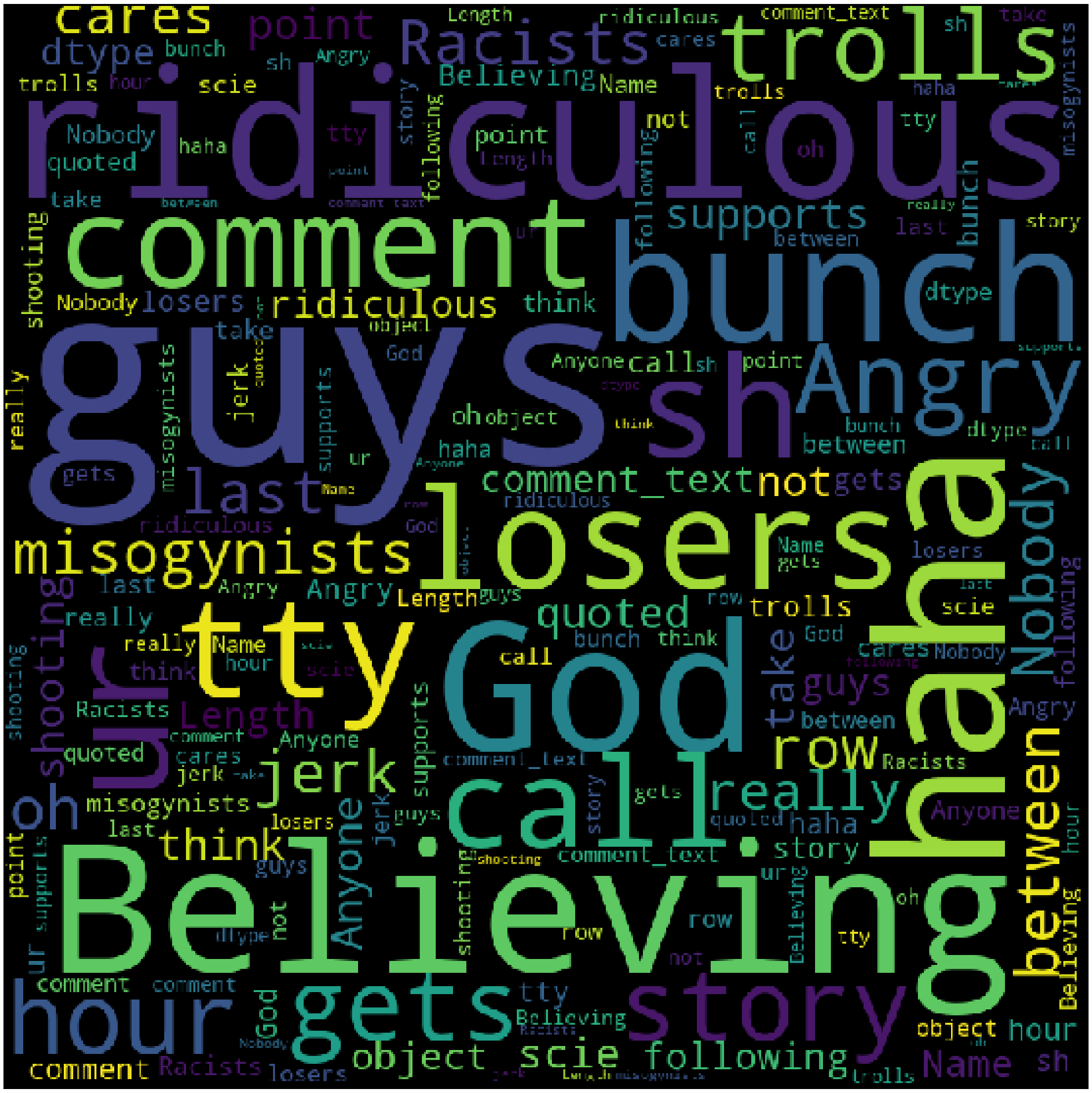


1.5 Word Cloud

[42]:
```
from wordcloud import WordCloud
def plot_word_cloud(comment,title):
    wordcloud = WordCloud(width = 800, height = 800,
                background_color ='black',
                stopwords = stopwords,
              min_font_size = 10,random_state=101,repeat=True).
 ↪generate(str(comment))

    # plot the WordCloud image
    plt.figure(figsize = (8, 8), facecolor = None)
    plt.title(title)
    plt.imshow(wordcloud)
    plt.axis("off")
    plt.tight_layout(pad = 0)
    plt.show()
```

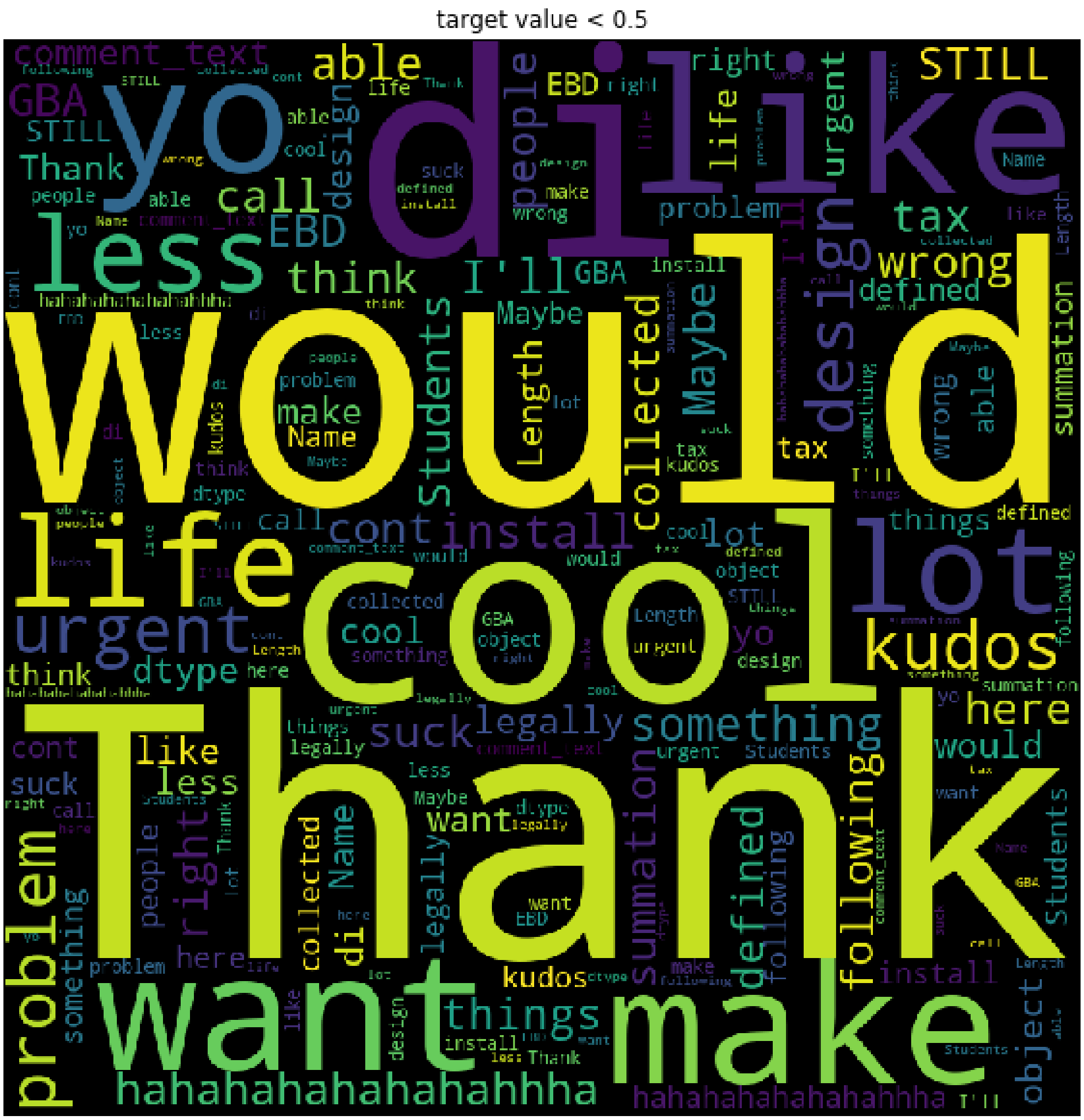
[43]:
```
plot_word_cloud(train_data.loc[train_data['target'] >= 0.5]['comment_text'],␣
 ↪'target value >= 0.5')
```

target value >= 0.5

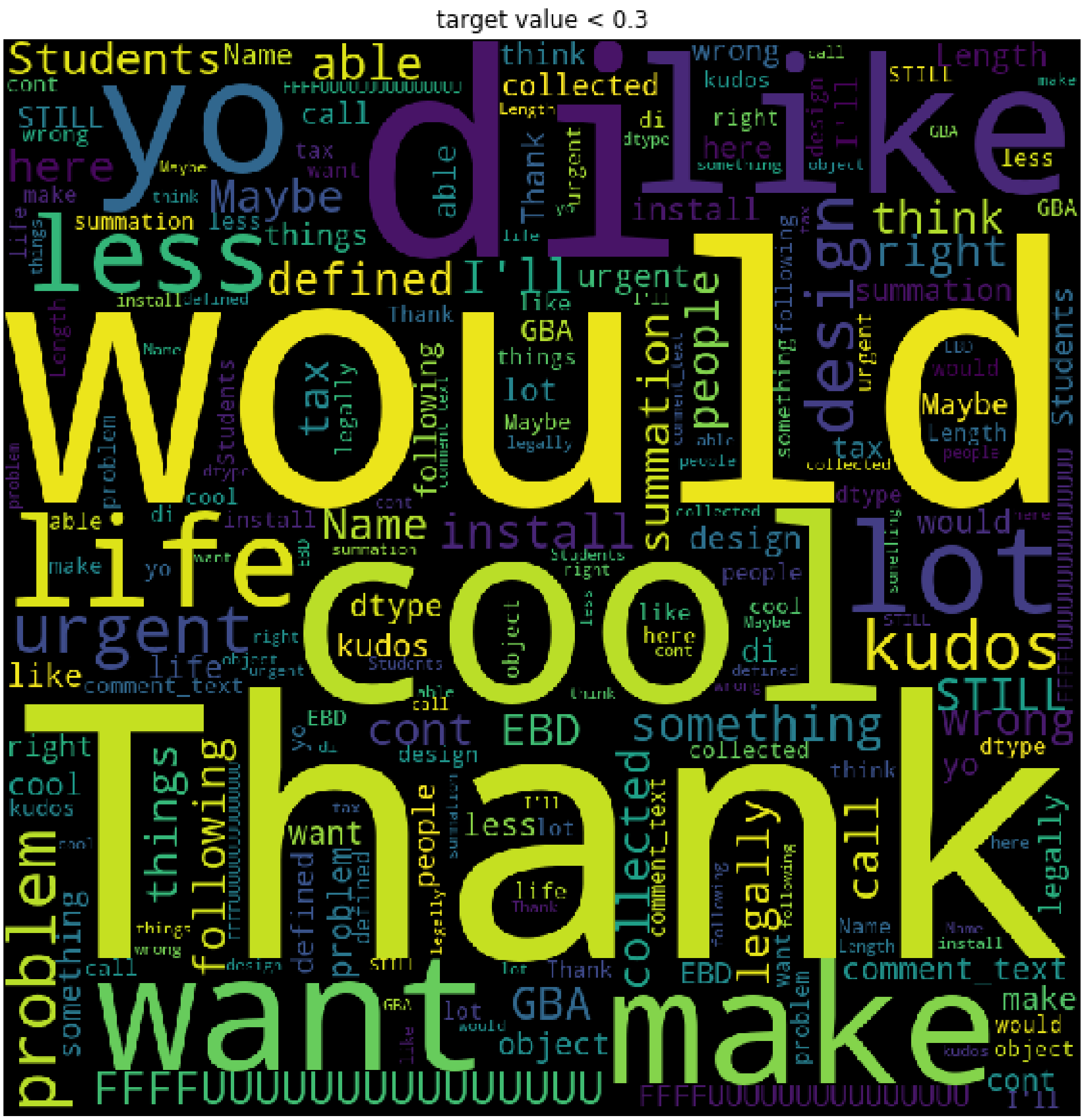


As we can see most used words having target >= 0.5 are slangs or related to religion or related to someone's behaviour and believes

[46]:
```
plot_word_cloud(train_data.loc[train_data['target'] < 0.5]['comment_text'],␣
 ↪'target value < 0.5')
```



[47]:
```
plot_word_cloud(train_data.loc[train_data['target'] < 0.3]['comment_text'], 'target value < 0.3')
```



most of the words used in comments having target<0.5 are normal english words that we use in our regular speaking. So we can say that our dataset doesnot has abnormal words i.e most probably toxic words and non toxic comments are labeled correctly.

[15]:
```
train_data_after_EDA =␣
↪train_data_filtered_bool[['id','comment_text','male','female','homosexual_gay_or_lesbian','
print(train_data_after_EDA.shape)
```

```
(1804874, 12)
```

[16]:
```
train_data_after_EDA.to_csv('train_data_after_EDA.csv')
```

2 Data Cleaning

[7]:
```python
def decontracted(phrase):
    # specific
    phrase = re.sub(r"won\'t", "will not", phrase)
    phrase = re.sub(r"can\'t", "can not", phrase)

    # general
    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)
    phrase = phrase.replace('\\r', ' ')
    phrase = phrase.replace('\\n', ' ')
    phrase = phrase.replace('\\"', ' ')
    phrase = re.sub('[^A-Za-z0-9]+', ' ', phrase)
    return phrase
```

[9]:
```python
def cleanComments(df, column):
    cleaned_comments = []
    lmtzr = WordNetLemmatizer()
    ps = PorterStemmer()
    for sentence in tqdm(df[column]):
        sent = decontracted(sentence)
        sent = ' '.join(e for e in sent.split() if e.lower() not in stopwords).
 ↪lower().strip()
# #         https://stackoverflow.com/questions/50685343/
 ↪how-to-lemmatize-a-list-of-sentences
# #         https://www.geeksforgeeks.org/python-stemming-words-with-nltk/
        sent = ' '.join(list(set(ps.stem(word) for word in␣
 ↪word_tokenize(sent))))
# #     https://www.geeksforgeeks.org/python-lemmatization-with-nltk/
        sent = ' '.join(list(set(lmtzr.lemmatize(word) for word in␣
 ↪word_tokenize(sent))))
        sent = ' '.join(e for e in sent.split() if e.lower() not in stopwords)
        cleaned_comments.append(sent)
    return cleaned_comments
```

[10]:
```python
cleaned_comments = cleanComments(train_data, 'comment_text')
cleaned_comments_test = cleanComments(test_data, 'comment_text')
```

```
100%|     | 1804874/1804874 [27:05<00:00, 1110.34it/s]
100%|     | 97320/97320 [01:27<00:00, 1107.66it/s]
```

[11]:
```
train_data['comment_text'] = cleaned_comments
test_data['comment_text'] = cleaned_comments_test
```

[12]:
```
train_data.comment_text.values[20383]
```

[12]: 'forward nicer littl peopl ok look pressur'

[13]:
```
train_data.comment_text.values[20000]
```

[13]: 'weapon start mr mani firearm take treat serious would becom cool peopl class order elrey around u publicli seriou tool requir carri agre seen fashion comfort god statement help'

[14]:
```
train_data.shape
```

[14]: (1804874, 45)

[15]:
```
train_data.to_csv('train_data_cleaned.csv', index_label=False)
test_data.to_csv('test_data_cleaned.csv', index_label=False)
```

[16]:
```
train_data=pd.read_csv('train_data_cleaned.csv')
test_data=pd.read_csv('test_data_cleaned.csv')
```

3 Train test split (80% - 20%)

using stratified sampling to avoid bias while splitting data

[17]:
```
train_data, validation_data = train_test_split(train_data, test_size=0.2,␣
 ↪stratify=train_data.target.values, random_state=2020)
print(train_data.shape)
print(validation_data.shape)
```

```
(1443899, 45)
(360975, 45)
```

Checking if test data is having approx same proportion of toxic comments compared to train data

[18]:
```
neg_train = train_data[train_data['target'] == True]
neg_train.shape
```

[18]: (115467, 45)

[19]:
```
neg_validation = validation_data[validation_data['target'] == True]
neg_validation.shape
```

[19]: (28867, 45)

[20]:
```
train_data.to_csv('train_data_splited.csv', index_label=False)
validation_data.to_csv('validation_data_splitted.csv', index_label=False)
```

[5]:
```
train_data=pd.read_csv('train_data_splited.csv')
validation_data=pd.read_csv('validation_data_splitted.csv')
test_data = pd.read_csv('test/test.csv')
```

[6]:
```
train_data.head()
```

[6]:
```
              id  target                                       comment_text  \
86452     348166   False  favorit equal one post misfortun part previou …
1156017  5529565   False                         justin abomin trudeau huge joke
111702    378780   False  www theguardian jun news 2015 http com count 0…
780699   5076044   False                           oh mainland higher tax mental
282234    587953   False  seen stock focus list valu fabric blinder clai…

         severe_toxicity  obscene  identity_attack   insult  threat  asian  \
86452           0.000000   0.0625         0.000000  0.18750     0.0    NaN
1156017         0.014493   0.0000         0.014493  0.42029     0.0    NaN
111702          0.000000   0.0000         0.000000  0.00000     0.0    NaN
780699          0.000000   0.0000         0.000000  0.00000     0.0    NaN
282234          0.000000   0.0000         0.000000  0.00000     0.0    NaN

         atheist  …  article_id    rating  funny  wow  sad  likes  disagree  \
86452        NaN  …      138562  approved      0    0    0      0         0
1156017      NaN  …      351636  rejected      0    0    0      0         0
111702       NaN  …      140837  approved      0    0    0      0         0
780699       NaN  …      323299  approved      0    1    0      0         0
282234       NaN  …      151058  approved      0    0    0      1         0

         sexual_explicit  identity_annotator_count  toxicity_annotator_count
86452           0.234375                         0                        64
1156017         0.000000                         0                        69
111702          0.000000                         0                         4
780699          0.000000                         0                         4
282234          0.000000                         0                         4

[5 rows x 45 columns]
```

[7]:
```
y_train = train_data['target']
y_validation = validation_data['target']
```

4 Defining Evaluation Metric

[8]:
```python
SUBGROUP_AUC = 'subgroup_auc'
BPSN_AUC = 'bpsn_auc'  # stands for background positive, subgroup negative
BNSP_AUC = 'bnsp_auc'  # stands for background negative, subgroup positive
identity_columns = [
    'male', 'female', 'homosexual_gay_or_lesbian', 'christian', 'jewish',
    'muslim', 'black', 'white', 'psychiatric_or_mental_illness']
def compute_auc(y_true, y_pred):
    try:
        return metrics.roc_auc_score(y_true, y_pred)
    except ValueError:
        return np.nan

def compute_subgroup_auc(df, subgroup, label, model_name):
    subgroup_examples = df[df[subgroup]]
    return compute_auc(subgroup_examples[label], subgroup_examples[model_name])

def compute_bpsn_auc(df, subgroup, label, model_name):
    """Computes the AUC of the within-subgroup negative examples and the␣
↪background positive examples."""
    subgroup_negative_examples = df[df[subgroup] & ~df[label]]
    non_subgroup_positive_examples = df[~df[subgroup] & df[label]]
    examples = subgroup_negative_examples.append(non_subgroup_positive_examples)
    return compute_auc(examples[label], examples[model_name])

def compute_bnsp_auc(df, subgroup, label, model_name):
    """Computes the AUC of the within-subgroup positive examples and the␣
↪background negative examples."""
    subgroup_positive_examples = df[df[subgroup] & df[label]]
    non_subgroup_negative_examples = df[~df[subgroup] & ~df[label]]
    examples = subgroup_positive_examples.append(non_subgroup_negative_examples)
    return compute_auc(examples[label], examples[model_name])

def compute_bias_metrics_for_model(dataset,
                                   subgroups,
                                   model,
                                   label_col,
                                   include_asegs=False):
    """Computes per-subgroup metrics for all subgroups and one model."""
    records = []
    for subgroup in subgroups:
        record = {
            'subgroup': subgroup,
            'subgroup_size': len(dataset[dataset[subgroup]])
        }
```

```
        record[SUBGROUP_AUC] = compute_subgroup_auc(dataset, subgroup,␣
↪label_col, model)
        record[BPSN_AUC] = compute_bpsn_auc(dataset, subgroup, label_col, model)
        record[BNSP_AUC] = compute_bnsp_auc(dataset, subgroup, label_col, model)
        records.append(record)
    return pd.DataFrame(records).sort_values('subgroup_auc', ascending=True)


# bias_metrics_df
```

[9]:
```
def calculate_overall_auc(df, model_name):
    true_labels = df['target']
    predicted_labels = df[model_name]
    return metrics.roc_auc_score(true_labels, predicted_labels)

def power_mean(series, p):
    total = sum(np.power(series, p))
    return np.power(total / len(series), 1 / p)

def get_final_metric(bias_df, overall_auc, POWER=-5, OVERALL_MODEL_WEIGHT=0.25):
    bias_score = np.average([
        power_mean(bias_df[SUBGROUP_AUC], POWER),
        power_mean(bias_df[BPSN_AUC], POWER),
        power_mean(bias_df[BNSP_AUC], POWER)
    ])
    return (OVERALL_MODEL_WEIGHT * overall_auc) + ((1 - OVERALL_MODEL_WEIGHT) *␣
↪bias_score)
def get_metric_value(validate_df, identity_columns, MODEL_NAME):
    bias_metrics_df = compute_bias_metrics_for_model(validate_df,␣
↪identity_columns, MODEL_NAME, 'target')
    return get_final_metric(bias_metrics_df, calculate_overall_auc(validate_df,␣
↪MODEL_NAME))
```

5 Machine Learning Models

5.1 Vectorizing Comment Text

[10]:
```
def vectorizeData(train, validation, test, vectorizing_method, dim,␣
↪n_gram_range):
    if vectorizing_method == 'bow':
        bow_vectorizer = CountVectorizer(ngram_range=n_gram_range, min_df=3,␣
↪max_df=0.9, max_features=dim)
        train_data_bow = bow_vectorizer.fit_transform(train)
        validation_data_bow = bow_vectorizer.transform(validation)
        test_data_bow = bow_vectorizer.transform(test)
```

```
        return train_data_bow, validation_data_bow, test_data_bow
    if vectorizing_method == 'tfidf':
        tfidf_vectorizer = TfidfVectorizer(ngram_range=n_gram_range, min_df=3,␣
↪max_df=0.9, max_features=dim)
        train_data_tfidf = tfidf_vectorizer.fit_transform(train)
        validation_data_tfidf = tfidf_vectorizer.transform(validation)
        test_data_tfidf = tfidf_vectorizer.transform(test)
        return train_data_tfidf, validation_data_tfidf, test_data_tfidf
```

[11]:
```
train_data['comment_text'] = train_data.comment_text.fillna('')
test_data['comment_text'] = test_data.comment_text.fillna('')
validation_data['comment_text'] = validation_data.comment_text.fillna('')
```

Considering 25000, 15000, 10000 dimentions

25000 top words in bow and tfidf

[12]:
```
train_comment_bow_25000, validation_comment_bow_25000, test_comment_bow_25000 =␣
↪vectorizeData(train_data['comment_text'], validation_data['comment_text'],␣
↪test_data['comment_text'], 'bow', 25000, (1,1))
print(f'train_bow : {train_comment_bow_25000.shape}')
print(f'validation_bow : {validation_comment_bow_25000.shape}')
print(f'test_bow : {test_comment_bow_25000.shape}')

train_comment_tfidf_25000, validation_comment_tfidf_25000,␣
↪test_comment_tfidf_25000 = vectorizeData(train_data['comment_text'],␣
↪validation_data['comment_text'], test_data['comment_text'], 'tfidf', 25000,␣
↪(1,1))
print(f'train_tfidf : {train_comment_tfidf_25000.shape}')
print(f'validation_tfidf : {validation_comment_tfidf_25000.shape}')
print(f'test_tfidf : {test_comment_tfidf_25000.shape}')
```

```
train_bow : (1443899, 25000)
validation_bow : (360975, 25000)
test_bow : (97320, 25000)
train_tfidf : (1443899, 25000)
validation_tfidf : (360975, 25000)
test_tfidf : (97320, 25000)
```

15000 top words in bow and tfidf

[13]:
```
train_comment_bow_15000, validation_comment_bow_15000, test_comment_bow_15000 =␣
↪vectorizeData(train_data['comment_text'], validation_data['comment_text'],␣
↪test_data['comment_text'], 'bow', 15000, (1,1))
print(f'train_bow : {train_comment_bow_15000.shape}')
print(f'validation_bow : {validation_comment_bow_15000.shape}')
```

```
print(f'test_bow : {test_comment_bow_15000.shape}')

train_comment_tfidf_15000, validation_comment_tfidf_15000,␣
↪test_comment_tfidf_15000 = vectorizeData(train_data['comment_text'],␣
↪validation_data['comment_text'], test_data['comment_text'], 'tfidf', 15000,␣
↪(1,1))
print(f'train_tfidf : {train_comment_tfidf_15000.shape}')
print(f'validation_tfidf : {validation_comment_tfidf_15000.shape}')
print(f'test_tfidf : {test_comment_tfidf_15000.shape}')
```

```
train_bow : (1443899, 15000)
validation_bow : (360975, 15000)
test_bow : (97320, 15000)
train_tfidf : (1443899, 15000)
validation_tfidf : (360975, 15000)
test_tfidf : (97320, 15000)
```

10000 top words in bow and tfidf

[14]:
```
train_comment_bow_10000, validation_comment_bow_10000, test_comment_bow_10000 =␣
↪vectorizeData(train_data['comment_text'], validation_data['comment_text'],␣
↪test_data['comment_text'], 'bow', 10000, (1,1))
print(f'train_bow : {train_comment_bow_10000.shape}')
print(f'validation_bow : {validation_comment_bow_10000.shape}')
print(f'test_bow : {test_comment_bow_10000.shape}')

train_comment_tfidf_10000, validation_comment_tfidf_10000,␣
↪test_comment_tfidf_10000 = vectorizeData(train_data['comment_text'],␣
↪validation_data['comment_text'], test_data['comment_text'], 'tfidf', 10000,␣
↪(1,1))
print(f'train_tfidf : {train_comment_tfidf_10000.shape}')
print(f'validation_tfidf : {validation_comment_tfidf_10000.shape}')
print(f'test_tfidf : {test_comment_tfidf_10000.shape}')
```

```
train_bow : (1443899, 10000)
validation_bow : (360975, 10000)
test_bow : (97320, 10000)
train_tfidf : (1443899, 10000)
validation_tfidf : (360975, 10000)
test_tfidf : (97320, 10000)
```

[17]:
```
#https://gist.github.com/shaypal5/94c53d765083101efc0240d776a23823
def plot_confusion_matrix(confusion_matrix, class_names, figsize = (6,4),␣
↪fontsize=14):
    df_cm = pd.DataFrame(
        confusion_matrix,index=class_names, columns=class_names
    )
```

```
    fig = plt.figure(figsize=figsize)
    heatmap = sns.heatmap(df_cm, annot=True, fmt="d")
    heatmap.yaxis.set_ticklabels(heatmap.yaxis.get_ticklabels(), rotation=0,␣
 ↪ha='right', fontsize=fontsize)
    heatmap.xaxis.set_ticklabels(heatmap.xaxis.get_ticklabels(), rotation=45,␣
 ↪ha='right', fontsize=fontsize)
    plt.ylabel('Actual label')
    plt.xlabel('Predicted label')
```

[18]:
```
# we are writing our own function for predict, with defined thresould
# we will pick a threshold that will give the least fpr

# (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is very high
# print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for threshold",␣
 ↪np.round(t,3))
def predict_with_best_t(proba, tpr, fpr, threshould):
    t = threshould[np.argmax(tpr*(1-fpr))]
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

Models we are going to try

Naive Bayes

Logistic Regression (SGD with 'log' loss)

SVM (SGD with 'hinge' loss)

XG-Boost

TabdomForestClassifier

Stacking above based on confusion matrix

5.1.1 Naive Bayes

Considering BOW featues

25000 features

[31]:
```
alpha = [1e-09, 1e-07, 1e-05, 1e-03, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
```

```python
for param in tqdm(alpha):
    MODEL_NAME = f'NB-BOW_25k_{param}'
    clf = MultinomialNB(alpha=param)
    clf.fit(train_comment_bow_25000, y_train)
    predicted_train = clf.predict_proba(train_comment_bow_25000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_bow_25000)[:,1]
    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|      | 6/6 [01:08<00:00, 11.49s/it]
```

[32]:
```python
import gc
gc.collect()
```

[32]: 20

[33]:
```python
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

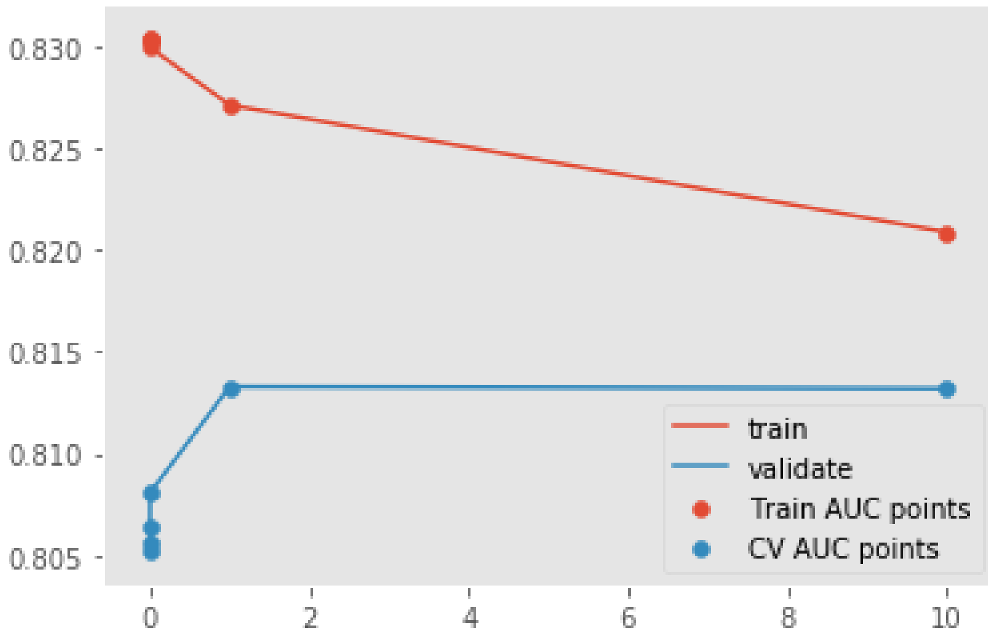
[33]:

	name	train_score	test_score
0	NB-BOW_25k_1e-09	0.830385	0.805230
1	NB-BOW_25k_1e-07	0.830369	0.805561
2	NB-BOW_25k_1e-05	0.830297	0.806373
3	NB-BOW_25k_0.001	0.829962	0.808092
5	NB-BOW_25k_10	0.820896	0.813198
4	NB-BOW_25k_1	0.827153	0.813289

[34]:
```python
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8303848235597261, 0.8303685885882189, 0.8302966785002497, 0.829961728468076,
0.827152860228968, 0.8208963212816531] [0.8052299001325809, 0.8055613532368453,
```

```
0.8063728503898459, 0.8080922245271929, 0.8132894711382146, 0.8131982861162018]
best hyperparameter got = NB-BOW_25k_1 ##### Best cv score got =
0.8132894711382146
```



[35]:
```
MODEL_NAME = 'NB_BOW_25k'
clf = MultinomialNB(alpha=1)
clf.fit(train_comment_bow_25000, y_train)
predicted_train = clf.predict_proba(train_comment_bow_25000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_bow_25000)[:,1]
```

[36]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.827152860228968
Validation score = 0.8132894711382146
```

[37]:
```
predicted_test = clf.predict_proba(test_comment_bow_25000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/NB_BOW_25k_submission.csv', index=False)
```

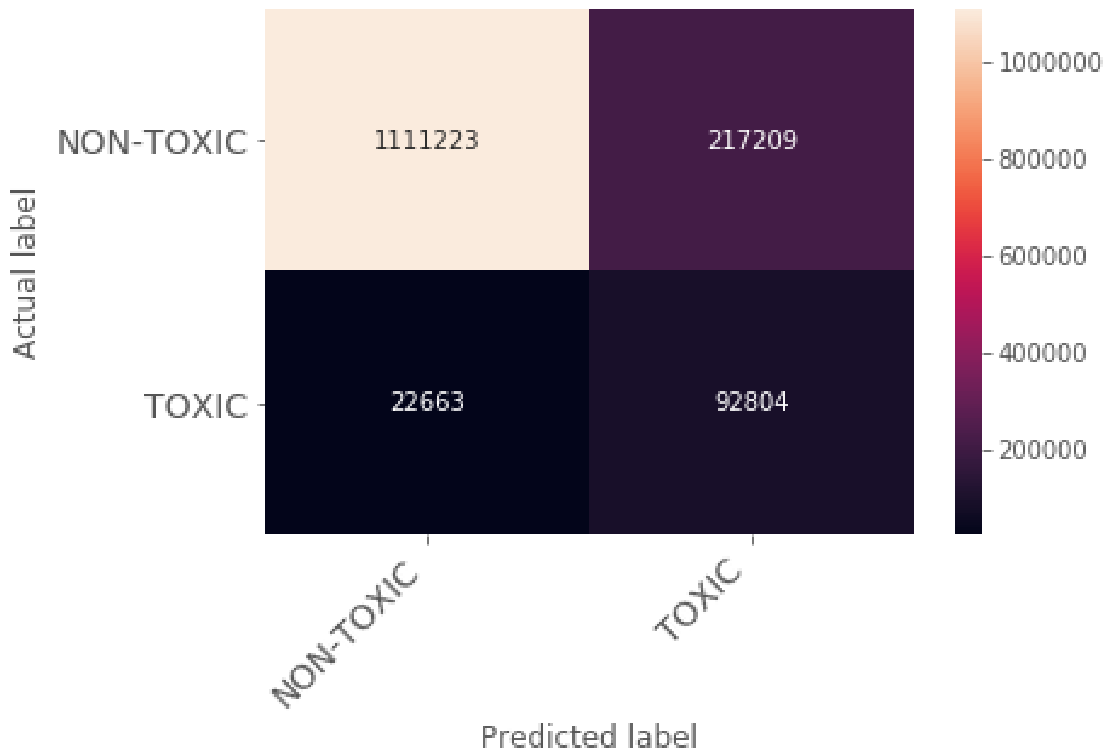
[38]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
```

```
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[39]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
```

```
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

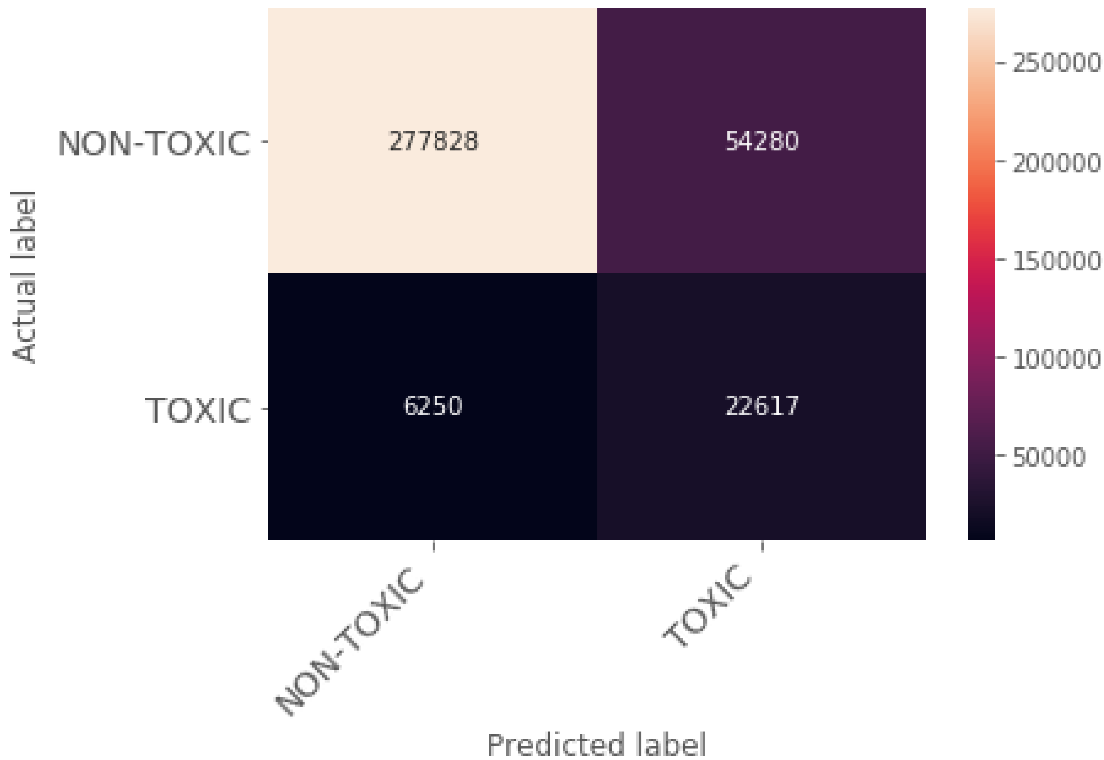
```
	TRAIN DATA CONFUSION MATRIX
```



=> 83.64 % of non-toxic comments predicted correctly => 80.37% of toxic comments predicted correctly

[40]:
```
pred_test =␣
↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 83.65 % of non-toxic comments predicted correctly => 78.37% of toxic comments predicted correctly

15000 features

[41]:
```
alpha = [1e-09, 1e-07, 1e-05, 1e-03, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'NB-BOW_15k_{param}'
    clf = MultinomialNB(alpha=param)
    clf.fit(train_comment_bow_15000, y_train)
    predicted_train = clf.predict_proba(train_comment_bow_15000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_bow_15000)[:,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
```

```
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|          | 6/6 [01:11<00:00, 11.86s/it]
```

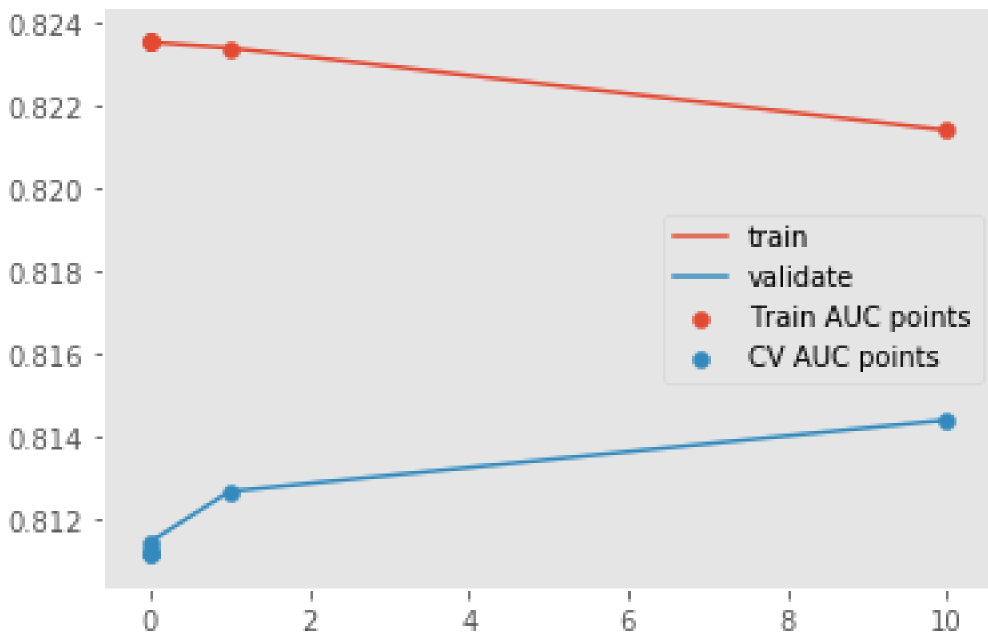
[42]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[42]:

	name	train_score	test_score
0	NB-BOW_15k_1e-09	0.823568	0.811151
1	NB-BOW_15k_1e-07	0.823568	0.811177
2	NB-BOW_15k_1e-05	0.823565	0.811245
3	NB-BOW_15k_0.001	0.823551	0.811434
4	NB-BOW_15k_1	0.823416	0.812662
5	NB-BOW_15k_10	0.821424	0.814395

[43]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8235684449002456, 0.8235677783155043, 0.8235650158577439, 0.8235510348300056,
0.8234156579630094, 0.8214236834988156] [0.811151273030675, 0.8111772725244157,
0.8112452836045302, 0.8114336536220598, 0.8126621147166926, 0.8143945561931168]
best hyperparameter got = NB-BOW_15k_10 ##### Best cv score got =
0.8143945561931168
```




```
[44]: MODEL_NAME = 'NB_BOW_15k'
clf = MultinomialNB(alpha=10)
clf.fit(train_comment_bow_15000, y_train)
predicted_train = clf.predict_proba(train_comment_bow_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_bow_15000)[:,1]
```

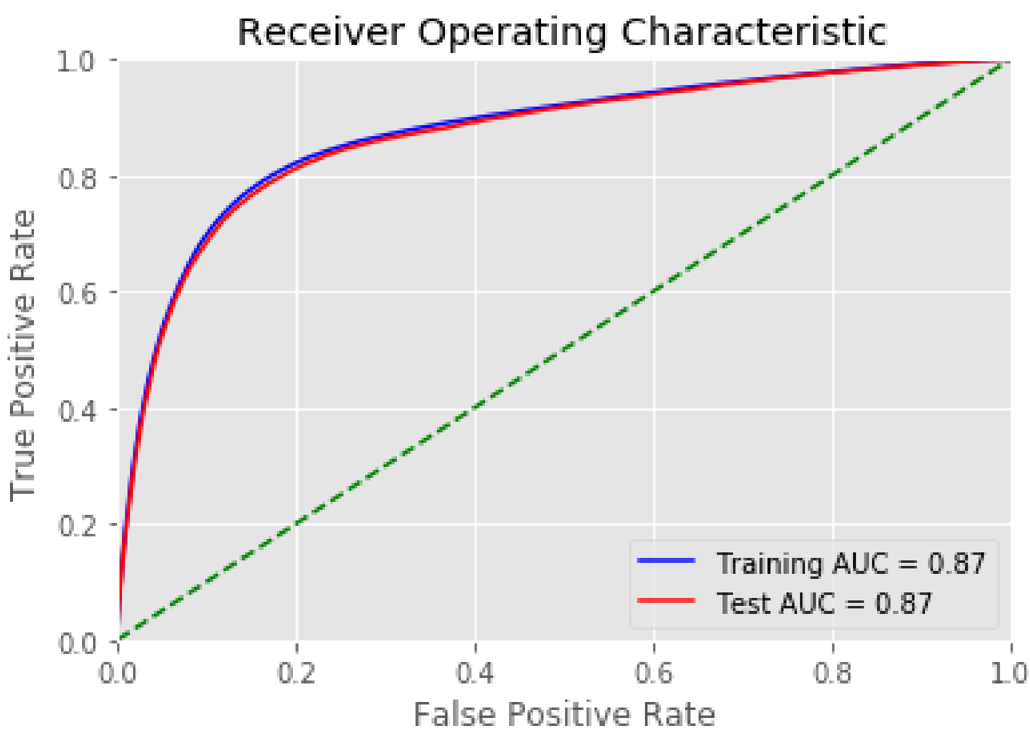
```
[45]: train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.8214236834988156
Validation score = 0.8143945561931168
```

```
[46]: predicted_test = clf.predict_proba(test_comment_bow_15000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/NB_BOW_15k_submission.csv', index=False)
```

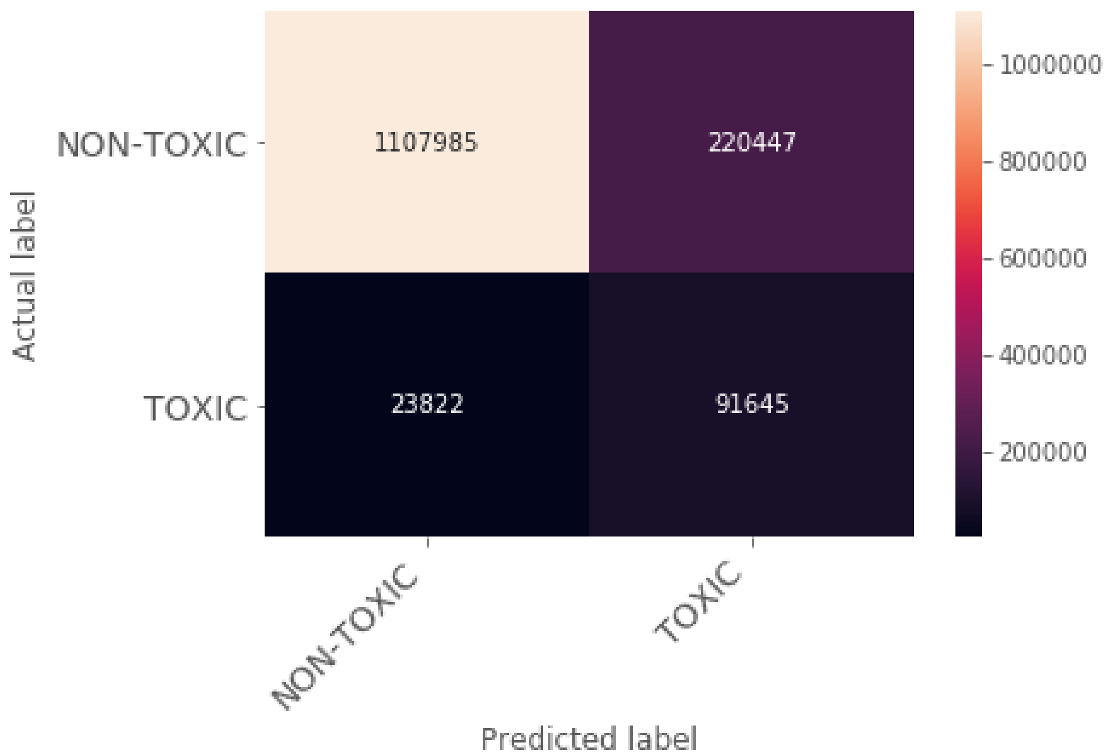
```
[47]: # https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
```

```
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[48]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

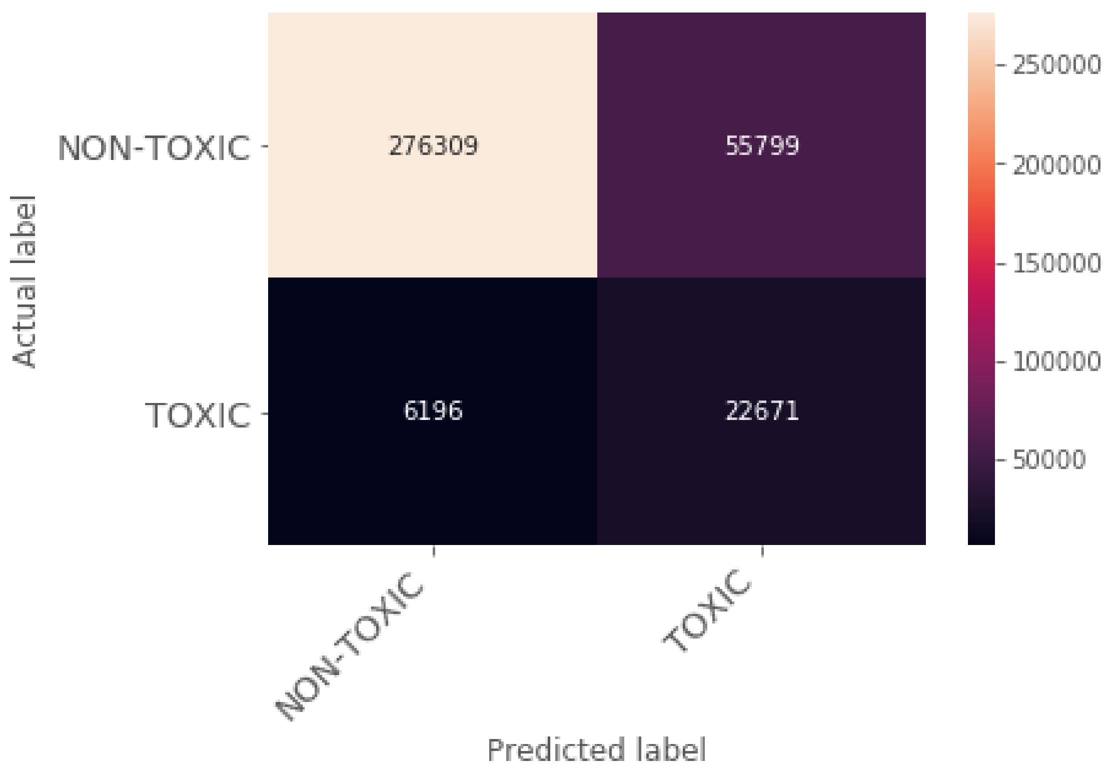
```
TRAIN DATA CONFUSION MATRIX
```



=> 83.64 % of non-toxic comments predicted correctly => 80.37% of toxic comments predicted correctly

[49]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
test DATA CONFUSION MATRIX
```



=> 83.64 % of non-toxic comments predicted correctly => 80.37% of toxic comments predicted correctly

10000 features

[50]:
```
alpha = [1e-09, 1e-07, 1e-05, 1e-03, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'NB-BOW_10k_{param}'
    clf = MultinomialNB(alpha=param)
    clf.fit(train_comment_bow_10000, y_train)
    predicted_train = clf.predict_proba(train_comment_bow_10000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_bow_10000)[:,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME))
```

```
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|          | 6/6 [01:16<00:00, 12.79s/it]
```

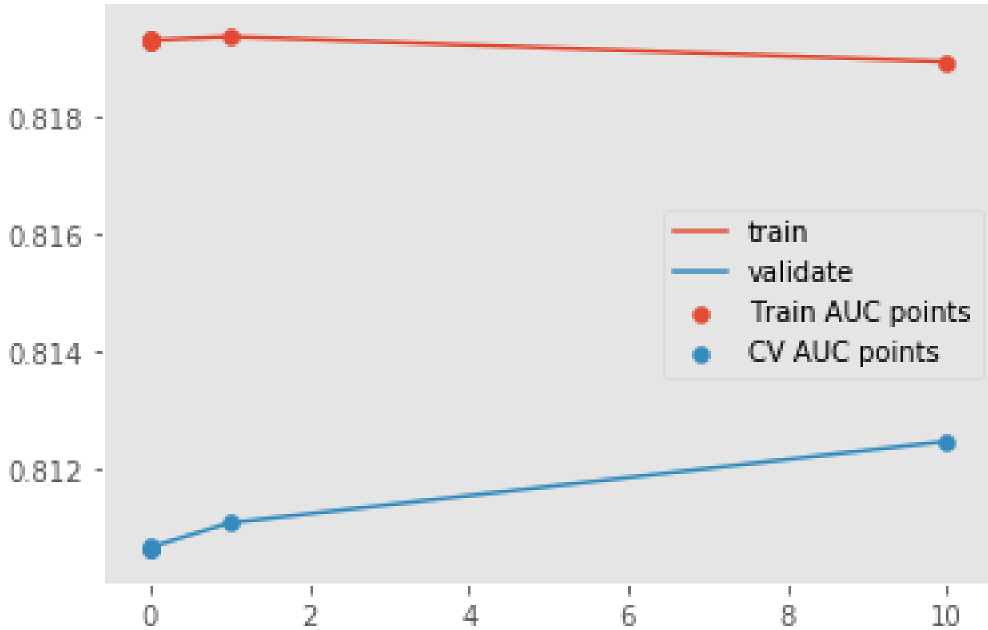
[51]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[51]:

	name	train_score	test_score
0	NB-BOW_10k_1e-09	0.819319	0.810637
1	NB-BOW_10k_1e-07	0.819319	0.810639
2	NB-BOW_10k_1e-05	0.819319	0.810644
3	NB-BOW_10k_0.001	0.819316	0.810660
4	NB-BOW_10k_1	0.819380	0.811077
5	NB-BOW_10k_10	0.818952	0.812470

[52]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8193192247971082, 0.8193191310344902, 0.8193187500257502, 0.8193163314649758,
0.8193802291582439, 0.8189522244639298] [0.8106369318316213, 0.8106388164386731,
0.8106442853842235, 0.8106595574355672, 0.8110768916283557, 0.8124702812251251]
best hyperparameter got = NB-BOW_10k_10 ##### Best cv score got =
0.8124702812251251
```



[53]:
```
MODEL_NAME = 'NB_BOW_10k'
clf = MultinomialNB(alpha=1)
clf.fit(train_comment_bow_10000, y_train)
predicted_train = clf.predict_proba(train_comment_bow_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_bow_10000)[:,1]
```

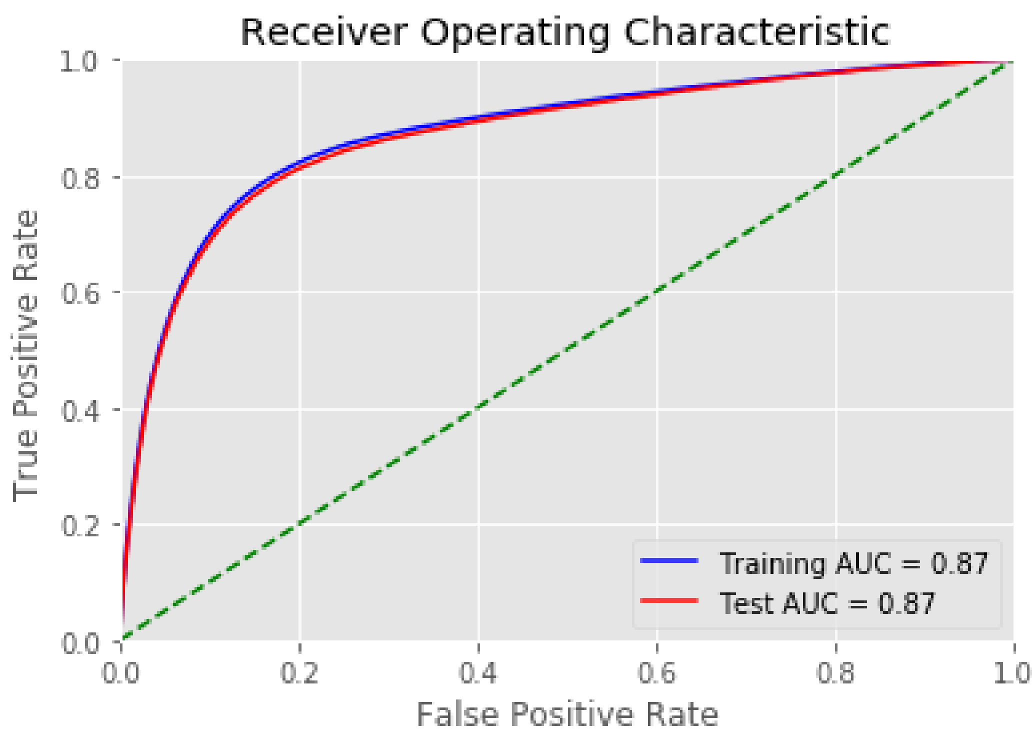
[54]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.8193802291582439
Validation score = 0.8110768916283557
```

[55]:
```
predicted_test = clf.predict_proba(test_comment_bow_10000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/NB_BOW_10k_submission.csv', index=False)
```

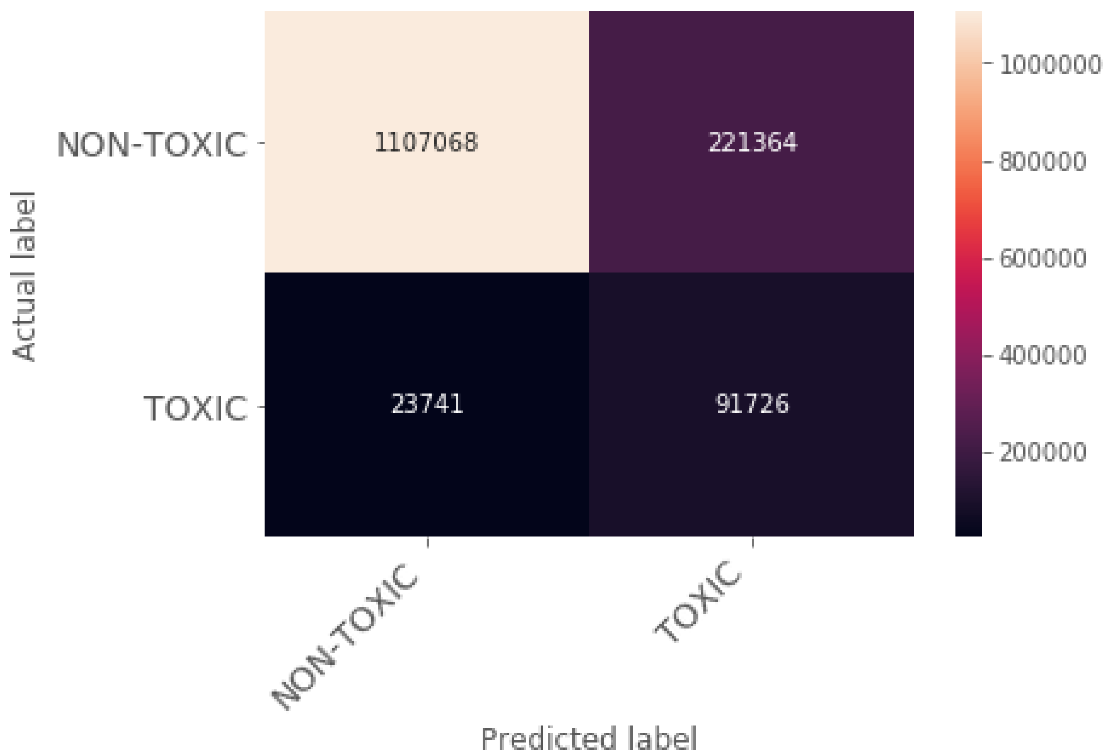
[56]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
```

```
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[57]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

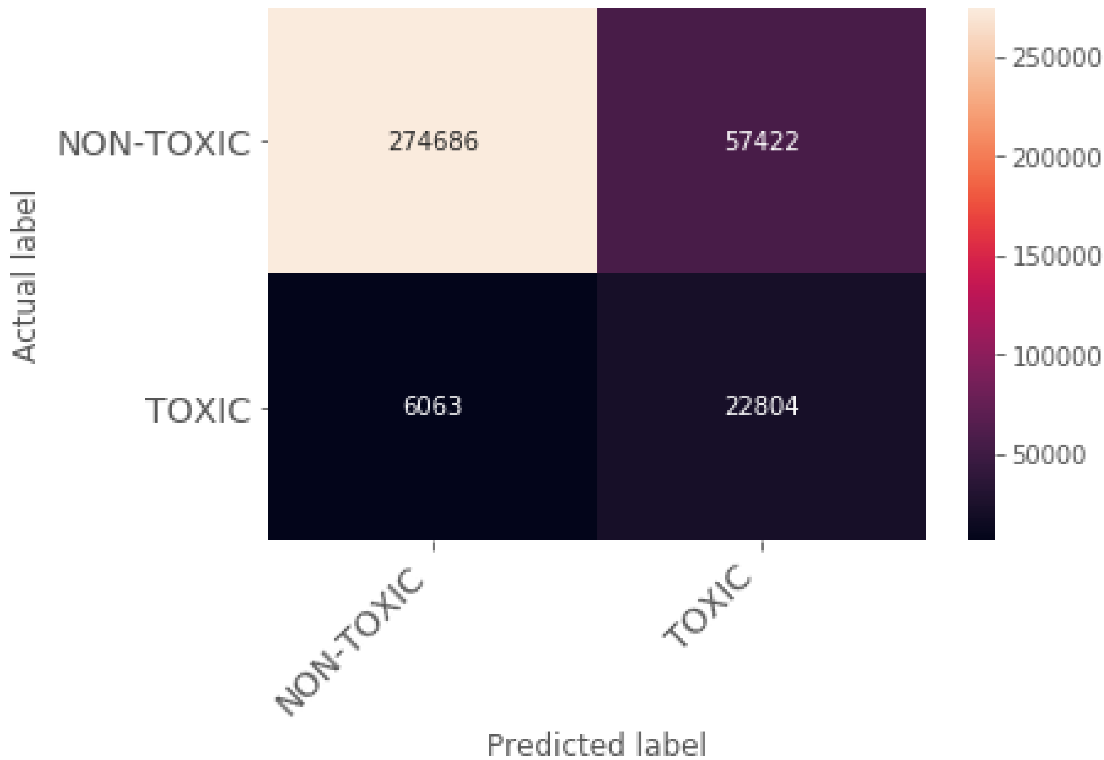
TRAIN DATA CONFUSION MATRIX



=> 83.64 % of non-toxic comments predicted correctly => 80.37% of toxic comments predicted correctly

[58]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

test DATA CONFUSION MATRIX



=> 83.64 % of non-toxic comments predicted correctly => 80.37% of toxic comments predicted correctly

Considering TFIDF

25000 features

[59]:
```
alpha = [1e-09, 1e-07, 1e-05, 1e-03, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'NB-tfidf_25k_{param}'
    clf = MultinomialNB(alpha=param)
    clf.fit(train_comment_tfidf_25000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_25000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_25000)[:
 ↪,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation
```

```
    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

100%| | 6/6 [01:19<00:00, 13.22s/it]

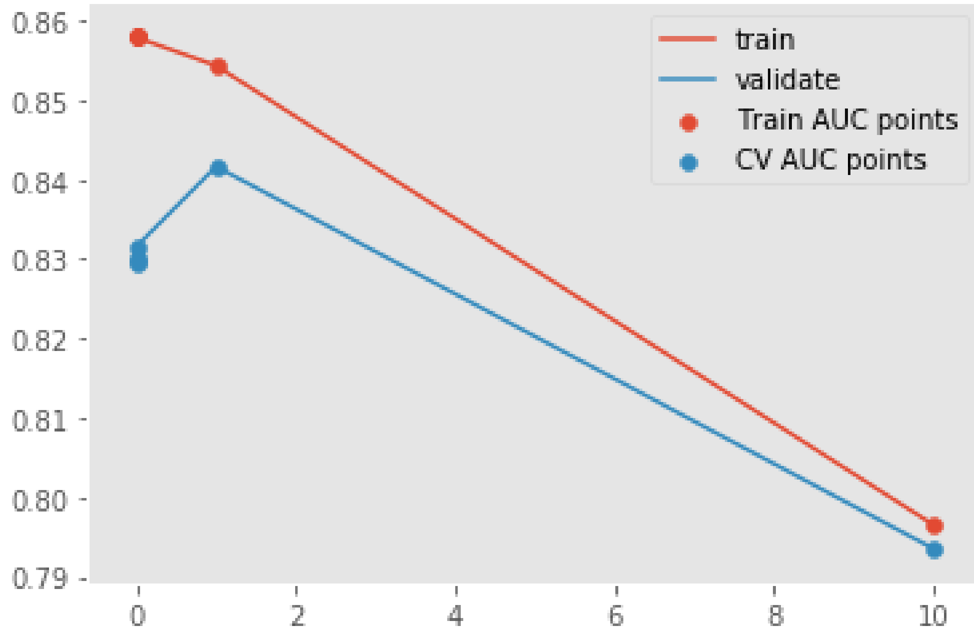
[60]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[60]:

	name	train_score	test_score
5	NB-tfidf_25k_10	0.796550	0.793550
0	NB-tfidf_25k_1e-09	0.858006	0.829614
1	NB-tfidf_25k_1e-07	0.858005	0.829701
2	NB-tfidf_25k_1e-05	0.857992	0.830077
3	NB-tfidf_25k_0.001	0.857891	0.831597
4	NB-tfidf_25k_1	0.854349	0.841650

[61]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8580058604880463, 0.8580045470157118, 0.8579923573881973, 0.8578913522811471,
0.8543485224611782, 0.7965498426042015] [0.8296141165672792, 0.829700624425765,
0.8300772749678597, 0.831597373696867, 0.841650375369775, 0.7935504787284842]
best hyperparameter got = NB-tfidf_25k_1 ##### Best cv score got =
0.841650375369775
```



[62]:
```
MODEL_NAME = 'NB_tfidf_25k'
clf = MultinomialNB(alpha=1)
clf.fit(train_comment_tfidf_25000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_25000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_25000)[:,1]
```

[63]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

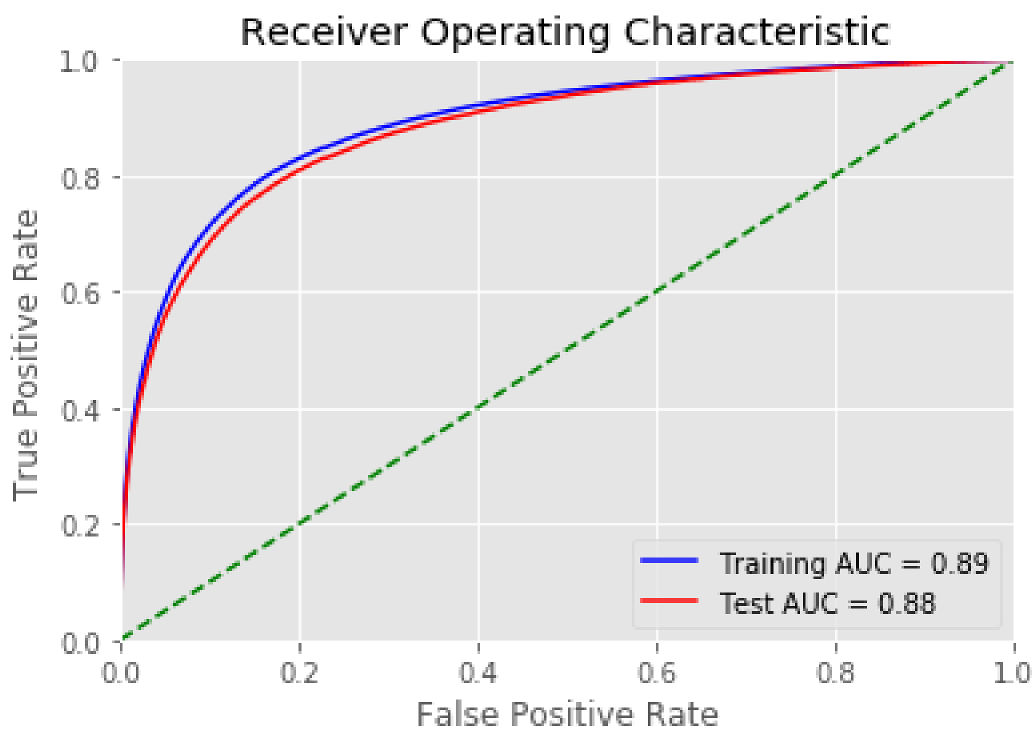
```
Train score = 0.8543485224611782
Validation score = 0.841650375369775
```

[64]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_25000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/NB_tfidf_25k_submission.csv', index=False)
```

[ ]:
```

```

[65]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)
```

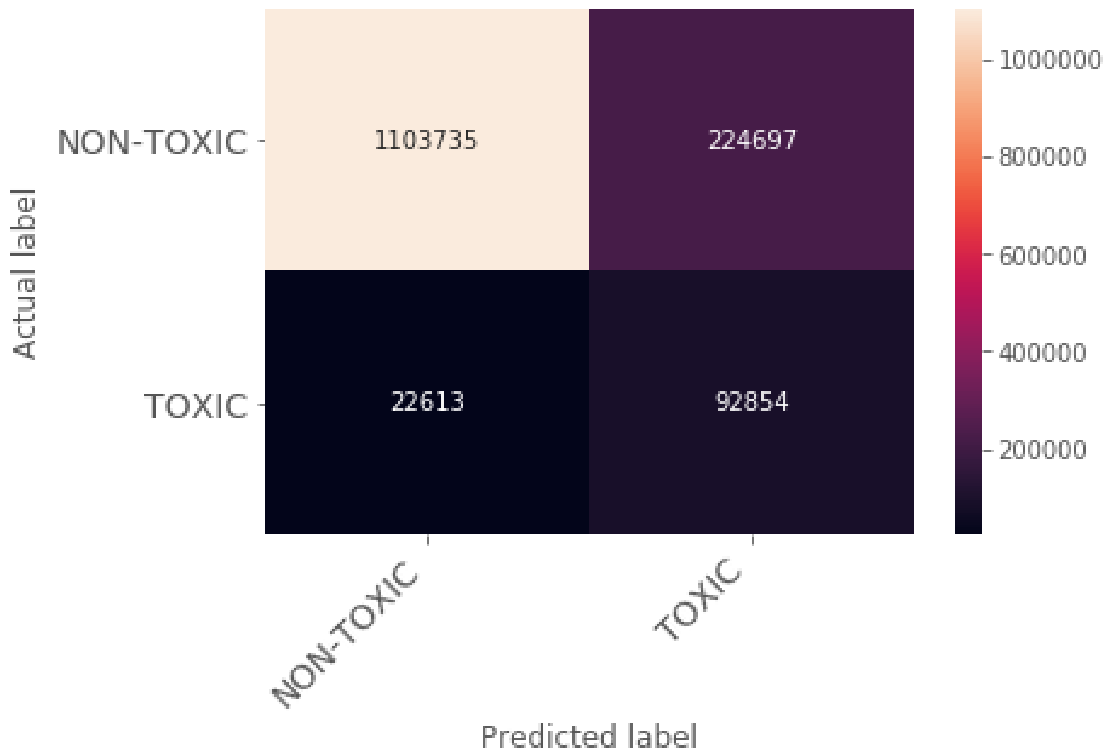
```
roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[66]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
```

```
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

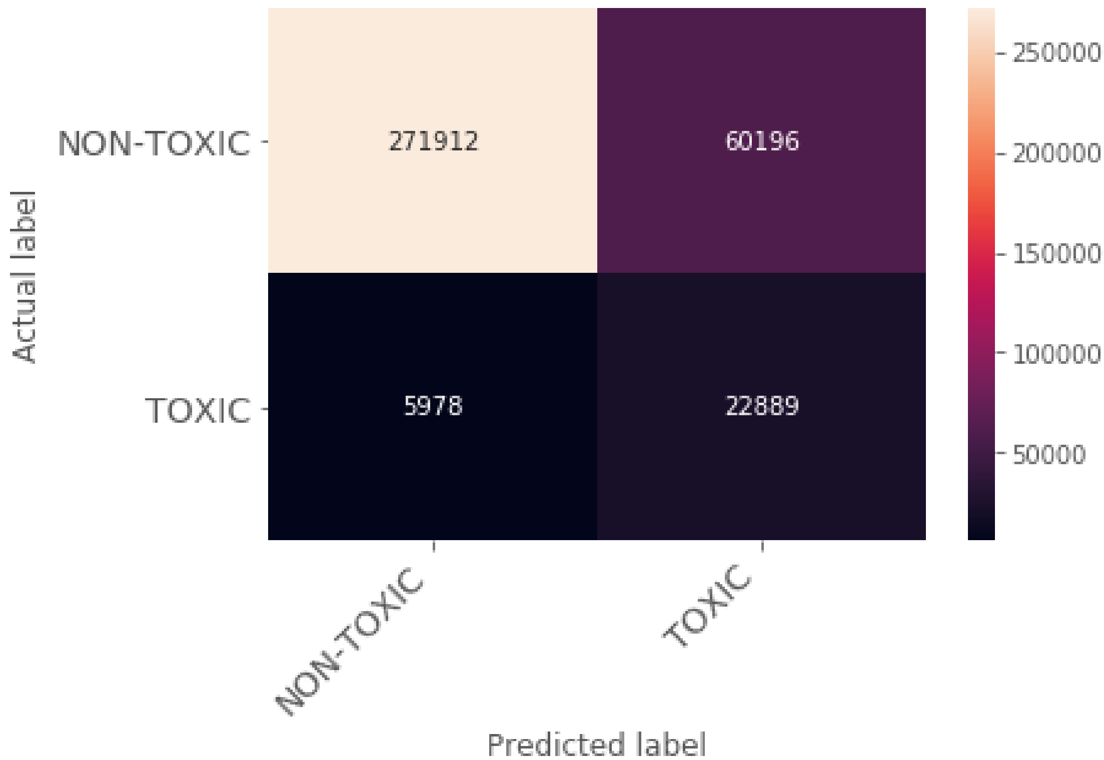
```
	TRAIN DATA CONFUSION MATRIX
```



=> 83.08 % of non-toxic comments predicted correctly => 80.37% of toxic comments predicted correctly

[67]:
```
pred_test = ␣
↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 83.64 % of non-toxic comments predicted correctly => 81.37% of toxic comments predicted correctly

15000 features

[68]:
```
alpha = [1e-09, 1e-07, 1e-05, 1e-03, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []##### 25000 features
for param in tqdm(alpha):
    MODEL_NAME = f'NB-tfidf_15k_{param}'
    clf = MultinomialNB(alpha=param)
    clf.fit(train_comment_tfidf_15000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:
 ↪,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME))
```

```
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|          | 6/6 [01:20<00:00, 13.44s/it]
```

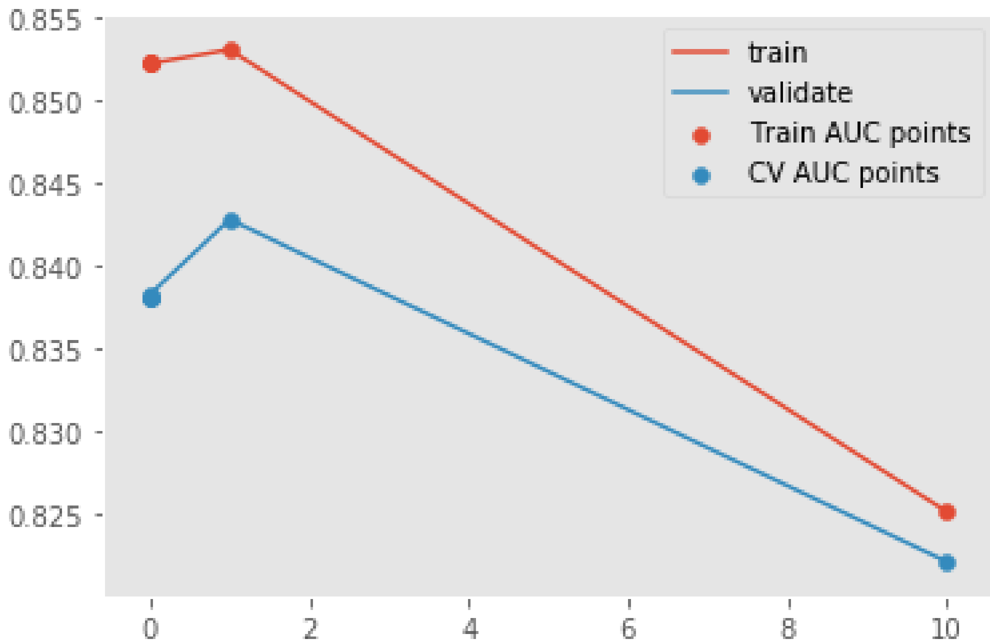
[69]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[69]:

	name	train_score	test_score
5	NB-tfidf_15k_10	0.825208	0.822186
0	NB-tfidf_15k_1e-09	0.852262	0.838132
1	NB-tfidf_15k_1e-07	0.852262	0.838139
2	NB-tfidf_15k_1e-05	0.852261	0.838179
3	NB-tfidf_15k_0.001	0.852260	0.838334
4	NB-tfidf_15k_1	0.853095	0.842844

[70]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8522619696619693, 0.8522619191058425, 0.8522614506947731, 0.8522597430300503,
0.8530951191819393, 0.8252077260229658] [0.8381319855023279, 0.8381391608991691,
0.8381789805232116, 0.8383343802973273, 0.8428440899522812, 0.8221860833729862]
best hyperparameter got = NB-tfidf_15k_1 ##### Best cv score got =
0.8428440899522812
```



[71]:
```
MODEL_NAME = 'NB_tfidf_15k'
clf = MultinomialNB(alpha=1)
clf.fit(train_comment_tfidf_15000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:,1]
```

[72]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.8530951191819393
Validation score = 0.8428440899522812
```

[73]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_15000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/NB_tfidf_15k_submission.csv', index=False)
```

[ ]:
```

```

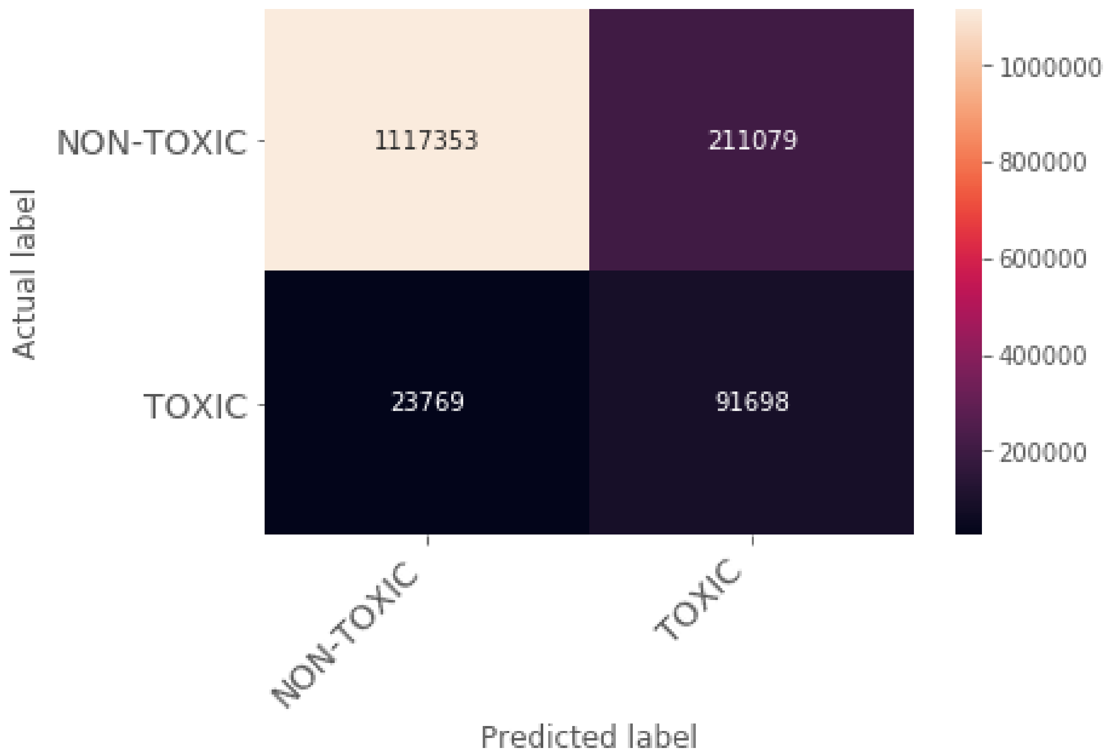
[74]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
```

```
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[75]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
```

```
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

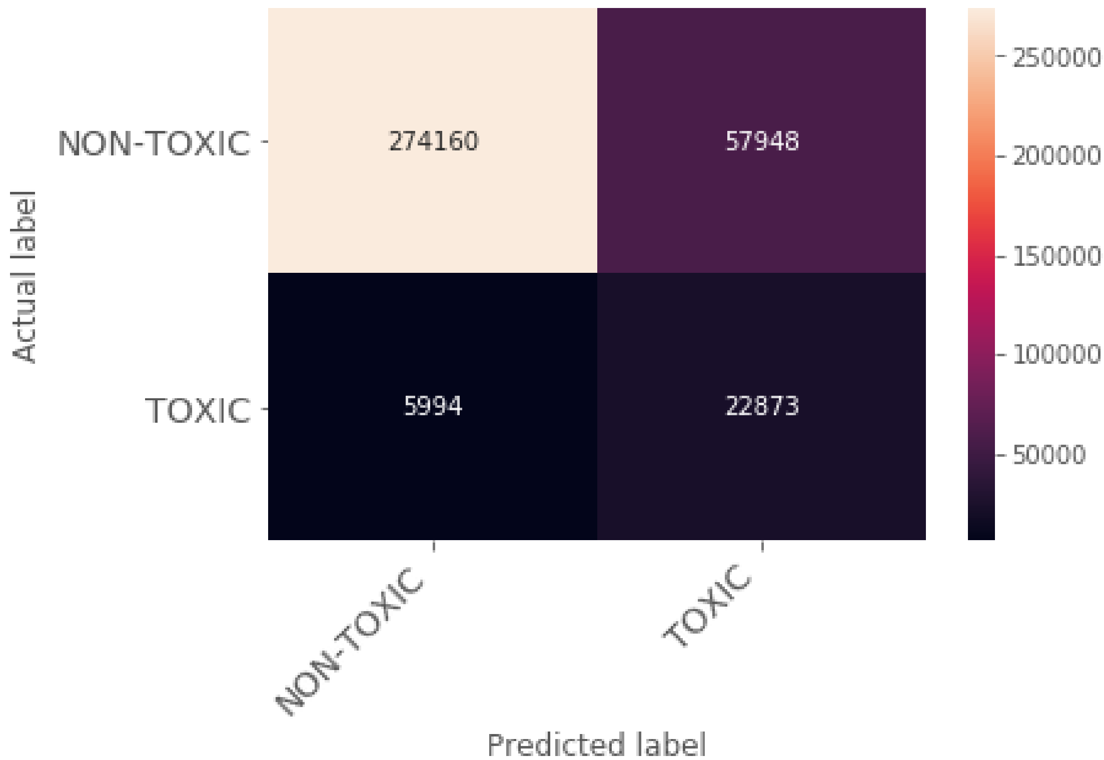
```
	TRAIN DATA CONFUSION MATRIX
```



=> 84.11 % of non-toxic comments predicted correctly => 79.41% of toxic comments predicted correctly

[76]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 82.55% of non-toxic comments predicted correctly => 79.73% of toxic comments predicted correctly

10000 features

[77]:
```
alpha = [1e-09, 1e-07, 1e-05, 1e-03, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []##### 25000 features
for param in tqdm(alpha):
    MODEL_NAME = f'NB-tfidf_10k_{param}'
    clf = MultinomialNB(alpha=param)
    clf.fit(train_comment_tfidf_10000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:
 ↪,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME))
```

```
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|          | 6/6 [01:23<00:00, 13.96s/it]
```

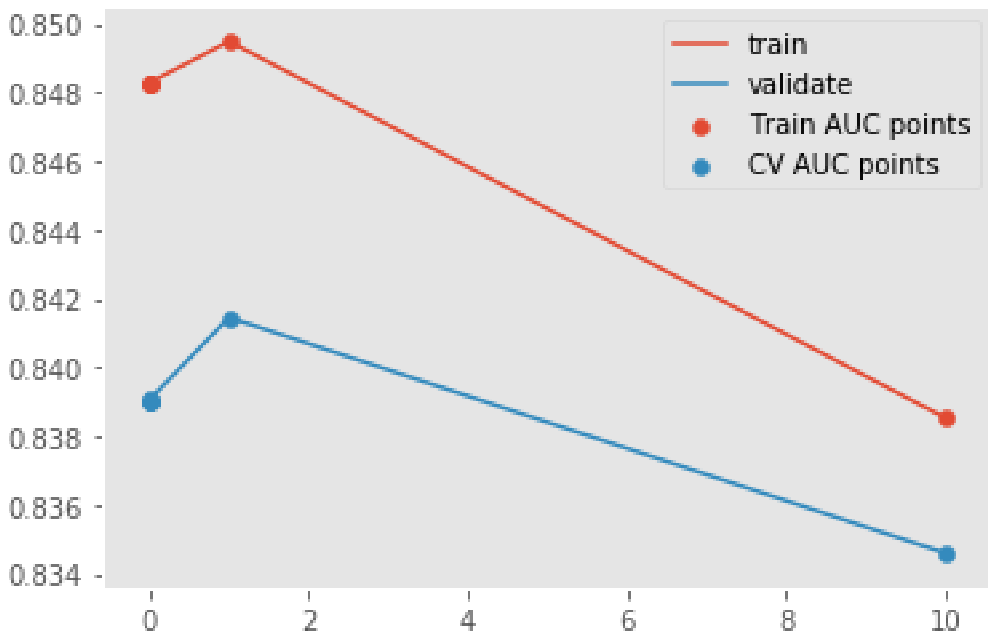
[78]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[78]:

	name	train_score	test_score
5	NB-tfidf_10k_10	0.838529	0.834594
0	NB-tfidf_10k_1e-09	0.848289	0.839049
1	NB-tfidf_10k_1e-07	0.848289	0.839049
2	NB-tfidf_10k_1e-05	0.848289	0.839050
3	NB-tfidf_10k_0.001	0.848290	0.839067
4	NB-tfidf_10k_1	0.849492	0.841459

[79]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8482890240897429, 0.848289017167702, 0.8482889367196303, 0.8482898011152245,
0.8494916500190987, 0.8385287368673903] [0.839048724447654, 0.83904880083159,
0.8390503286699291, 0.8390668321924513, 0.8414590279205327, 0.8345943754450087]
best hyperparameter got = NB-tfidf_10k_1 ##### Best cv score got =
0.8414590279205327
```



[80]:
```
MODEL_NAME = 'NB_tfidf_10k'
clf = MultinomialNB(alpha=1)
clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]
```

[81]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

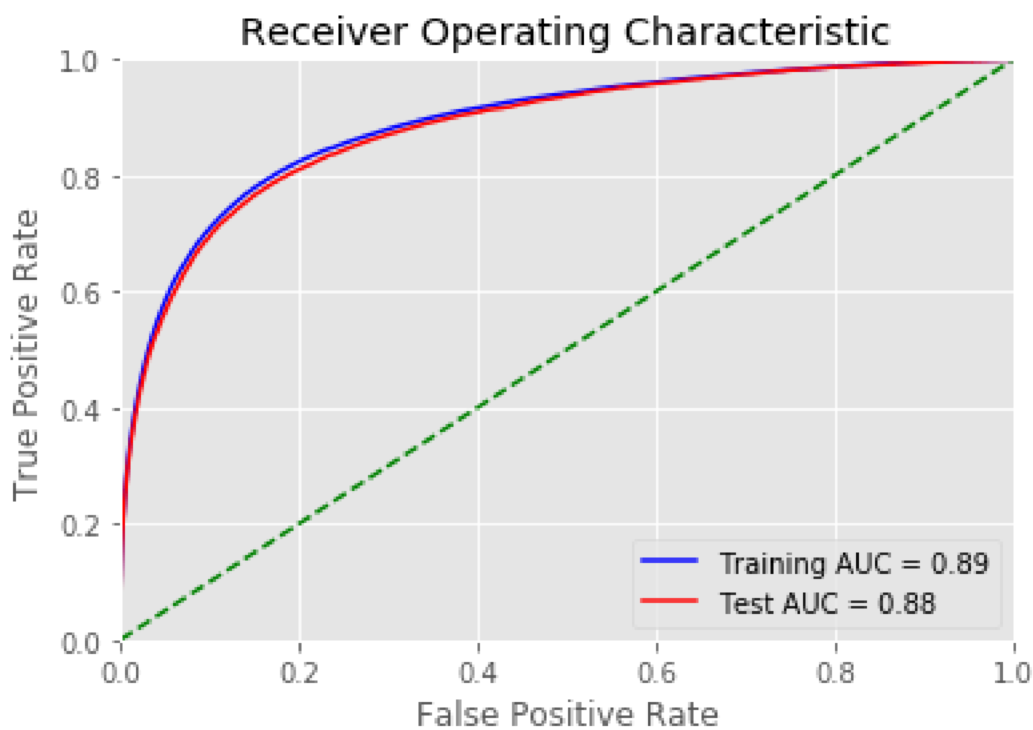
```
Train score = 0.8494916500190987
Validation score = 0.8414590279205327
```

[82]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_10000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/NB_tfidf_10k_submission.csv', index=False)
```

[ ]:
```
```

[83]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)
```

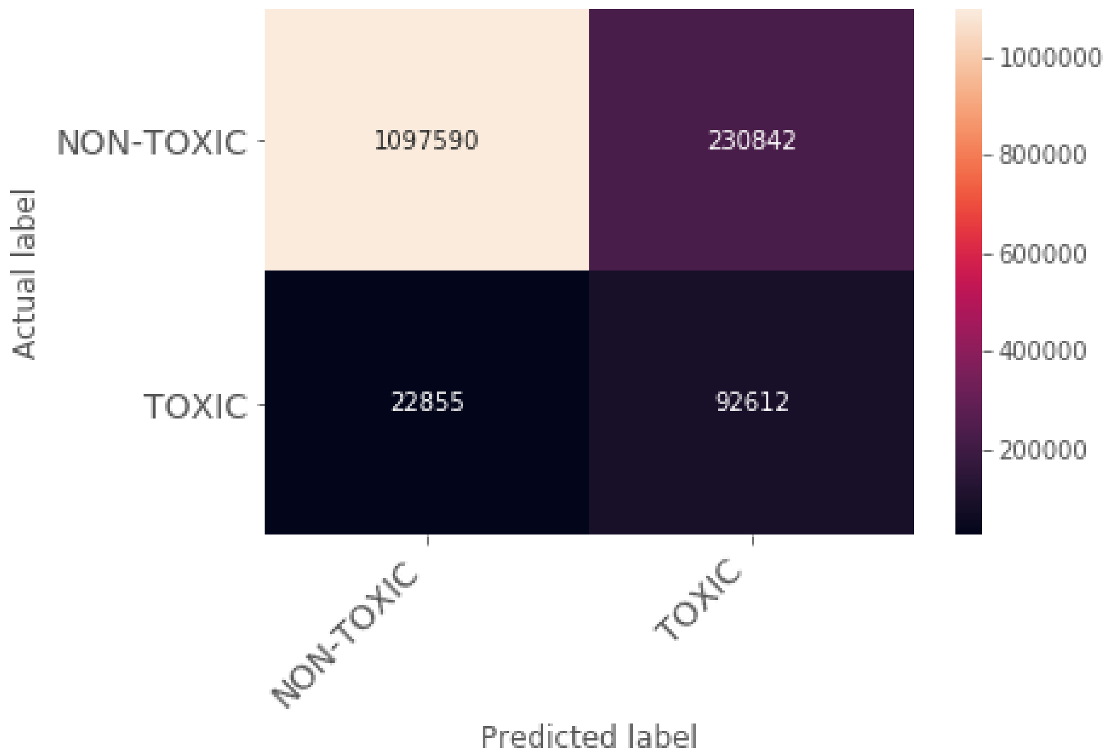
```
roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[84]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
```

```
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

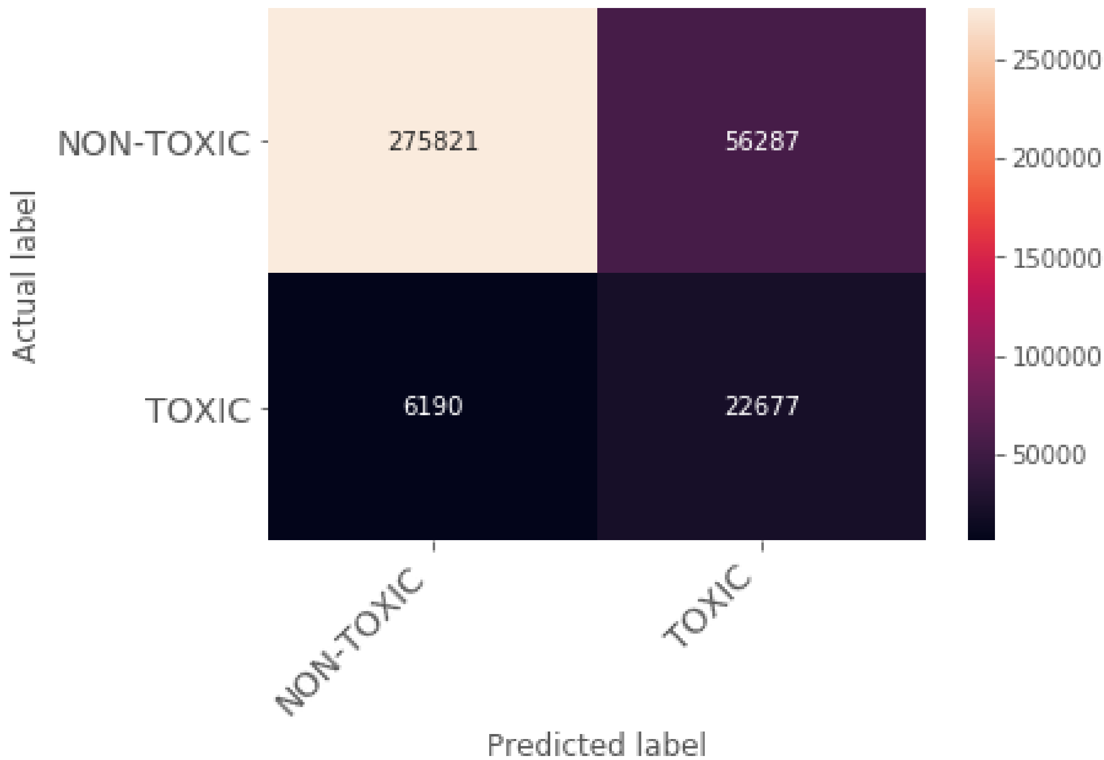
```
	TRAIN DATA CONFUSION MATRIX
```



=> 82.52 % of non-toxic comments predicted correctly => 80.20% of toxic comments predicted correctly

[85]:
```
pred_test = 
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 83.05 % of non-toxic comments predicted correctly => 79.04% of toxic comments predicted correctly

5.1.2 Logistic Regression

Considering BOW

25000 features

[86]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'LR-BOW_25k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='log',␣
↪penalty='l2')
    clf.fit(train_comment_bow_25000, y_train)
#     clf = CalibratedClassifierCV(clf, method="sigmoid")
#     clf.fit(train_comment_bow_25000, y_train)
    predicted_train = clf.predict_proba(train_comment_bow_25000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_bow_25000)[:,1]
```

```
    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|      | 7/7 [02:13<00:00, 19.07s/it]
```

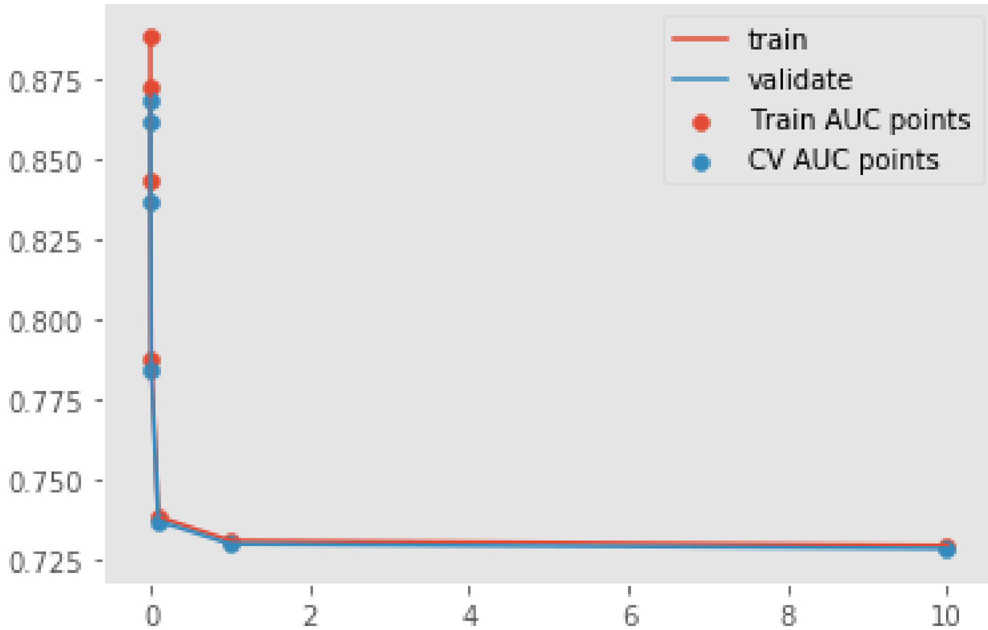
[87]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[87]:

	name	train_score	test_score
6	LR-BOW_25k_10	0.729246	0.728246
5	LR-BOW_25k_1	0.730751	0.729667
4	LR-BOW_25k_0.1	0.738181	0.736869
3	LR-BOW_25k_0.01	0.787471	0.784409
2	LR-BOW_25k_0.001	0.843153	0.836826
1	LR-BOW_25k_0.0001	0.872860	0.861781
0	LR-BOW_25k_1e-05	0.888376	0.868502

[88]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8883764040261166, 0.8728596102026178, 0.8431525884311164, 0.78747086488579,
0.7381814282033289, 0.7307513181859522, 0.7292459221422967] [0.8685024682817755,
0.8617813205230369, 0.8368256005198109, 0.784409386454797, 0.7368686535128023,
0.7296670343536258, 0.7282463762307846]
best hyperparameter got = LR-BOW_25k_1e-05 ##### Best cv score got =
0.8685024682817755
```



[89]:
```
MODEL_NAME = 'LR_bow_25k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
clf.fit(train_comment_bow_25000, y_train)
predicted_train = clf.predict_proba(train_comment_bow_25000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_bow_25000)[:,1]
```

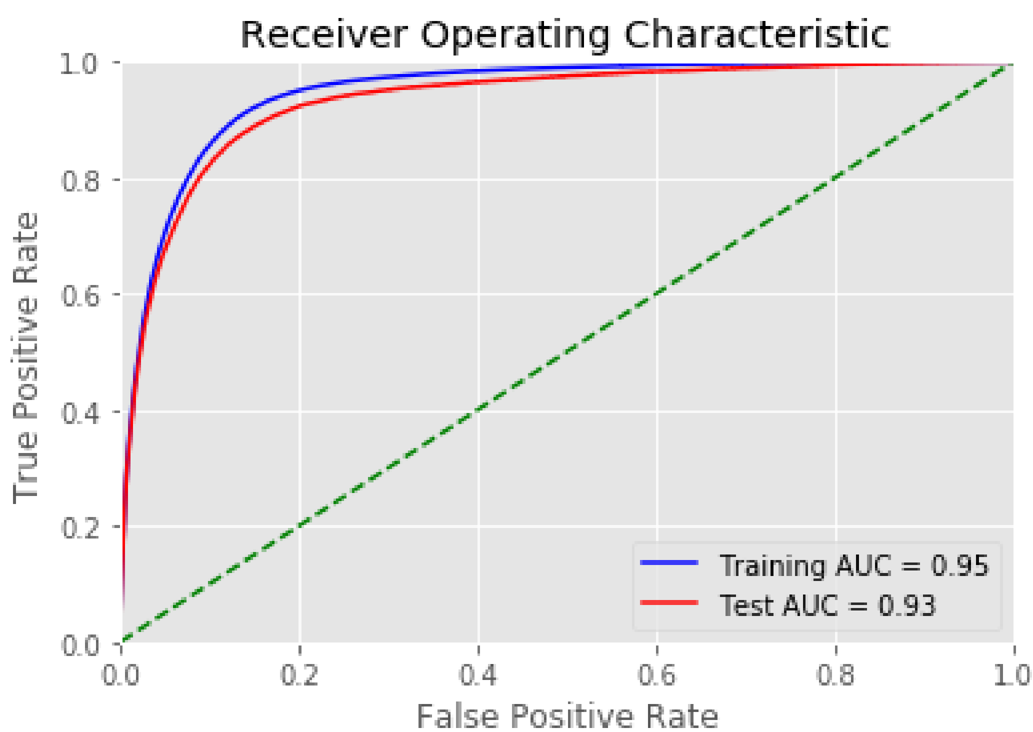
[90]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.8855870072660815
Validation score = 0.8658516271542865
```

[91]:
```
predicted_test = clf.predict_proba(test_comment_bow_25000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/LR_bow_25k_submission.csv', index=False)
```

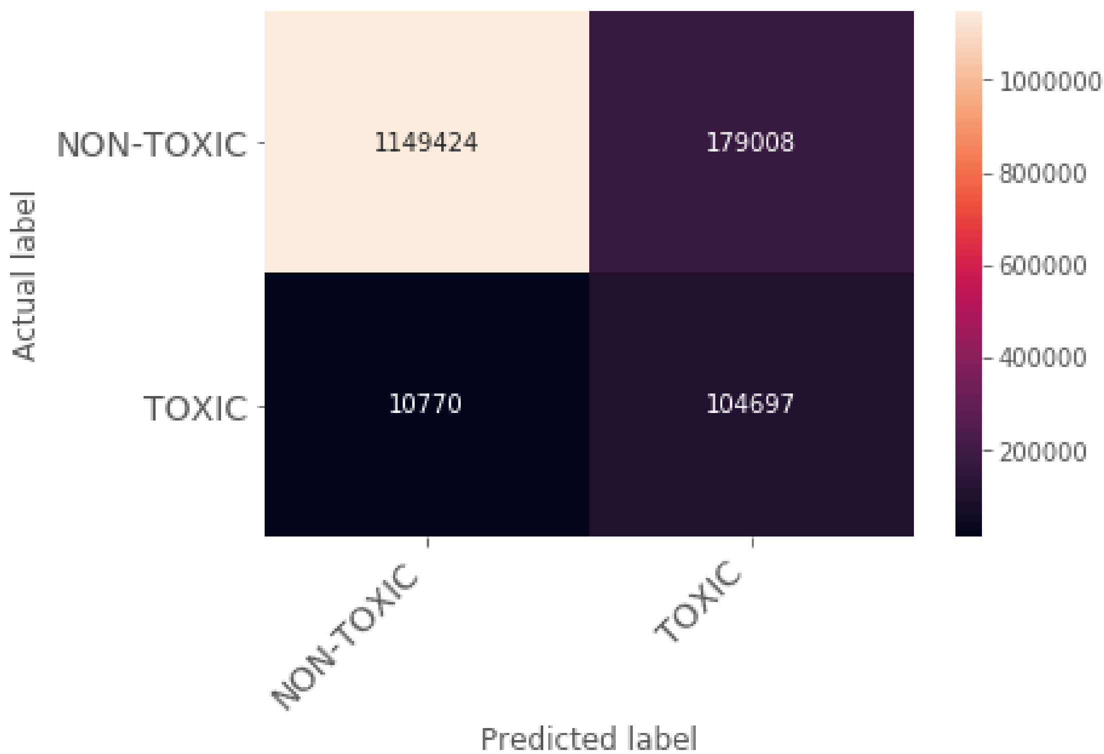
[92]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)
```

```
roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[93]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

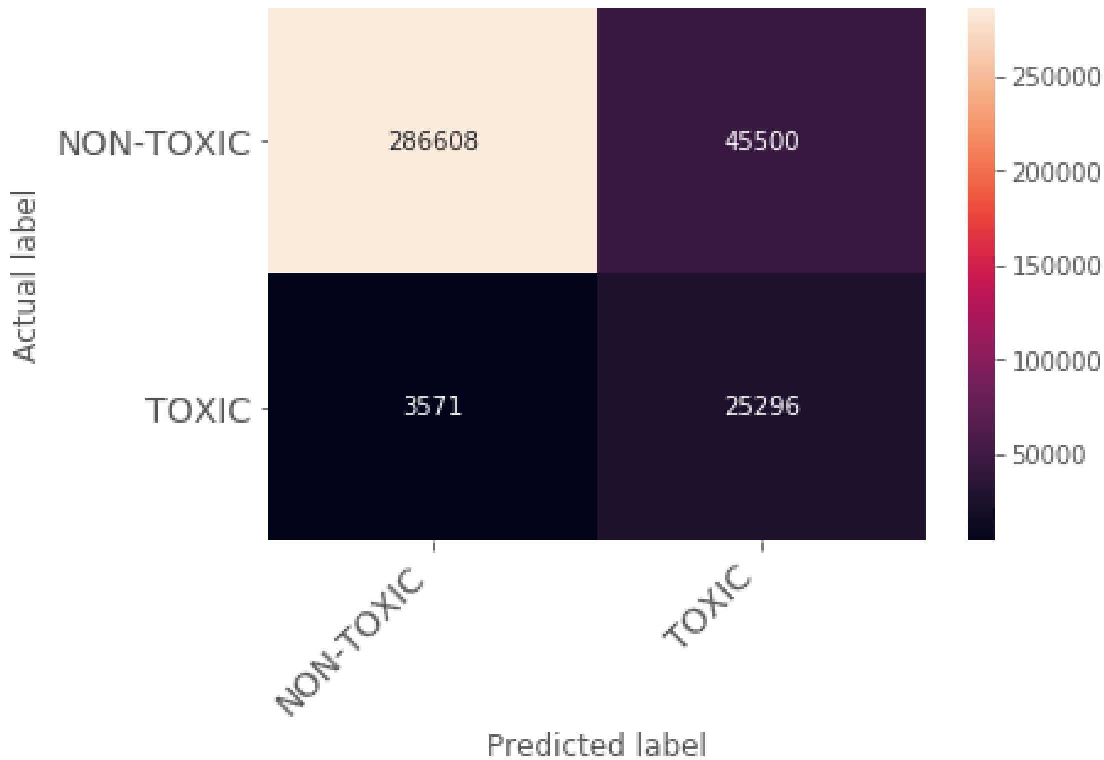
```
TRAIN DATA CONFUSION MATRIX
```



=> 86.52 % of non-toxic comments predicted correctly => 90.17% of toxic comments predicted correctly

[94]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
test DATA CONFUSION MATRIX
```



=> 86.29 % of non-toxic comments predicted correctly => 88.17% of toxic comments predicted correctly

15000 features

[95]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'LR-BOW_15k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
    clf.fit(train_comment_bow_15000, y_train)
#     clf = CalibratedClassifierCV(clf, method="sigmoid")
#     clf.fit(train_comment_bow_15000, y_train)
    predicted_train = clf.predict_proba(train_comment_bow_15000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_bow_15000)[:,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation
```

```
    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

100%| | 7/7 [02:18<00:00, 19.83s/it]

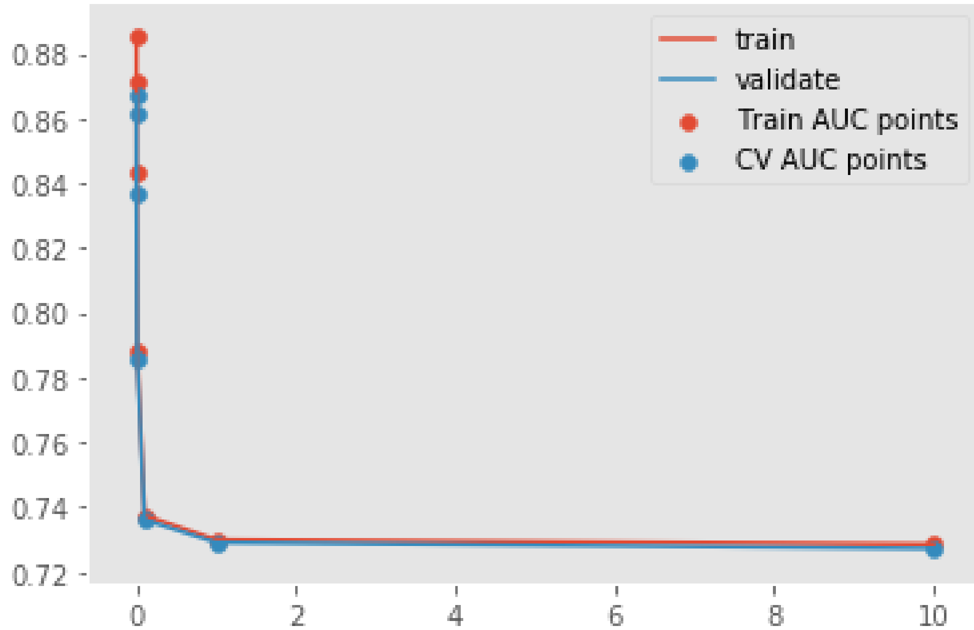
[96]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[96]:

	name	train_score	test_score
6	LR-BOW_15k_10	0.728575	0.727211
5	LR-BOW_15k_1	0.729960	0.729090
4	LR-BOW_15k_0.1	0.737433	0.736097
3	LR-BOW_15k_0.01	0.788353	0.785380
2	LR-BOW_15k_0.001	0.842992	0.836769
1	LR-BOW_15k_0.0001	0.871725	0.861307
0	LR-BOW_15k_1e-05	0.885256	0.867154

[97]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8852563636754947, 0.8717246904498954, 0.8429924070403463, 0.7883527587420291,
0.7374330897002882, 0.7299600382169944, 0.7285752730332522] [0.867154022484939,
0.8613073302574822, 0.8367693709621655, 0.7853799758740808, 0.736096702505924,
0.7290902929699002, 0.7272107612840208]
best hyperparameter got = LR-BOW_15k_1e-05 ##### Best cv score got =
0.867154022484939
```



[98]:
```
MODEL_NAME = 'LR_bow_15k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
clf.fit(train_comment_bow_15000, y_train)
predicted_train = clf.predict_proba(train_comment_bow_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_bow_15000)[:,1]
```

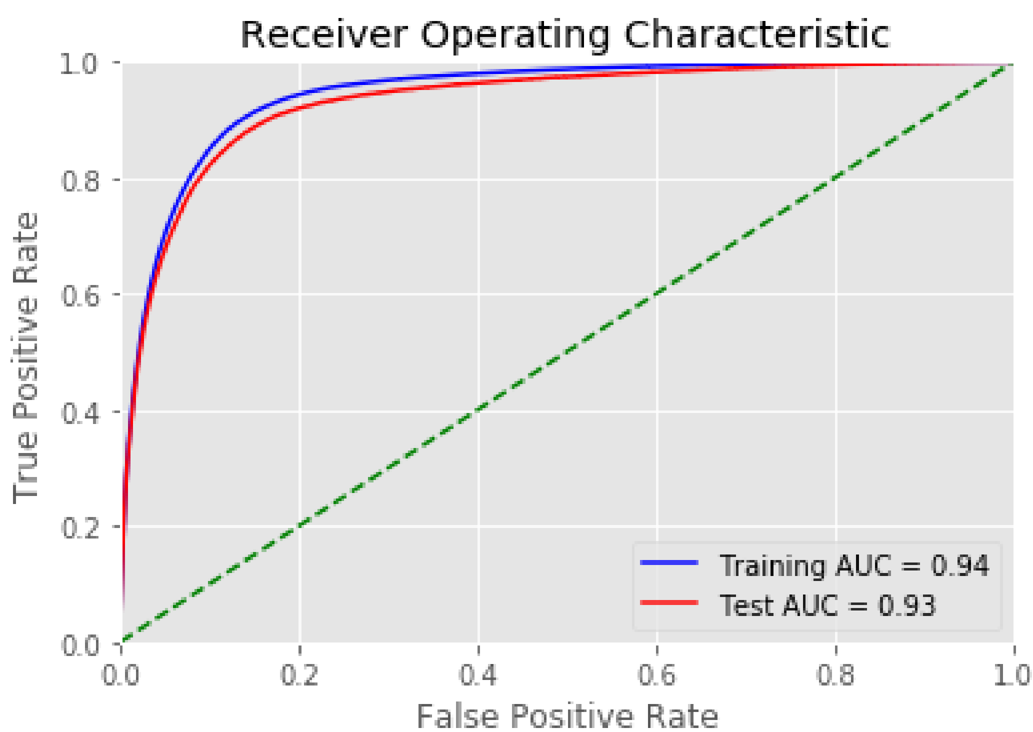
[99]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.884694041115146
Validation score = 0.8668547299807178
```

[100]:
```
predicted_test = clf.predict_proba(test_comment_bow_15000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/LR_bow_15k_submission.csv', index=False)
```

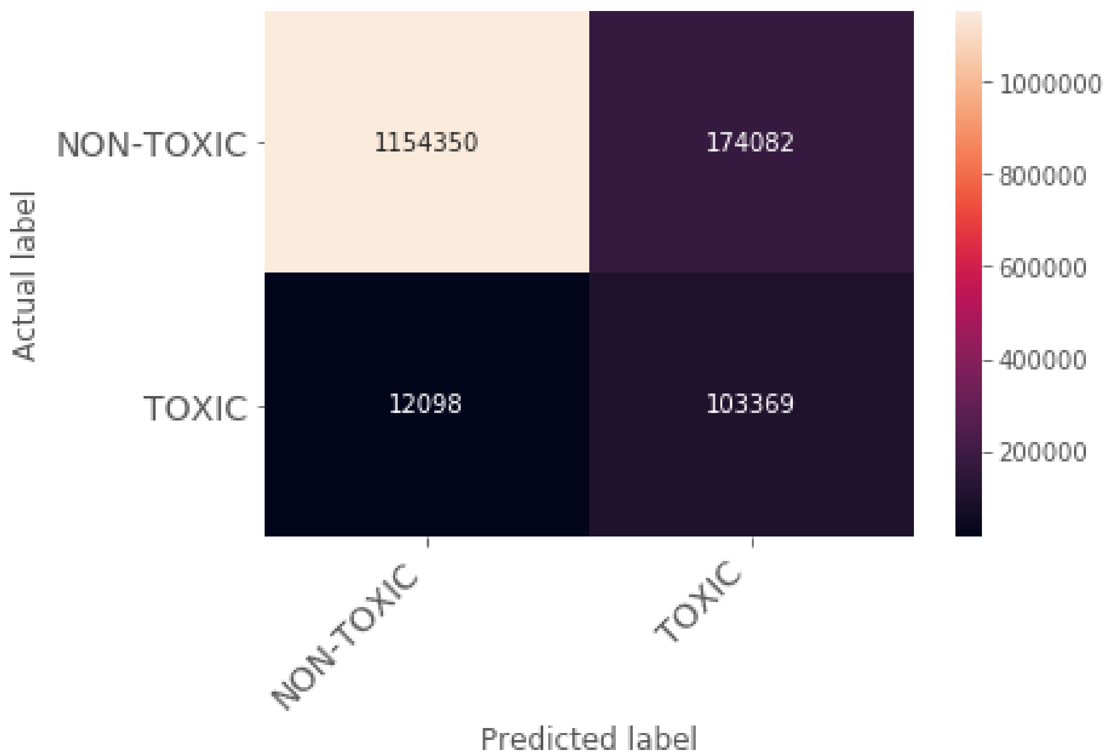
[101]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)
```

```
roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[102]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

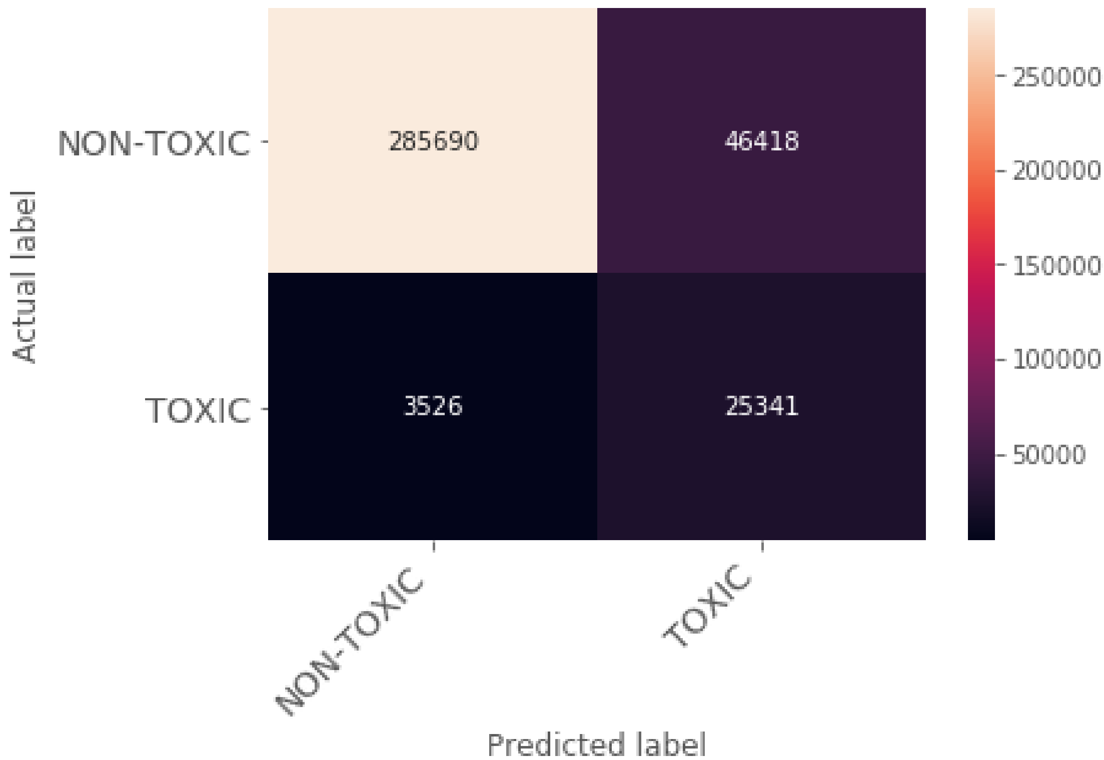
TRAIN DATA CONFUSION MATRIX



=> 86.89 % of non-toxic comments predicted correctly => 89.52% of toxic comments predicted correctly

[103]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

test DATA CONFUSION MATRIX



=> 86.02 % of non-toxic comments predicted correctly => 88.33% of toxic comments predicted correctly

10000 features

[104]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'LR-BOW_10k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
    clf.fit(train_comment_bow_10000, y_train)
#     clf = CalibratedClassifierCV(clf, method="sigmoid")
#     clf.fit(train_comment_bow_10000, y_train)
    predicted_train = clf.predict_proba(train_comment_bow_10000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_bow_10000)[:,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation
```

```
    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

100%| | 7/7 [02:22<00:00, 20.33s/it]

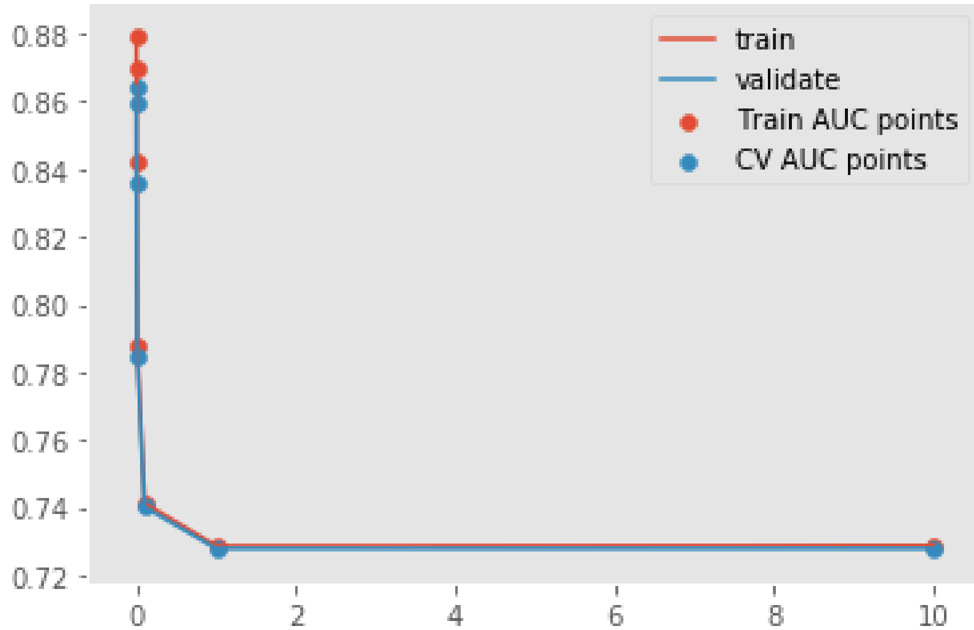
[105]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[105]:

	name	train_score	test_score
5	LR-BOW_10k_1	0.728729	0.727951
6	LR-BOW_10k_10	0.728852	0.727953
4	LR-BOW_10k_0.1	0.741374	0.740229
3	LR-BOW_10k_0.01	0.787858	0.784922
2	LR-BOW_10k_0.001	0.841920	0.835783
1	LR-BOW_10k_0.0001	0.869799	0.859878
0	LR-BOW_10k_1e-05	0.879191	0.864436

[106]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8791914041561264, 0.8697988757289951, 0.8419202161656001, 0.7878577939714233,
0.7413741273602321, 0.7287285347560886, 0.7288519182154476] [0.8644363381705658,
0.8598782548103915, 0.8357830918384859, 0.7849215563767598, 0.7402294893350438,
0.7279511226767879, 0.7279532162599258]
best hyperparameter got = LR-BOW_10k_1e-05 ##### Best cv score got =
0.8644363381705658
```



[107]:
```
MODEL_NAME = 'LR_bow_10k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='log',␣
↪penalty='l2')
clf.fit(train_comment_bow_10000, y_train)
predicted_train = clf.predict_proba(train_comment_bow_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_bow_10000)[:,1]
```

[108]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
↪MODEL_NAME)}')
```

```
Train score = 0.8751021308860036
Validation score = 0.859595458254724
```

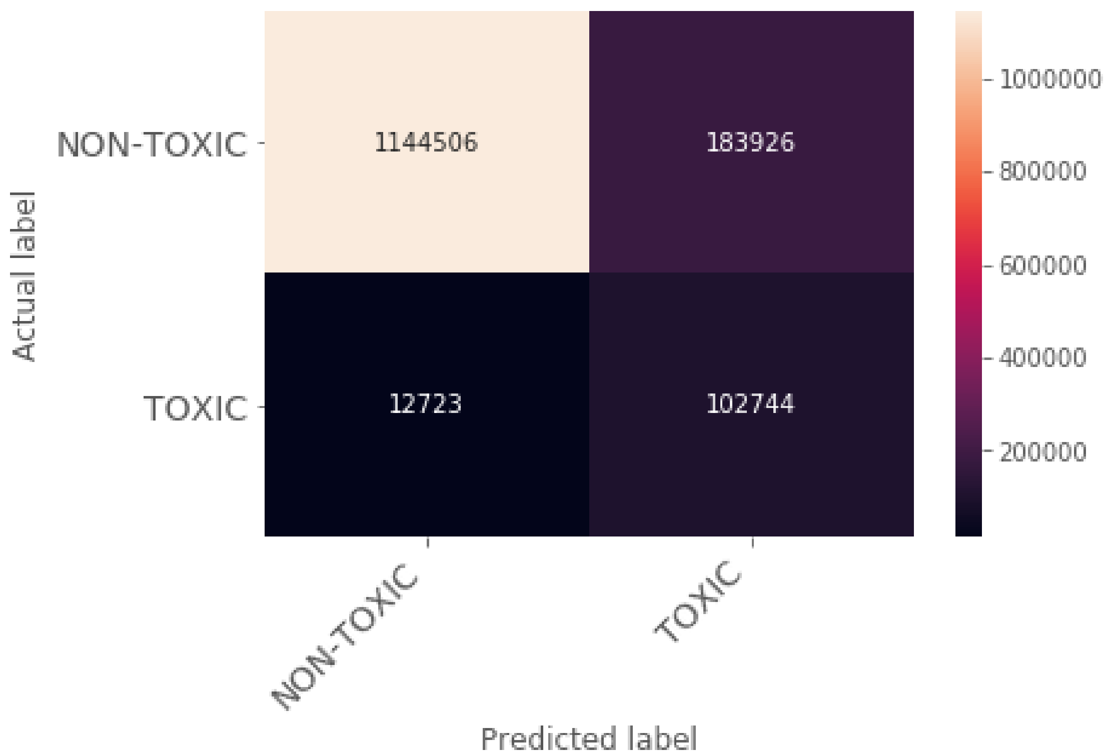
[109]:
```
predicted_test = clf.predict_proba(test_comment_bow_10000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/LR_bow_10k_submission.csv', index=False)
```

[110]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
↪predicted_validation)
```

```
roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[111]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

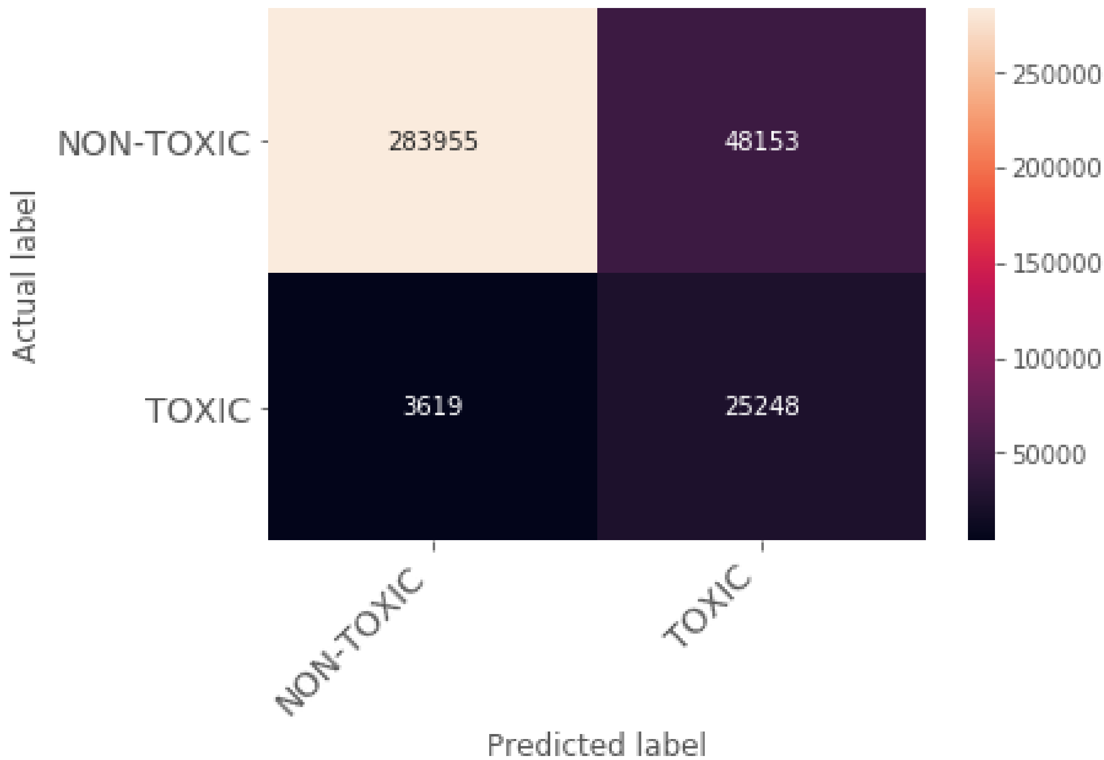
TRAIN DATA CONFUSION MATRIX



=> 86.15 % of non-toxic comments predicted correctly => 88.98% of toxic comments predicted correctly

[112]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

test DATA CONFUSION MATRIX



=> 85.50 % of non-toxic comments predicted correctly => 88.01% of toxic comments predicted correctly

Considering TFIDF

25000 features

[113]:
```
import gc
gc.collect()
```

[113]: 26411

[114]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'LR-tfidf_25k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
    clf.fit(train_comment_tfidf_25000, y_train)
#     clf = CalibratedClassifierCV(clf, method="sigmoid")
```

```
#     clf.fit(train_comment_tfidf_25000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_25000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_25000)[:
↪,1]


    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|      | 7/7 [02:17<00:00, 19.64s/it]
```

[115]:

```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

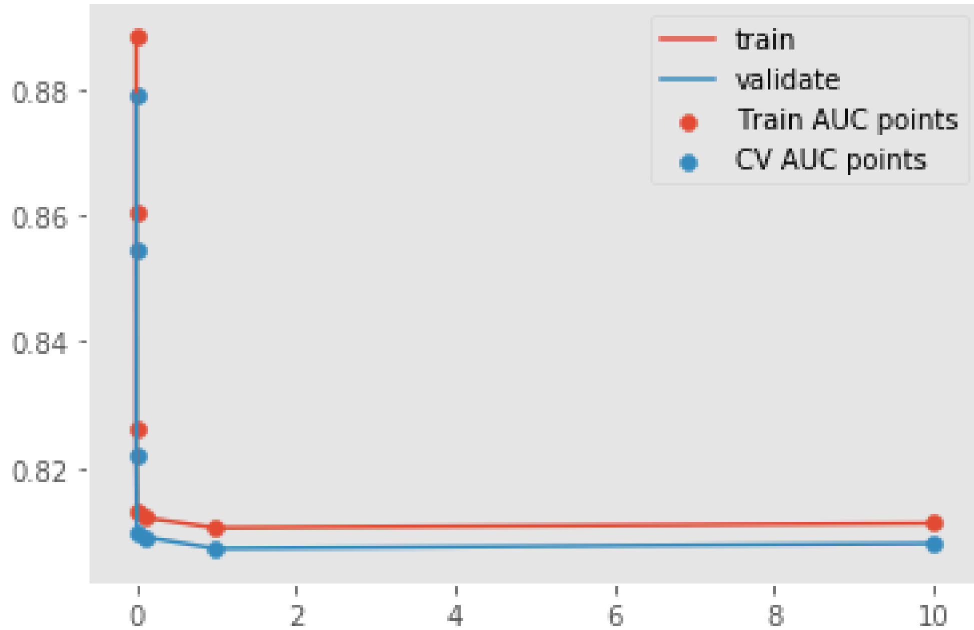
[115]:

	name	train_score	test_score
5	LR-tfidf_25k_1	0.810516	0.807215
6	LR-tfidf_25k_10	0.811231	0.808033
4	LR-tfidf_25k_0.1	0.812138	0.809069
3	LR-tfidf_25k_0.01	0.812970	0.809628
2	LR-tfidf_25k_0.001	0.826055	0.822004
1	LR-tfidf_25k_0.0001	0.860375	0.854431
0	LR-tfidf_25k_1e-05	0.888359	0.879074

[116]:

```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8883589444562898, 0.8603753586108874, 0.826055031353244, 0.8129701080826565,
0.8121382918349923, 0.8105158008134189, 0.8112311832421755] [0.8790736879001076,
0.8544308878174316, 0.8220039261864243, 0.8096283463665845, 0.8090685059079621,
0.8072150818648656, 0.8080333922373485]
best hyperparameter got = LR-tfidf_25k_1e-05 ##### Best cv score got =
0.8790736879001076
```



[117]:
```
MODEL_NAME = 'LR_tfidf_25k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
clf.fit(train_comment_tfidf_25000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_25000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_25000)[:,1]
```

[118]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.8884860097510427
Validation score = 0.8792506623862287
```

[119]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_25000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/LR_tfidf_25k_submission.csv', index=False)
```

[ ]:
```
```

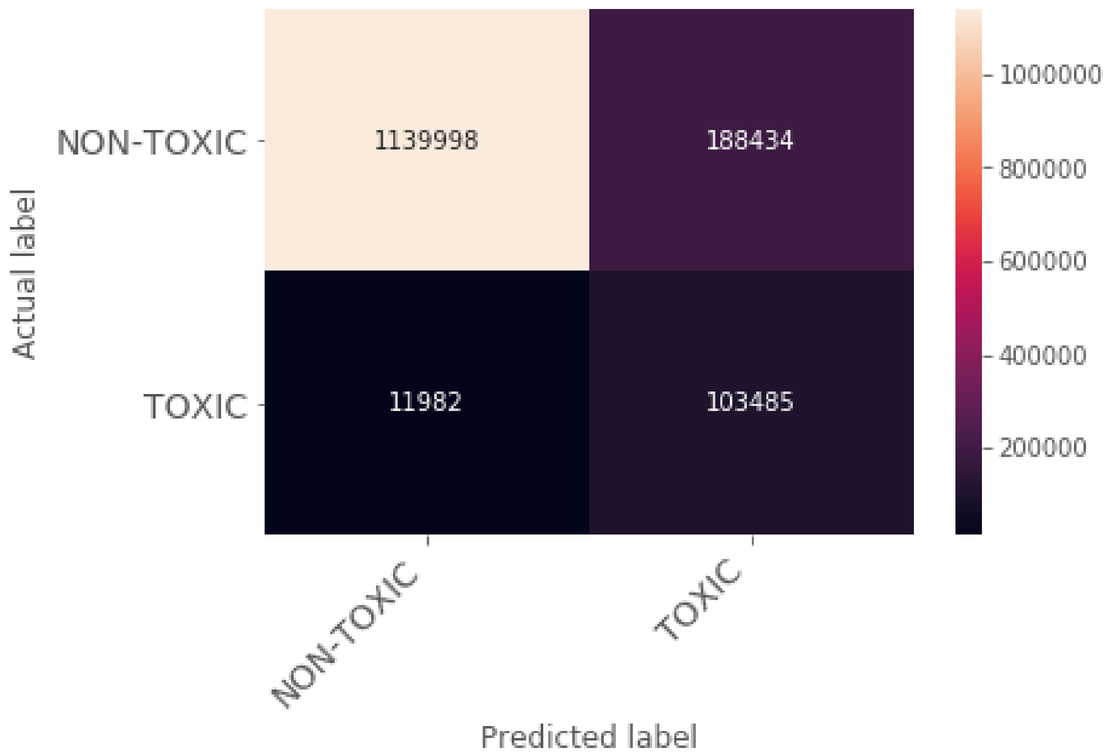
[120]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
```

```
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[121]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
```

```
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

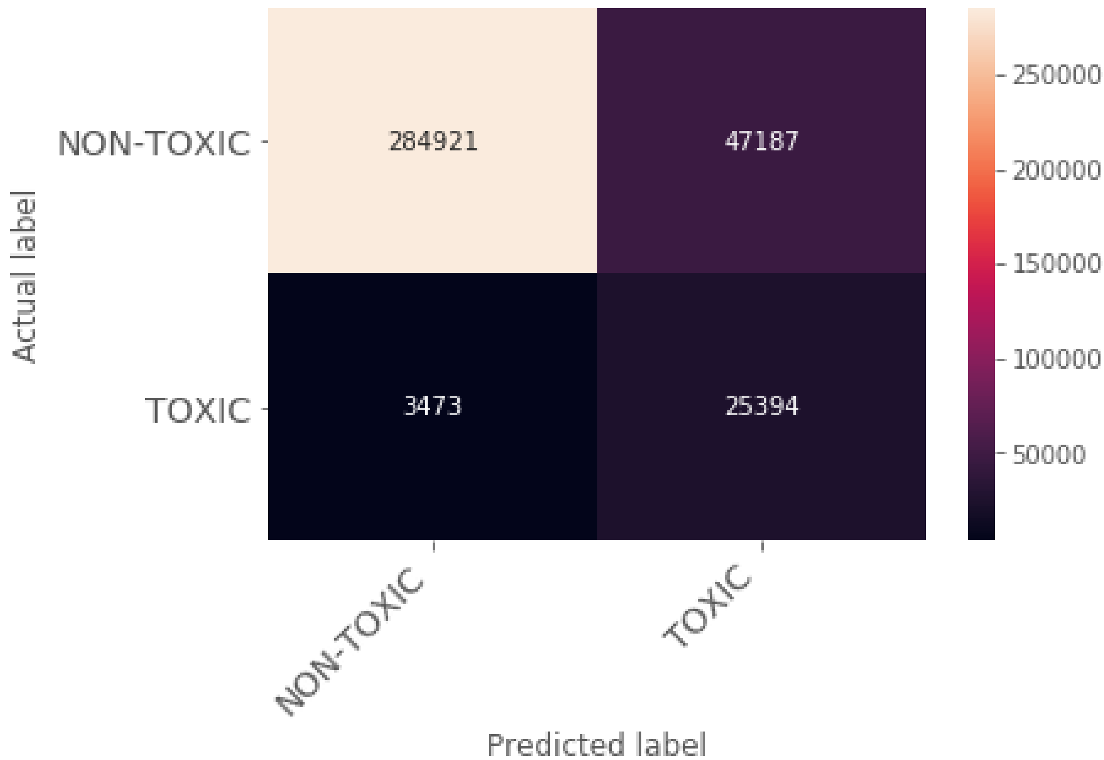
```
	TRAIN DATA CONFUSION MATRIX
```



=> 85.81 % of non-toxic comments predicted correctly => 89.62% of toxic comments predicted correctly

[122]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 85.79 % of non-toxic comments predicted correctly => 88.52% of toxic comments predicted correctly

15000 features

[123]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'LR-tfidf_15k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='log',␣
↪penalty='l2')
    clf.fit(train_comment_tfidf_15000, y_train)
#     clf = CalibratedClassifierCV(clf, method="sigmoid")
#     clf.fit(train_comment_tfidf_15000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:
↪,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation
```

```
    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|          | 7/7 [02:22<00:00, 20.42s/it]
```

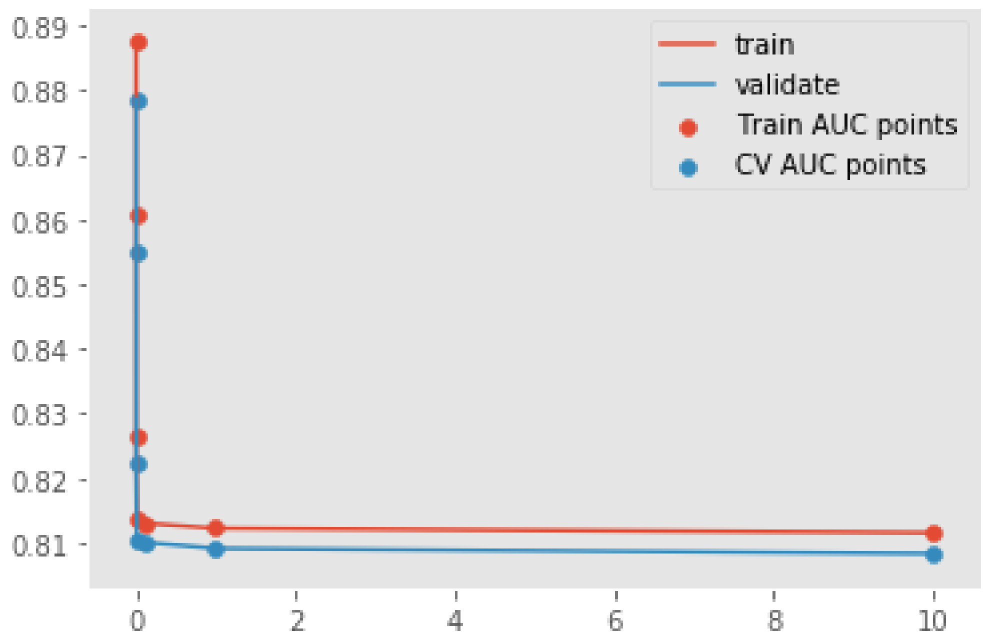
[124]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[124]:

	name	train_score	test_score
6	LR-tfidf_15k_10	0.811563	0.808329
5	LR-tfidf_15k_1	0.812242	0.809136
4	LR-tfidf_15k_0.1	0.813041	0.810073
3	LR-tfidf_15k_0.01	0.813771	0.810451
2	LR-tfidf_15k_0.001	0.826632	0.822499
1	LR-tfidf_15k_0.0001	0.860811	0.854865
0	LR-tfidf_15k_1e-05	0.887478	0.878648

[125]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8874782707651374, 0.8608110760758877, 0.8266316949731487, 0.8137705074207171,
0.8130409528654141, 0.8122418726520166, 0.811562758955933] [0.878648271939579,
0.8548654582687194, 0.8224987463709735, 0.8104508401330929, 0.81007337461985,
0.8091362953089876, 0.8083285875956953]
best hyperparameter got = LR-tfidf_15k_1e-05 ##### Best cv score got =
0.878648271939579
```



[126]:
```
MODEL_NAME = 'LR_tfidf_15k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='log',␣
↪penalty='l2')
clf.fit(train_comment_tfidf_15000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:,1]
```

[127]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
↪MODEL_NAME)}')
```

```
Train score = 0.8872380229794584
Validation score = 0.878449056596368
```

[128]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_15000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/LR_tfidf_15k_submission.csv', index=False)
```

[ ]:
```

```

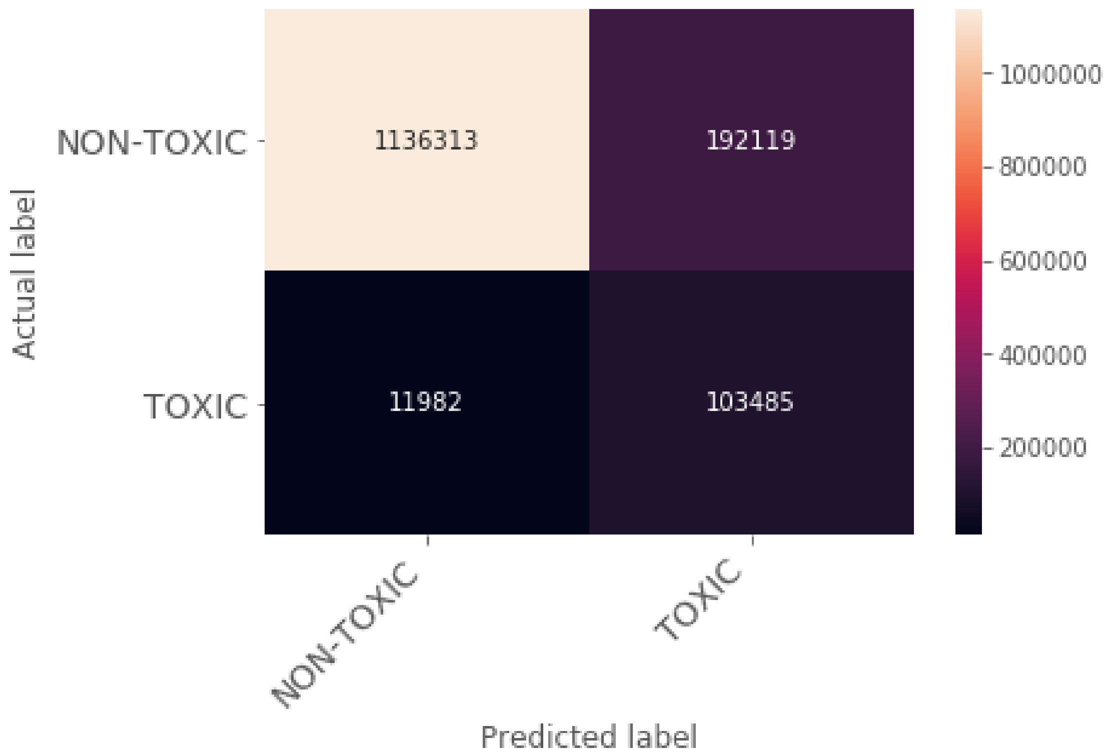
[129]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
```

```
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[130]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
```

```
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

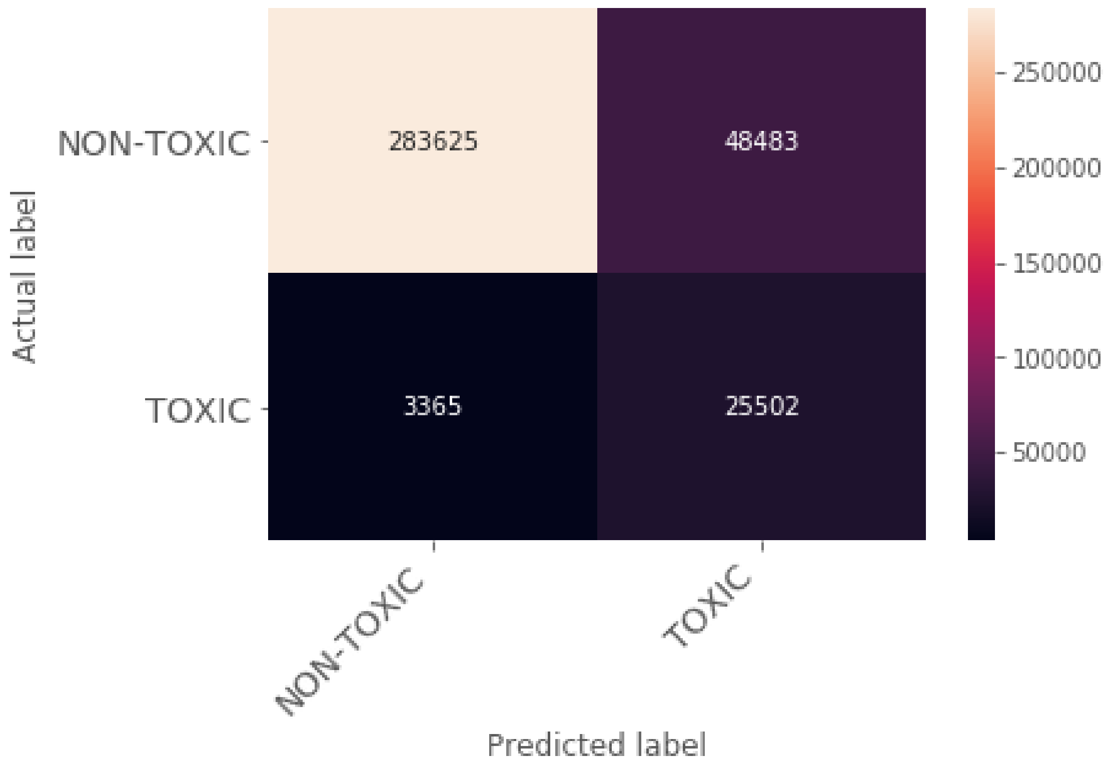
```
	TRAIN DATA CONFUSION MATRIX
```



=> 85.53 % of non-toxic comments predicted correctly => 89.62% of toxic comments predicted correctly

[131]:
```
pred_test = 
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 85.40 % of non-toxic comments predicted correctly => 88.89% of toxic comments predicted correctly

10000 features

[132]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'LR-tfidf_10k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
    clf.fit(train_comment_tfidf_10000, y_train)
#     clf = CalibratedClassifierCV(clf, method="sigmoid")
#     clf.fit(train_comment_tfidf_10000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:
 ↪,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation
```

```
    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

100%| | 7/7 [02:26<00:00, 20.93s/it]

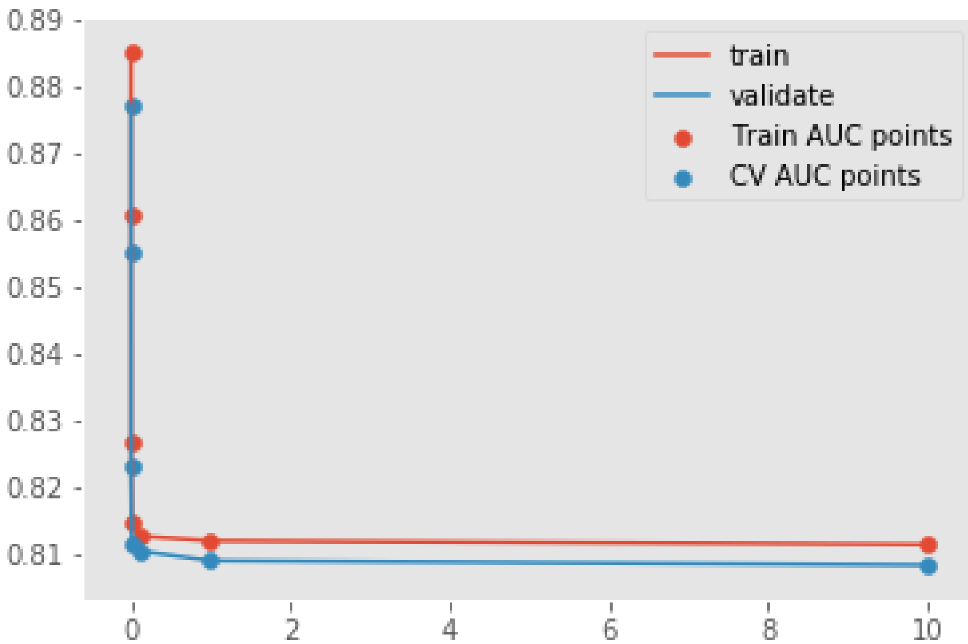
[133]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[133]:

	name	train_score	test_score
6	LR-tfidf_10k_10	0.811468	0.808384
5	LR-tfidf_10k_1	0.812026	0.809038
4	LR-tfidf_10k_0.1	0.812718	0.810515
3	LR-tfidf_10k_0.01	0.814661	0.811691
2	LR-tfidf_10k_0.001	0.826914	0.822966
1	LR-tfidf_10k_0.0001	0.860607	0.855021
0	LR-tfidf_10k_1e-05	0.885048	0.877142

[134]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8850477949471514, 0.860606632317165, 0.8269141138245488, 0.8146609570366554,
0.8127180876243518, 0.8120258043083588, 0.8114678002992664] [0.8771421110683988,
0.8550209766014671, 0.8229664609181242, 0.8116905364534729, 0.8105154686961777,
0.8090381136644589, 0.8083837093406189]
best hyperparameter got = LR-tfidf_10k_1e-05 ##### Best cv score got =
0.8771421110683988
```



[135]:
```
MODEL_NAME = 'LR_tfidf_10k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='log',␣
↪penalty='l2')
clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]
```

[136]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
↪MODEL_NAME)}')
```

```
Train score = 0.8848560381994712
Validation score = 0.8768401612236583
```

[137]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_10000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/LR_tfidf_10k_submission.csv', index=False)
```

[ ]:
```
```

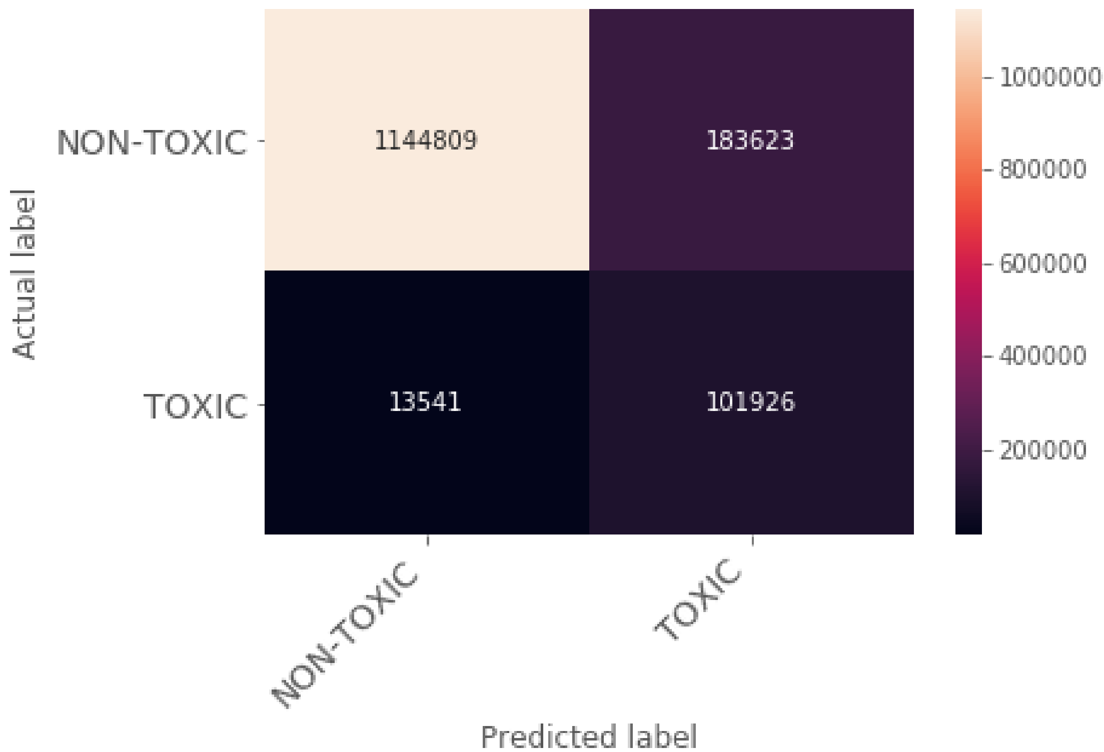
[138]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
```

```
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[139]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
```

```
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

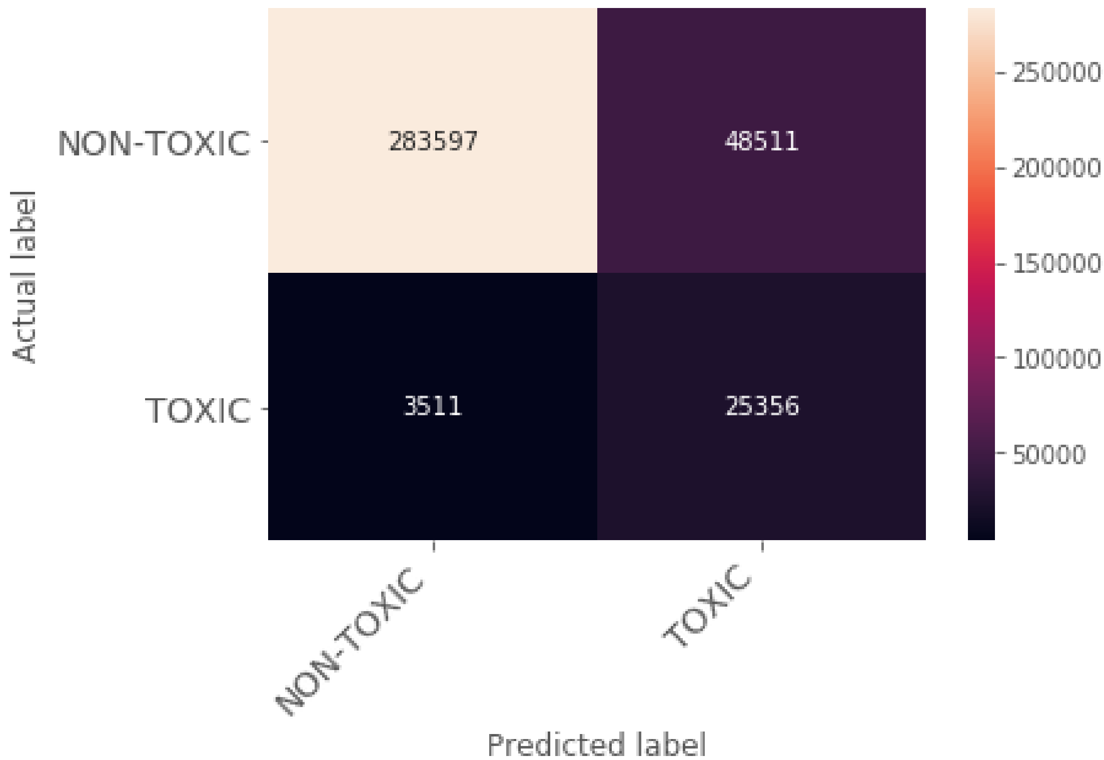
```
	TRAIN DATA CONFUSION MATRIX
```



=> 86.17 % of non-toxic comments predicted correctly => 88.27% of toxic comments predicted correctly

[140]:
```
pred_test = 
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 85.39 % of non-toxic comments predicted correctly => 88.38% of toxic comments predicted correctly

[141]:
```
gc.collect()
```

[141]: 39299

5.1.3 SVM

Considering TFIDF

25000 features

[142]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'svm-tfidf_25k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='hinge',␣
 ↪penalty='l2')
    clf.fit(train_comment_tfidf_25000, y_train)
```

```
    clf = CalibratedClassifierCV(clf, method="sigmoid")
    clf.fit(train_comment_tfidf_25000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_25000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_25000)[:
↪,1]

    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation

    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

```
100%|          | 7/7 [04:42<00:00, 40.36s/it]
```

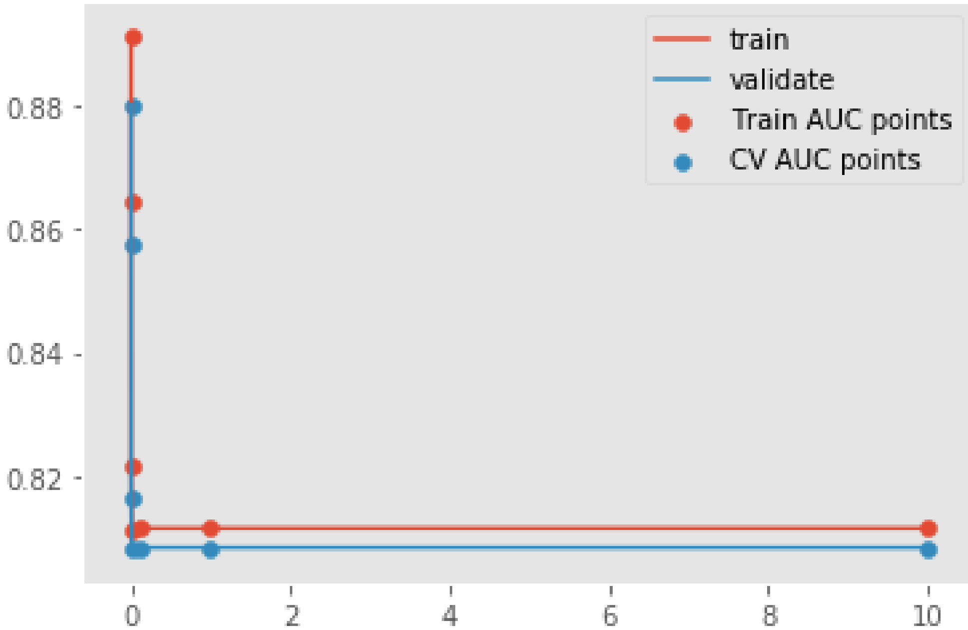
[143]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[143]:

	name	train_score	test_score
3	svm-tfidf_25k_0.01	0.811327	0.808182
4	svm-tfidf_25k_0.1	0.811490	0.808345
5	svm-tfidf_25k_1	0.811490	0.808345
6	svm-tfidf_25k_10	0.811490	0.808345
2	svm-tfidf_25k_0.001	0.821717	0.816406
1	svm-tfidf_25k_0.0001	0.864645	0.857521
0	svm-tfidf_25k_1e-05	0.891313	0.880202

[144]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8913132106095535, 0.864644777765612, 0.8217171085751638, 0.8113269134720448,
0.8114898882220797, 0.8114898881974566, 0.8114898882237095] [0.880202263518974,
0.857520541444115, 0.8164061631885171, 0.8081815897401121, 0.8083445796631972,
0.8083445796631972, 0.8083445796631972]
best hyperparameter got = svm-tfidf_25k_1e-05 ##### Best cv score got =
0.880202263518974
```



[145]:
```
MODEL_NAME = 'svm_tfidf_25k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='hinge',␣
↪penalty='l2')
clf.fit(train_comment_tfidf_25000, y_train)
clf = CalibratedClassifierCV(clf, method="sigmoid")
clf.fit(train_comment_tfidf_25000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_25000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_25000)[:,1]
```

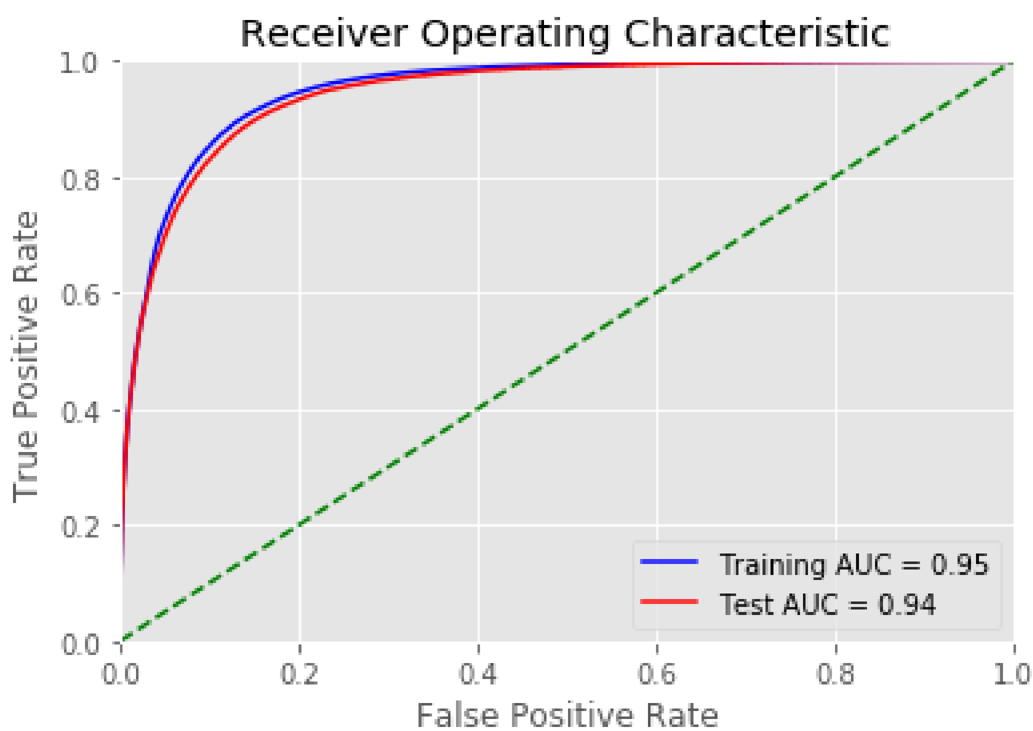
[146]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
↪MODEL_NAME)}')
```

```
Train score = 0.8913848127985691
Validation score = 0.8801859160326639
```

[147]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_25000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/svm_tfidf_25k_submission.csv', index=False)
```

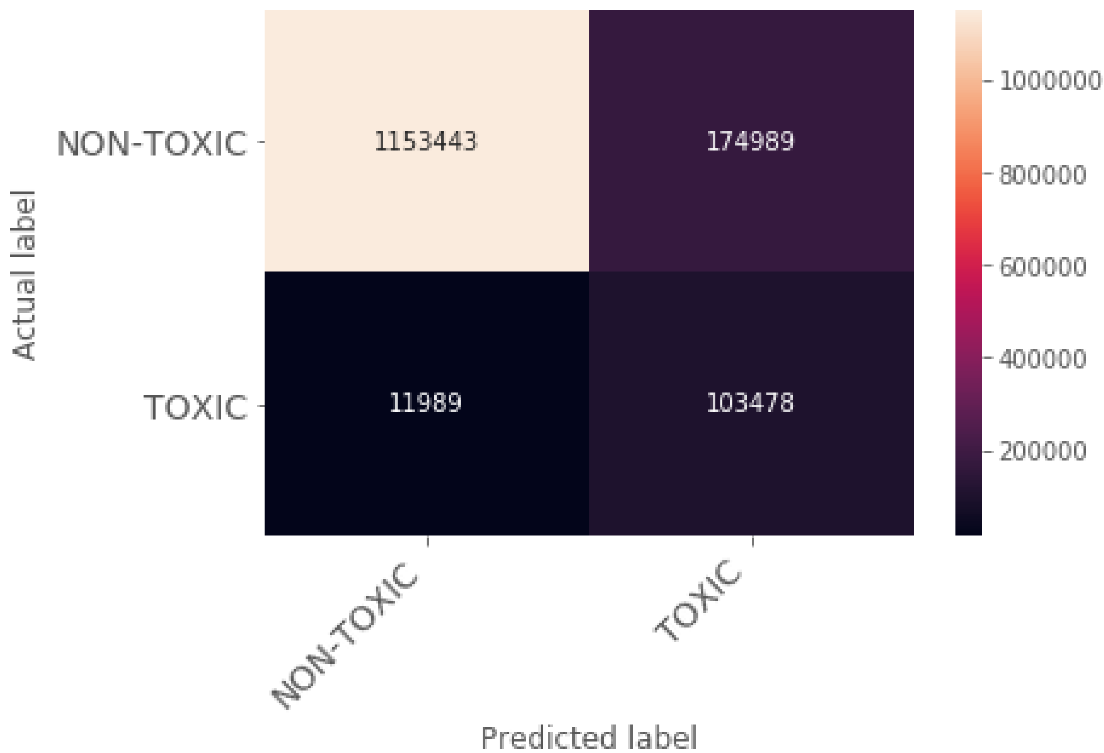
[ ]:
```
```

[148]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[149]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

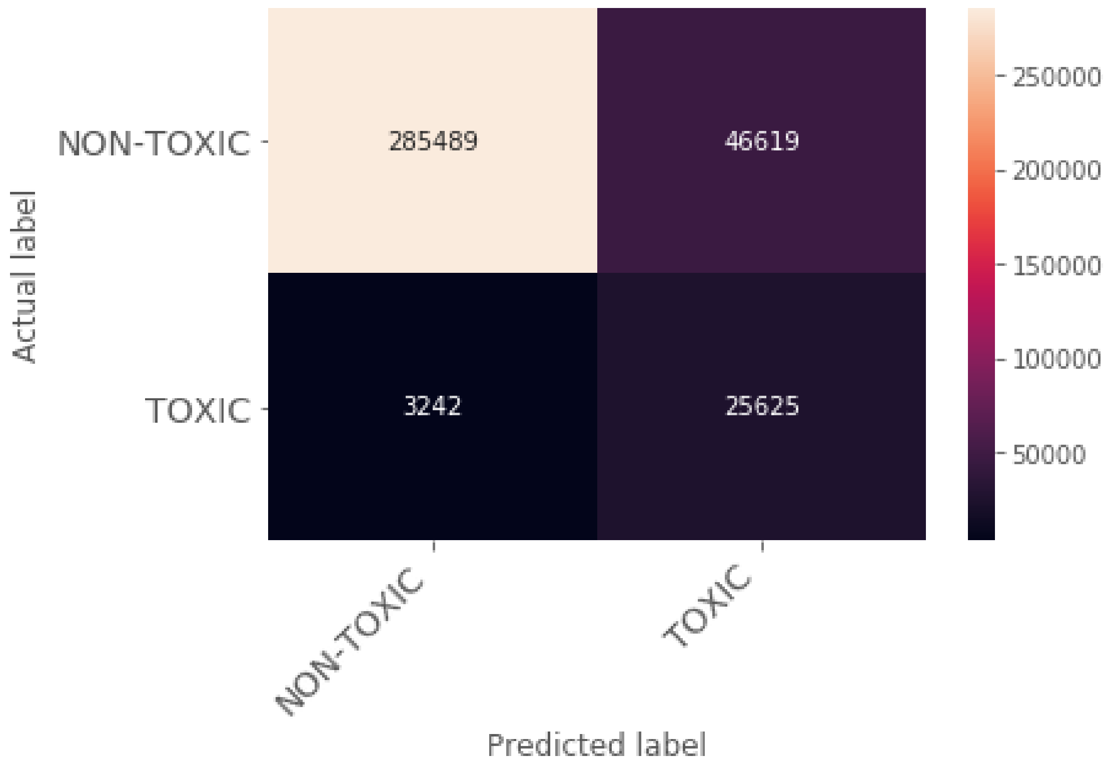
```
	TRAIN DATA CONFUSION MATRIX
```



=> 86.82 % of non-toxic comments predicted correctly => 89.61% of toxic comments predicted correctly

[150]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 85.96 % of non-toxic comments predicted correctly => 89.32% of toxic comments predicted correctly

15000 features

[151]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'svm-tfidf_15k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='hinge',␣
 ↪penalty='l2')
    clf.fit(train_comment_tfidf_15000, y_train)
    clf = CalibratedClassifierCV(clf, method="sigmoid")
    clf.fit(train_comment_tfidf_15000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:
 ↪,1]
    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation
```

```
    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

100%| | 7/7 [04:38<00:00, 39.75s/it]

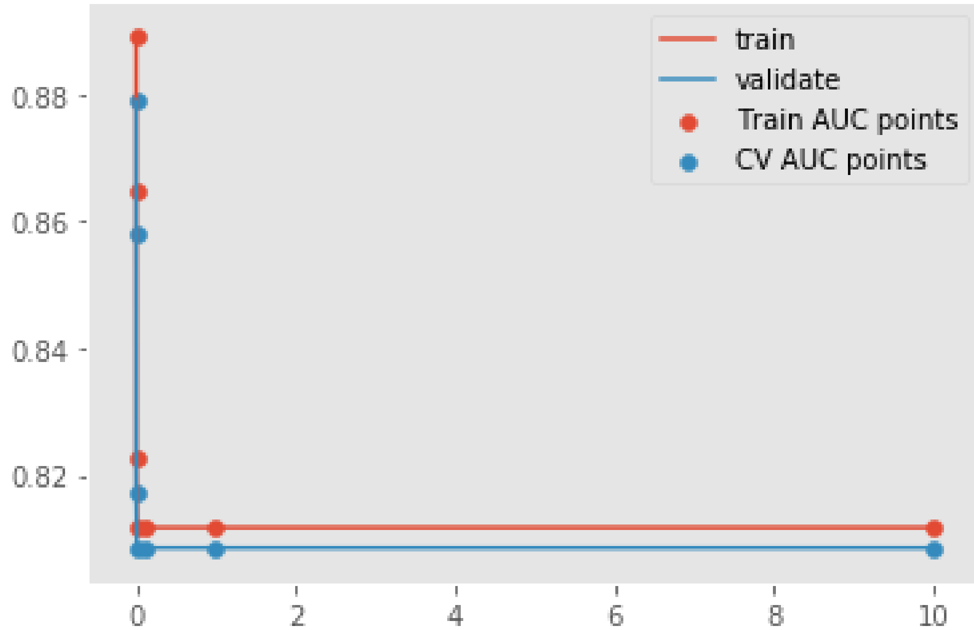
[152]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[152]:

	name	train_score	test_score
3	svm-tfidf_15k_0.01	0.811666	0.808471
4	svm-tfidf_15k_0.1	0.811782	0.808587
5	svm-tfidf_15k_1	0.811782	0.808587
6	svm-tfidf_15k_10	0.811782	0.808587
2	svm-tfidf_15k_0.001	0.822798	0.817372
1	svm-tfidf_15k_0.0001	0.864762	0.857834
0	svm-tfidf_15k_1e-05	0.889035	0.878969

[153]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

[0.8890348991369909, 0.8647621003386462, 0.8227981573703355, 0.8116660775481254, 0.8117819975992921, 0.8117819975992921, 0.8117819975992921] [0.8789687931833012, 0.8578336021805566, 0.8173721678374075, 0.8084708725513468, 0.8085867979393189, 0.8085867979393189, 0.8085867979393189]
best hyperparameter got = svm-tfidf_15k_1e-05 ##### Best cv score got = 0.8789687931833012



[154]:
```
MODEL_NAME = 'svm_tfidf_15k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='hinge',␣
 ↪penalty='l2')
clf.fit(train_comment_tfidf_15000, y_train)
clf = CalibratedClassifierCV(clf, method="sigmoid")
clf.fit(train_comment_tfidf_15000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:,1]
```

[155]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.8895580758634982
Validation score = 0.879360781648051
```

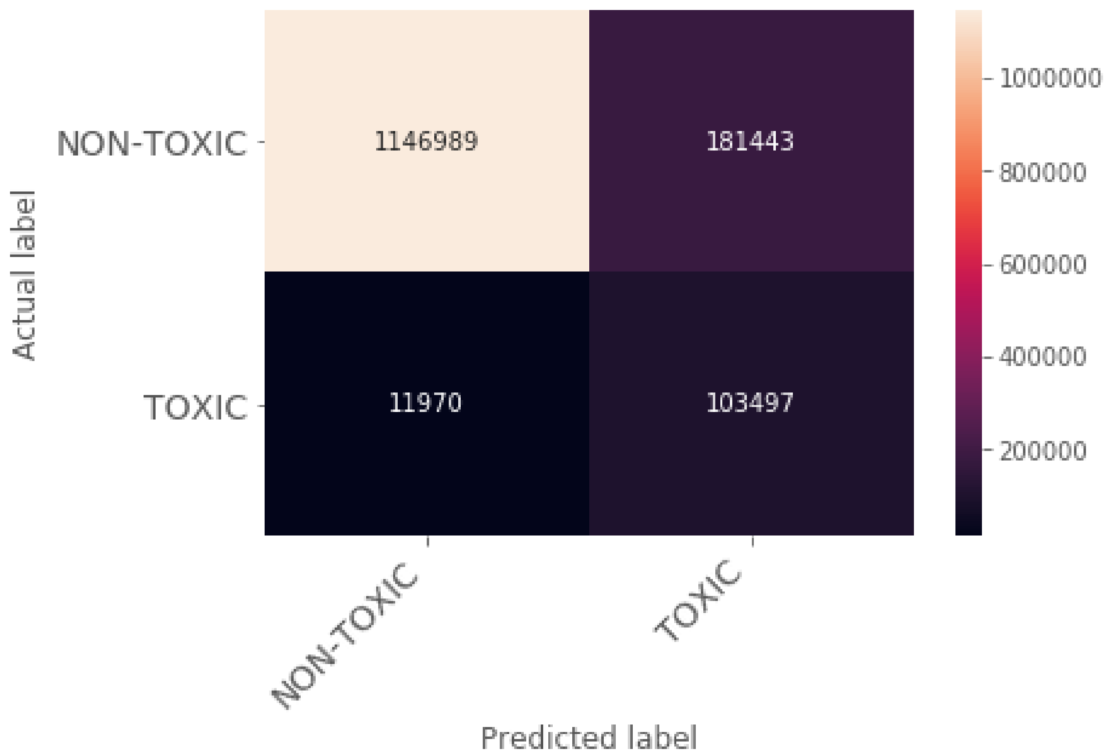
[156]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_15000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/svm_tfidf_15k_submission.csv', index=False)
```

[ ]:
```
```

[157]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

[158]:
```
pred_train = predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

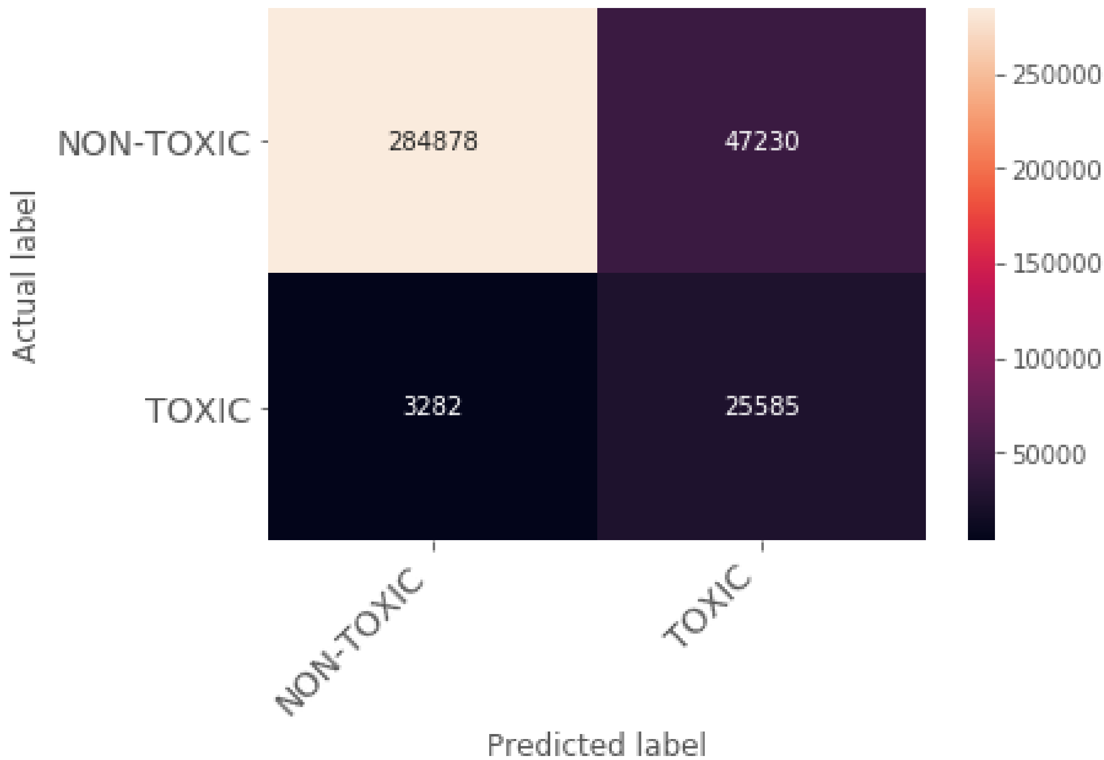
```
	TRAIN DATA CONFUSION MATRIX
```



=> 86.34 % of non-toxic comments predicted correctly => 89.63% of toxic comments predicted correctly

[159]:
```
pred_test = predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 85.77 % of non-toxic comments predicted correctly => 89.18% of toxic comments predicted correctly

10000 features

[160]:
```
alpha = [0.00001, 0.0001, 0.001, 0.01, 0.1, 1, 10]
train_auc_list = []
validation_auc_list = []
names = []
for param in tqdm(alpha):
    MODEL_NAME = f'svm-tfidf_10k_{param}'
    clf = SGDClassifier(alpha=param, class_weight='balanced', loss='hinge',␣
 ↪penalty='l2')
    clf.fit(train_comment_tfidf_10000, y_train)
    clf = CalibratedClassifierCV(clf, method="sigmoid")
    clf.fit(train_comment_tfidf_10000, y_train)
    predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
    predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:
 ↪,1]
    train_data[MODEL_NAME] = predicted_train
    validation_data[MODEL_NAME] = predicted_validation
```

```
    train_auc_list.append(get_metric_value(train_data, identity_columns,␣
↪MODEL_NAME))
    validation_auc_list.append(get_metric_value(validation_data,␣
↪identity_columns, MODEL_NAME))
    names.append(MODEL_NAME)
```

100%| | 7/7 [04:51<00:00, 41.67s/it]

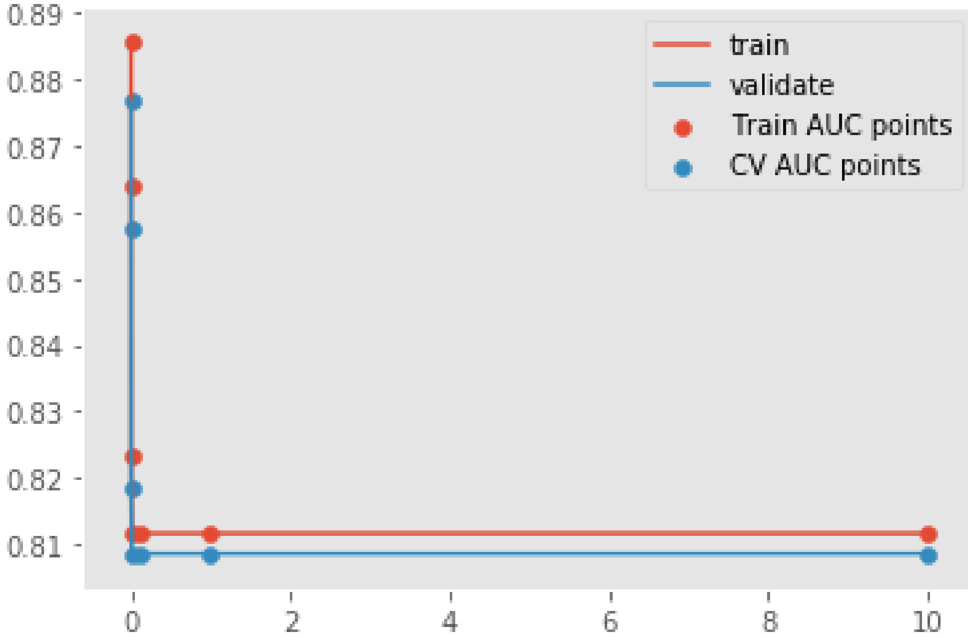
[161]:
```
score = pd.DataFrame({'name':names, 'train_score':train_auc_list, 'test_score':
↪validation_auc_list}).sort_values(by=['test_score'])
score
```

[161]:

	name	train_score	test_score
3	svm-tfidf_10k_0.01	0.811532	0.808482
6	svm-tfidf_10k_10	0.811668	0.808620
5	svm-tfidf_10k_1	0.811668	0.808620
4	svm-tfidf_10k_0.1	0.811668	0.808620
2	svm-tfidf_10k_0.001	0.823545	0.818405
1	svm-tfidf_10k_0.0001	0.863934	0.857572
0	svm-tfidf_10k_1e-05	0.885669	0.876793

[162]:
```
print(train_auc_list,validation_auc_list)
print(f'best hyperparameter got = {score.name.values[-1]} ##### Best cv score␣
↪got = {score.test_score.values[-1]}')
plt.plot(alpha, train_auc_list, label='train')
plt.plot(alpha, validation_auc_list, label='validate')
plt.scatter(alpha, train_auc_list, label='Train AUC points')
plt.scatter(alpha, validation_auc_list, label='CV AUC points')
plt.legend()
plt.grid()
plt.show()
```

```
[0.8856686504648588, 0.8639337539335741, 0.8235451574133681, 0.811531834901979,
0.8116679298145992, 0.8116679298594802, 0.8116679298234563] [0.8767930396434684,
0.8575715048044434, 0.8184052179126222, 0.8084815746247286, 0.8086197295460223,
0.8086197294835358, 0.8086197294574587]
best hyperparameter got = svm-tfidf_10k_1e-05 ##### Best cv score got =
0.8767930396434684
```



[163]:
```
MODEL_NAME = 'svm_tfidf_10k'
clf = SGDClassifier(alpha=1e-05, class_weight='balanced', loss='hinge',␣
 ↪penalty='l2')
clf.fit(train_comment_tfidf_10000, y_train)
clf = CalibratedClassifierCV(clf, method="sigmoid")
clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]
```

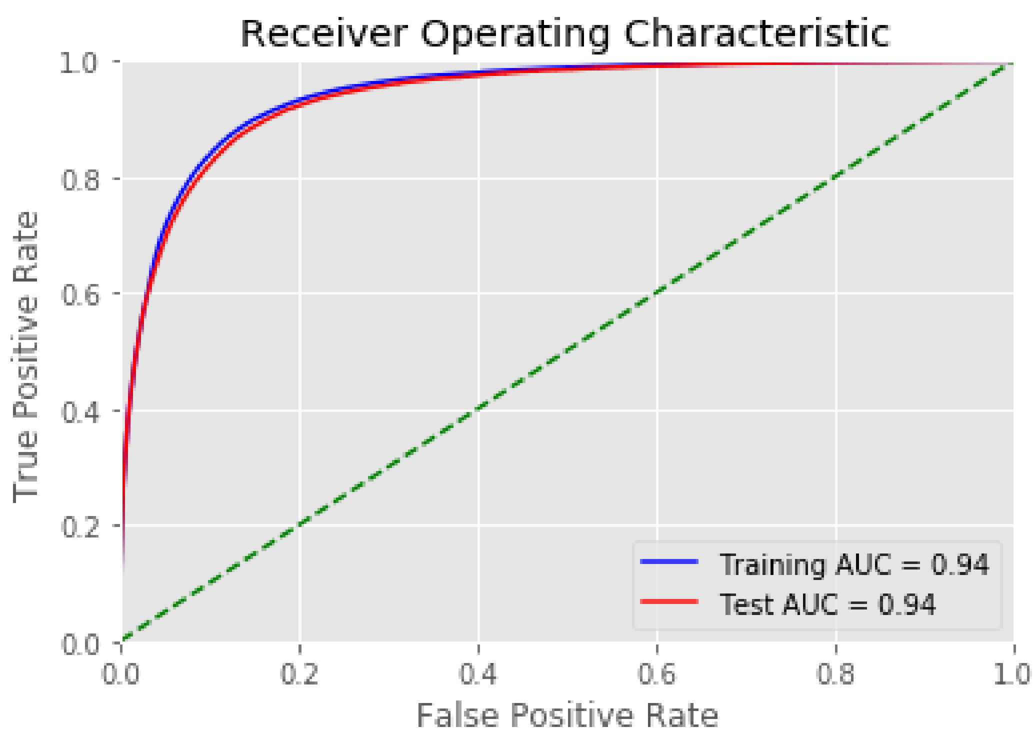
[164]:
```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(f'Train score = {get_metric_value(train_data, identity_columns,␣
 ↪MODEL_NAME)}')
print(f'Validation score = {get_metric_value(validation_data, identity_columns,␣
 ↪MODEL_NAME)}')
```

```
Train score = 0.8853153367543201
Validation score = 0.8764942399219395
```

[165]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_10000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/svm_tfidf_10k_submission.csv', index=False)
```

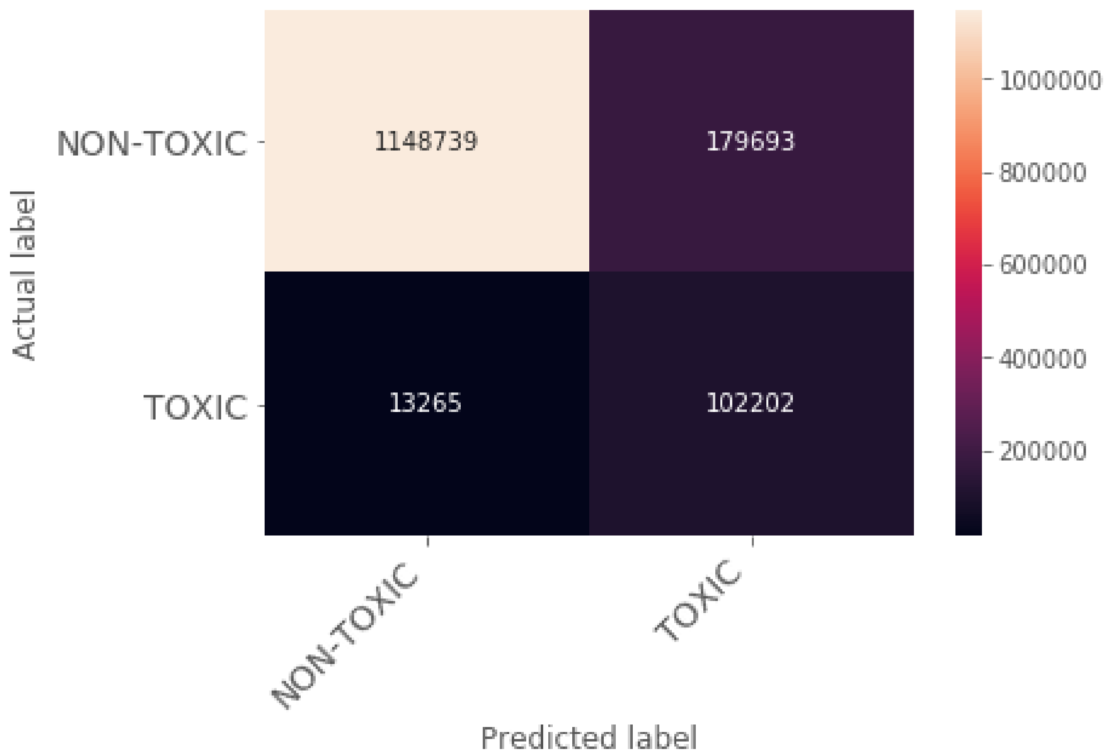
[ ]:
```
```

[166]:
```python
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[167]:
```
pred_train =␣
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

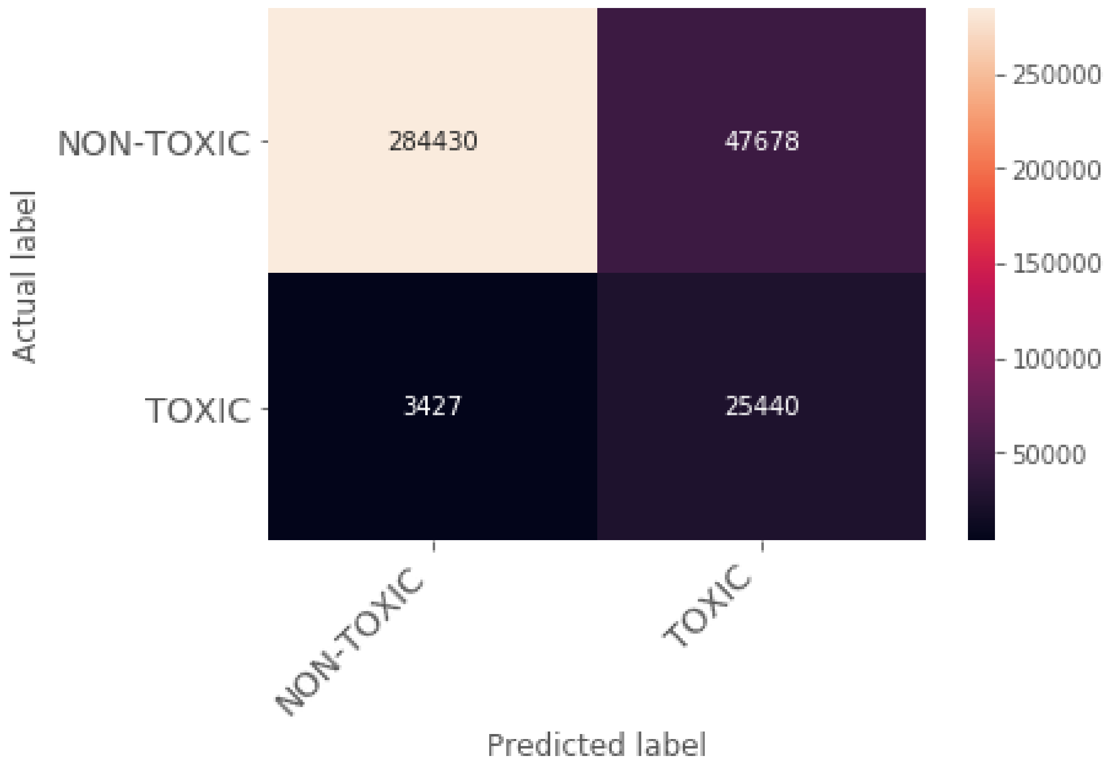
```
	TRAIN DATA CONFUSION MATRIX
```



=> 86.47 % of non-toxic comments predicted correctly => 88.51% of toxic comments predicted correctly

[168]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 85.64 % of non-toxic comments predicted correctly => 88.68% of toxic comments predicted correctly

[169]:
```
gc.collect()
```

[169]: 2753

5.1.4 XG-Boost

- Because of the momery constraint I am going to train XG-Boost and Random Forest models with single parameter at a time and finally pick up the best hyperparameter to be used in the final models.

[170]:
```
# train_auc_list = []
# validation_auc_list = []
MODEL_NAME = f'xgb_15k'
clf = XGBClassifier(scale_pos_weight=99,n_estimators=600, n_jobs=-1)
clf.fit(train_comment_tfidf_15000, y_train)
# clf = CalibratedClassifierCV(clf, method="sigmoid")
# clf.fit(train_comment_tfidf_15000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:,1]
```

```
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation

print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.8454389696554394
0.8308588587754047
```

[171]:
```
gc.collect()
```

[171]: 20

[172]:
```
# train_auc_list = []
# validation_auc_list = []
MODEL_NAME = f'xgb_15k'
clf = XGBClassifier(scale_pos_weight=99,n_estimators=1000, n_jobs=-1)
clf.fit(train_comment_tfidf_15000, y_train)
# clf = CalibratedClassifierCV(clf, method="sigmoid")
# clf.fit(train_comment_tfidf_15000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:,1]
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation

print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.8629956494551478
0.846324172468981
```

[173]:
```
gc.collect()
```

[173]: 20

[174]:
```
# train_auc_list = []
# validation_auc_list = []
MODEL_NAME = f'xgb_15k'
clf = XGBClassifier(scale_pos_weight=99,n_estimators=1500, n_jobs=-1)
clf.fit(train_comment_tfidf_15000, y_train)
# clf = CalibratedClassifierCV(clf, method="sigmoid")
# clf.fit(train_comment_tfidf_15000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:,1]
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
```

```
print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.8750813511870685
0.855662883466987
```

[175]:
```
gc.collect()
```

[175]: 20

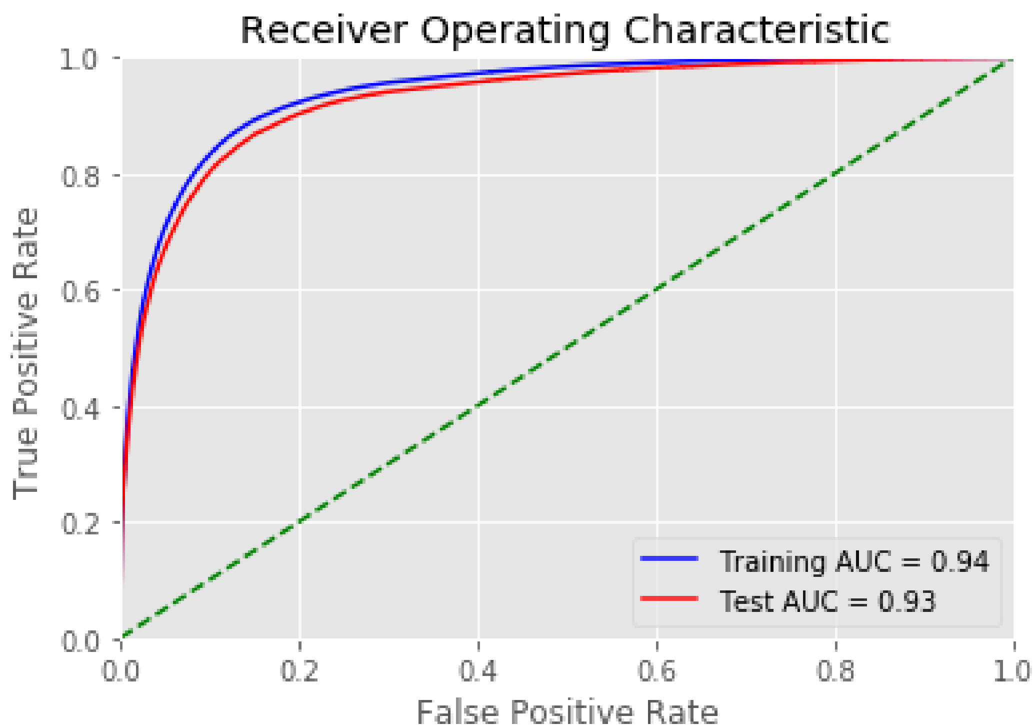
[27]:
```
# train_auc_list = []
# validation_auc_list = []
MODEL_NAME = f'xgb_10k'
clf = XGBClassifier(scale_pos_weight=99,n_estimators=2000, n_jobs=-1)
clf.fit(train_comment_tfidf_10000, y_train)
# clf = CalibratedClassifierCV(clf, method="sigmoid")
# clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation

print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.8834831095144419
0.8618897095328113
```

[28]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_10000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/xgb_10k_submission.csv', index=False)
```

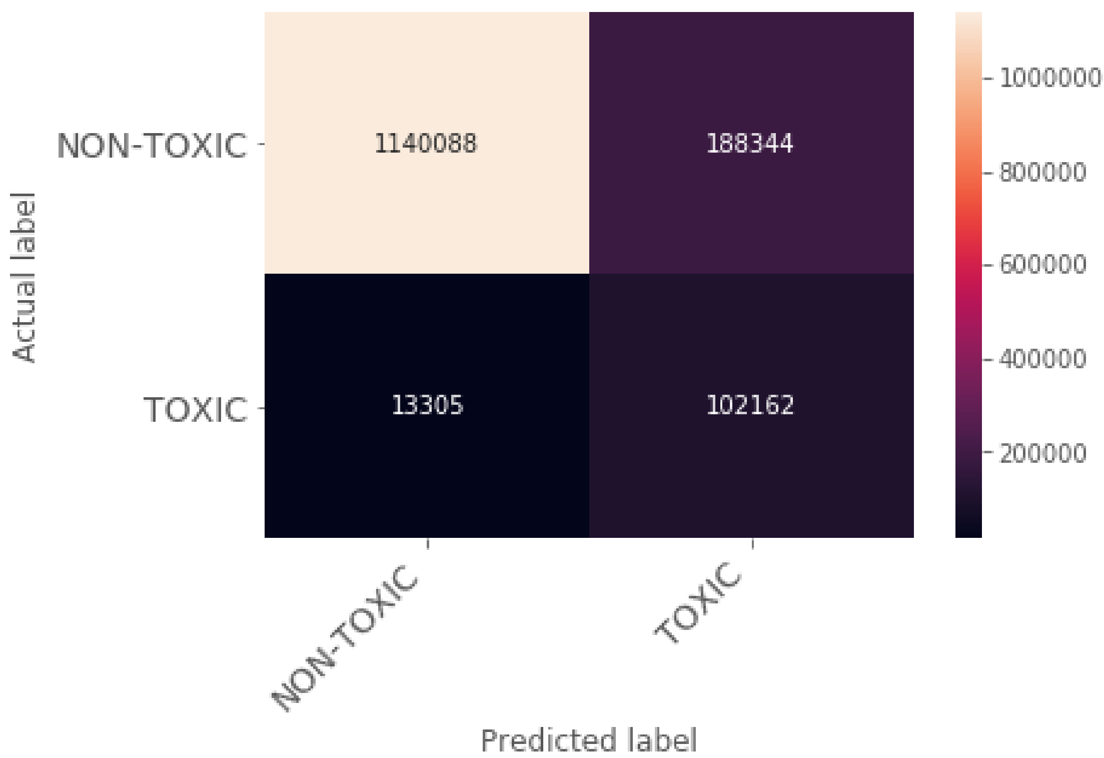
[177]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)
```

```
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[178]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

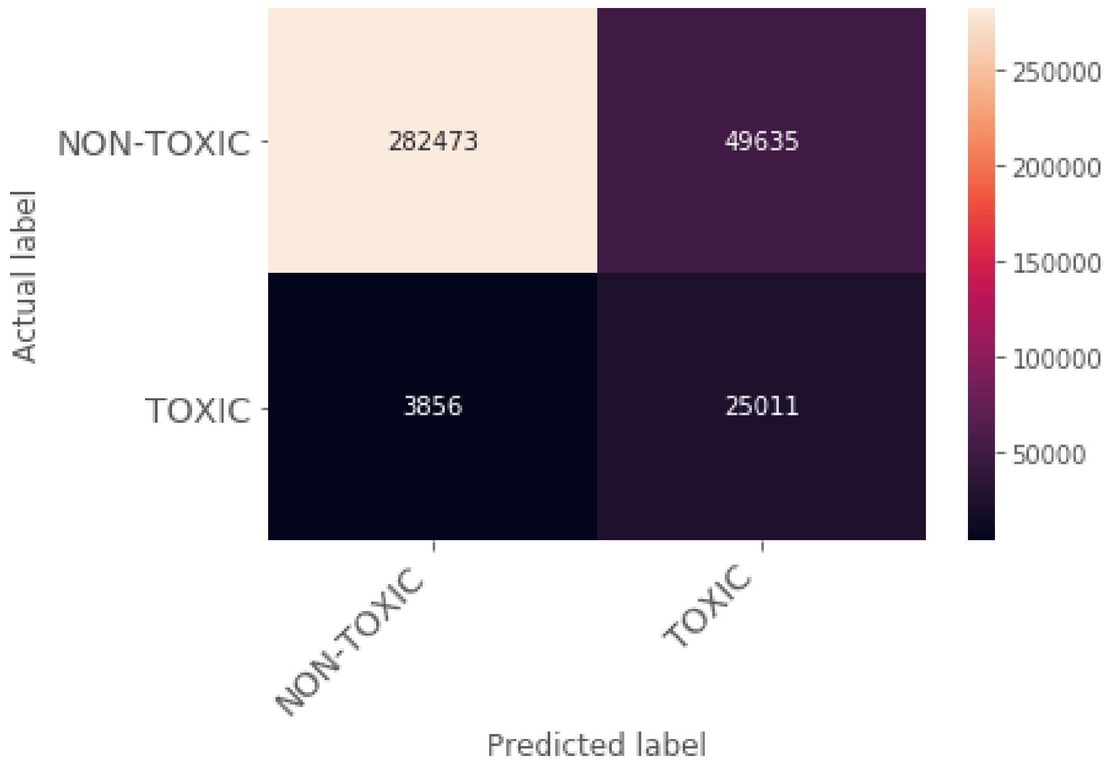
```
	TRAIN DATA CONFUSION MATRIX
```



=> 85.82 % of non-toxic comments predicted correctly => 88.47% of toxic comments predicted correctly

[179]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 85.05 % of non-toxic comments predicted correctly => 87.18% of toxic comments predicted correctly

[180]:
```
gc.collect()
```

[180]: 10071

5.1.5 RandomForest Classifier

[181]:
```
n_estimators = 1000
max_depth= 6
n_jobs = -1
class_weight = 'balanced'

MODEL_NAME = f'RF-tfidf_10k'
clf = RandomForestClassifier(n_estimators=n_estimators, max_depth=max_depth,␣
 ↪class_weight=class_weight, n_jobs=n_jobs)
clf.fit(train_comment_tfidf_10000, y_train)
clf = CalibratedClassifierCV(clf, method="sigmoid")
clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
```

```
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]

train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation

print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.780364485192717
0.7710341053802323
```

[182]:
```
gc.collect()
```

[182]: 188

[183]:
```
n_estimators = 1500
max_depth= 12
n_jobs = -1
class_weight = 'balanced'

MODEL_NAME = f'RF-tfidf_10k'
clf = RandomForestClassifier(n_estimators=n_estimators, max_depth=max_depth,␣
 ↪class_weight=class_weight, n_jobs=n_jobs)
clf.fit(train_comment_tfidf_10000, y_train)
clf = CalibratedClassifierCV(clf, method="sigmoid")
clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]

train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation

print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.803692756142839
0.7863449270650648
```

[184]:
```
gc.collect()
```

[184]: 92

[185]:
```
n_estimators = 2000
max_depth= 6
n_jobs = -1
class_weight = 'balanced'
```

```
MODEL_NAME = f'RF-tfidf_10k'
clf = RandomForestClassifier(n_estimators=n_estimators, max_depth=max_depth,␣
 ↪class_weight=class_weight, n_jobs=n_jobs)
clf.fit(train_comment_tfidf_10000, y_train)
clf = CalibratedClassifierCV(clf, method="sigmoid")
clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]

train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation

print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.7867186851683692
0.7774001591947981
```

[186]:
```
gc.collect()
```

[186]: 68

[29]:
```
n_estimators = 2000
max_depth= 12
n_jobs = -1
class_weight = 'balanced'

MODEL_NAME = f'RF-tfidf_10k'
clf = RandomForestClassifier(n_estimators=n_estimators, max_depth=max_depth,␣
 ↪class_weight=class_weight, n_jobs=n_jobs)
clf.fit(train_comment_tfidf_10000, y_train)
clf = CalibratedClassifierCV(clf, method="sigmoid")
clf.fit(train_comment_tfidf_10000, y_train)
predicted_train = clf.predict_proba(train_comment_tfidf_10000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_10000)[:,1]

train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation

print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.8039419785272921
0.7866102845131482
```

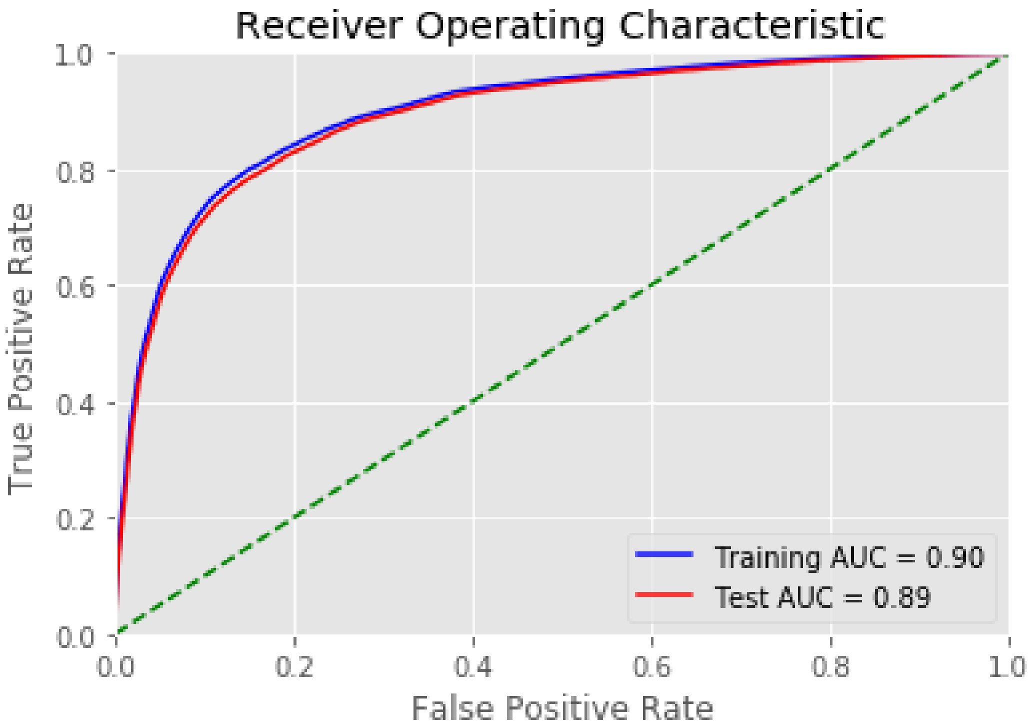
[30]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_10000)[:,1]
test_data['prediction'] = predicted_test
```

```
test_data.to_csv('test_preds/rf_10k_submission.csv', index=False)
```

[188]:
```
gc.collect()
```

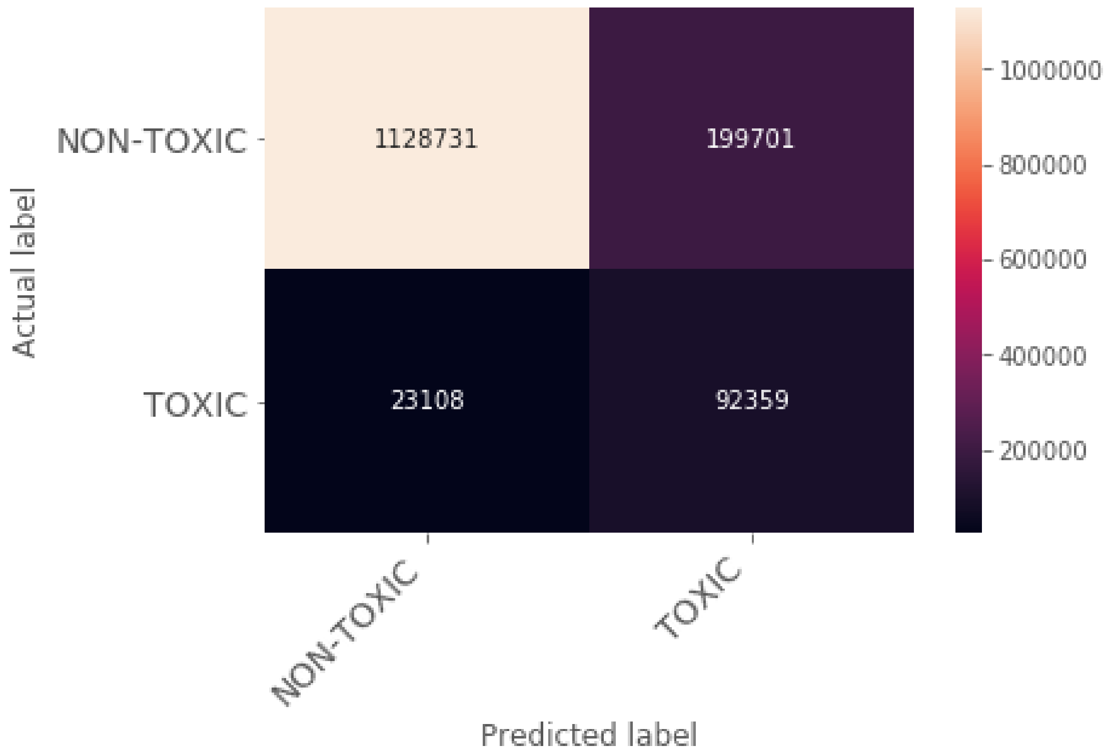
[188]: 68

[189]:
```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[190]:
```
pred_train = 
 ↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

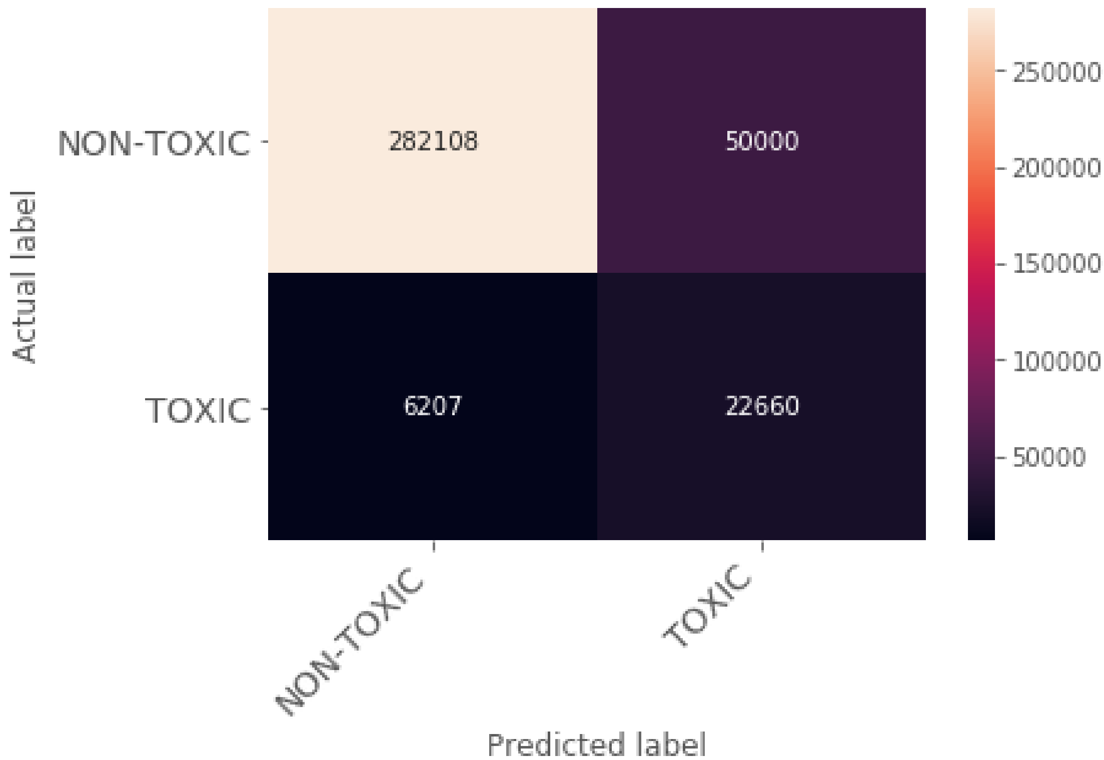
```
	TRAIN DATA CONFUSION MATRIX
```



=> 84.96 % of non-toxic comments predicted correctly => 79.98% of toxic comments predicted correctly

[191]:
```
pred_test =␣
 ↪predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 84.94 % of non-toxic comments predicted correctly => 78.99% of toxic comments predicted correctly

5.1.6 Stacking Classifier

Models with best hyperparameters

[19]:
```
nb_model = clf = MultinomialNB(alpha=1)
logistic_model = SGDClassifier(alpha=1e-5, class_weight='balanced', loss='log',␣
 ↪penalty='l2')
svm_model = SGDClassifier(alpha=1e-5, class_weight='balanced', loss='hinge',␣
 ↪penalty='l2')
xg_model = XGBClassifier(scale_pos_weight=99,n_estimators=2000, n_jobs=-1)
```

[20]:
```
import gc
gc.collect()
```

[20]: 40

Stacking models

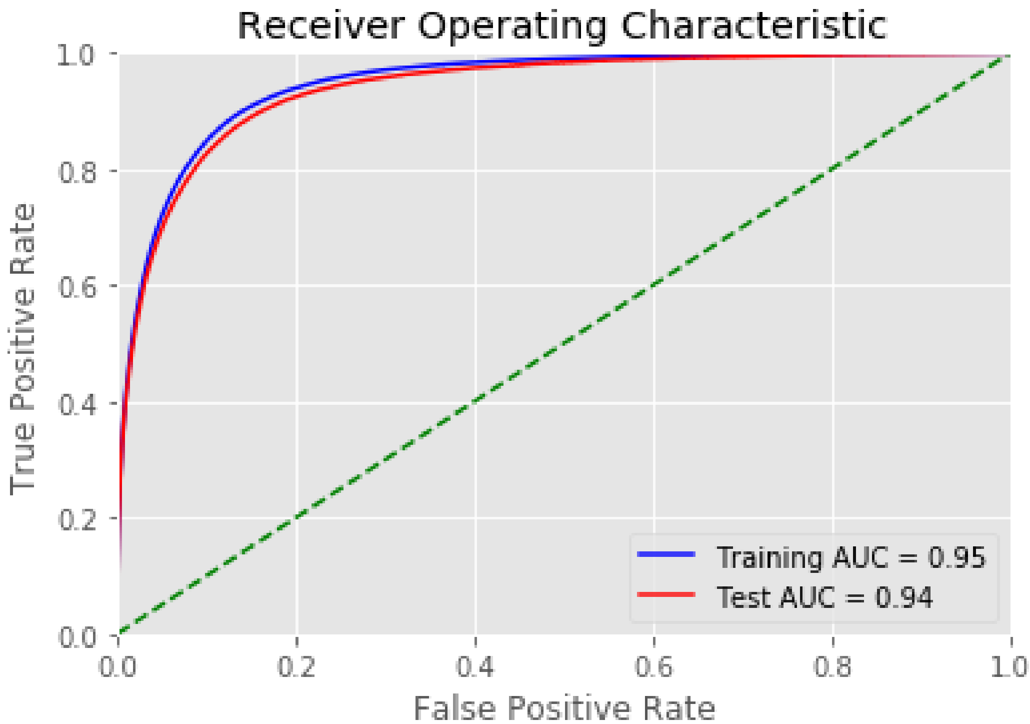
[21]:

```
estimators = [
    ('nb', nb_model),
    ('lr', logistic_model),
    ('xg', xg_model),
    ('svm', CalibratedClassifierCV(svm_model, method='sigmoid'))
]
clf = StackingClassifier(
    estimators=estimators, final_estimator=LogisticRegression(), n_jobs=-1,␣
 ↪verbose=5
)
clf.fit(train_comment_tfidf_15000, y_train)

predicted_train = clf.predict_proba(train_comment_tfidf_15000)[:,1]
predicted_validation = clf.predict_proba(validation_comment_tfidf_15000)[:,1]

MODEL_NAME = 'stacking'
train_data[MODEL_NAME] = predicted_train
validation_data[MODEL_NAME] = predicted_validation
print(get_metric_value(train_data, identity_columns, MODEL_NAME))
print(get_metric_value(validation_data, identity_columns, MODEL_NAME))
```

```
0.8917818215411302
0.8789805612696694
```

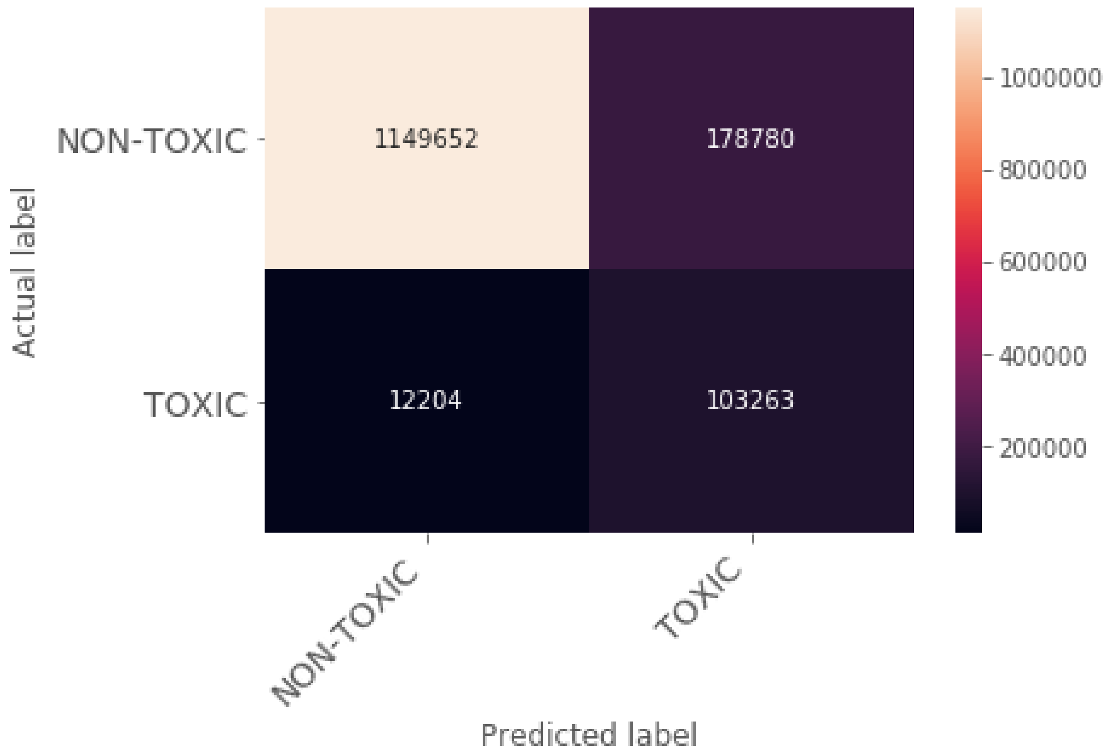
[22]:

```
# https://stackoverflow.com/questions/25009284/how-to-plot-roc-curve-in-python
fpr_train, tpr_train, threshold_train = roc_curve(y_train, predicted_train)
fpr_test, tpr_test, threshold_test = roc_curve(y_validation,␣
 ↪predicted_validation)

roc_auc_train = auc(fpr_train, tpr_train)
roc_auc_test = auc(fpr_test, tpr_test)


plt.title('Receiver Operating Characteristic')

plt.plot(fpr_train, tpr_train, 'b', label = 'Training AUC = %0.2f' %␣
 ↪roc_auc_train)
plt.plot(fpr_test, tpr_test, 'r', label = 'Test AUC = %0.2f' % roc_auc_test)

plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'g--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```



[23]:
```
pred_train =␣
↪predict_with_best_t(predicted_train,tpr_train,fpr_train,threshold_train)
cm = confusion_matrix(y_train, pred_train)
print("\tTRAIN DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

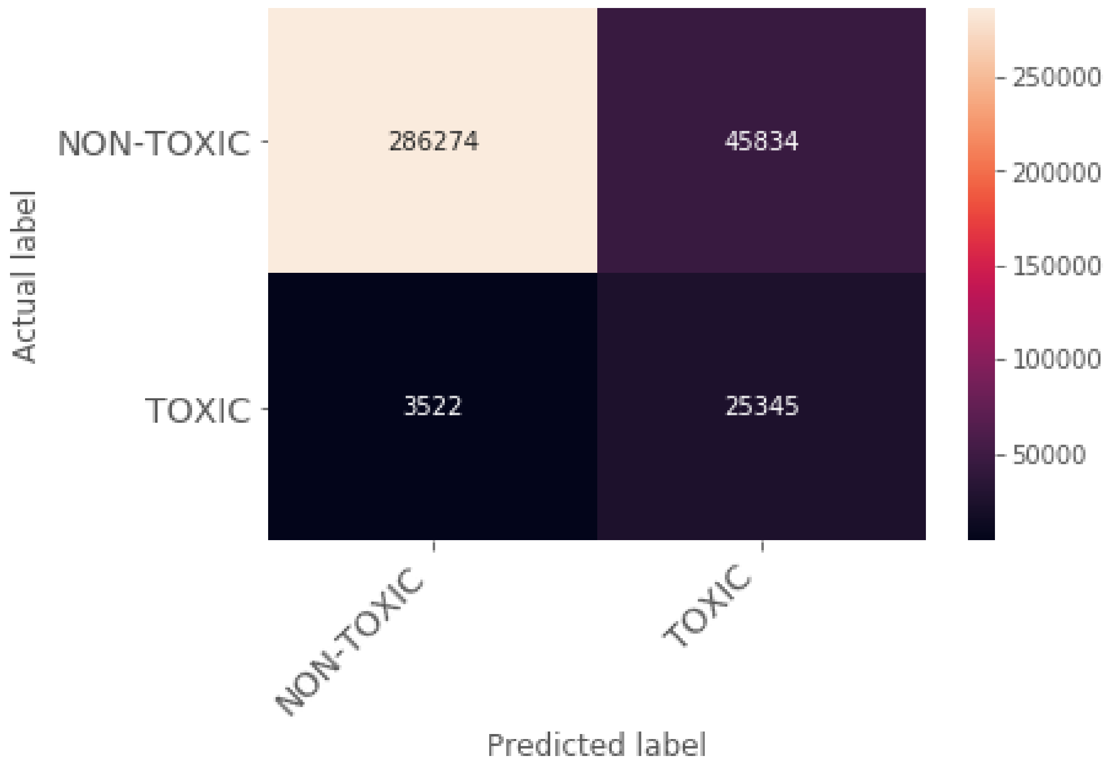
```
        TRAIN DATA CONFUSION MATRIX
```



=> 86.73 % of non-toxic comments predicted correctly => 89.43% of toxic comments predicted correctly

[25]:
```
pred_test = predict_with_best_t(predicted_validation,tpr_test,fpr_test,threshold_test)
cm = confusion_matrix(y_validation, pred_test)
print("\ttest DATA CONFUSION MATRIX")
plot_confusion_matrix(cm,class_names=['NON-TOXIC','TOXIC'])
```

```
	test DATA CONFUSION MATRIX
```



=> 86.19 % of non-toxic comments predicted correctly => 88.35% of toxic comments predicted correctly

[26]:
```
predicted_test = clf.predict_proba(test_comment_tfidf_15000)[:,1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/stacking_15k_submission.csv', index=False)
```

6 Deep Learning Models

[1]:
```
import numpy as np
import pandas as pd
import tensorflow as tf
from keras import backend as K
import keras
print(tf.__version__)
# tf.compat.v1.disable_v2_behavior()
from sklearn.model_selection import train_test_split
from keras.models import Model
from keras.layers import Input, Dense, Embedding, SpatialDropout1D, add,␣
 ↪concatenate
```

```python
from keras.layers import LSTM, Bidirectional, GlobalMaxPooling1D,␣
↪GlobalAveragePooling1D, GRU
from keras.layers import Conv1D, MaxPooling1D, AveragePooling1D, Flatten,␣
↪Dropout, Bidirectional
from keras.utils import to_categorical, plot_model
from keras.preprocessing import text, sequence
from gensim.models import KeyedVectors
from tqdm import tqdm
import pickle
import gc
gc.collect()

import re
import nltk
nltk.download('punkt')
nltk.download('wordnet')
from nltk.stem.wordnet import WordNetLemmatizer
from nltk import word_tokenize
from nltk.stem import PorterStemmer

from IPython.display import Image,YouTubeVideo,HTML

from sklearn import metrics
```

```
/home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:526: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint8 = np.dtype([("qint8", np.int8, 1)])
/home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:527: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:528: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint16 = np.dtype([("qint16", np.int16, 1)])
/home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:529: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:530: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
```

```
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/dtypes.py:535: FutureWarning: Passing
(type, 1) or '1type' as a synonym of type is deprecated; in a future version of
numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np_resource = np.dtype([("resource", np.ubyte, 1)])
Using TensorFlow backend.
```

```
1.13.1
```

```
[nltk_data] Downloading package punkt to /home/user/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to /home/user/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

[2]:
```python
import logging
logger = logging.getLogger("distributed.worker")
logger1 = logging.getLogger("distributed.utils_perf")
logger.setLevel(logging.ERROR)
logger1.setLevel(logging.ERROR)
```

[3]:
```python
from dask.distributed import Client, progress
client = Client(processes=False, threads_per_worker=12, n_workers=1,␣
 ↪memory_limit='6GB')
client
```

[3]:
```
<Client: 'inproc://192.168.0.107/24002/1' processes=1 threads=12, memory=6.00
GB>
```

[26]:
```python
EMBEDDING_FILES = [
    'deep learning/convolutional_model/crawl-300d-2M.gensim',
    'deep learning/convolutional_model/glove.840B.300d.gensim'
]
NUM_MODELS = 2
BATCH_SIZE = 60
LSTM_UNITS = 128
DENSE_HIDDEN_UNITS = 4 * LSTM_UNITS
EPOCHS = 4
MAX_LEN = 220
IDENTITY_COLUMNS = [
    'male', 'female', 'homosexual_gay_or_lesbian', 'christian', 'jewish',
    'muslim', 'black', 'white', 'psychiatric_or_mental_illness'
]
AUX_COLUMNS = ['target', 'severe_toxicity', 'obscene', 'identity_attack',␣
 ↪'insult', 'threat']
TEXT_COLUMN = 'comment_text'
TARGET_COLUMN = 'target'
```

```
CHARS_TO_REMOVE = '!"#$%&()*+,-./:;<=>?@[\\]^_`{|}~\t\n""’\'∞÷•à− ³‘´°£€\×√²−
'
```

[5]:
```python
def build_matrix(word_index, path):
    embedding_index = KeyedVectors.load(path, mmap='r')
    embedding_matrix = np.zeros((len(word_index) + 1, 300))
    for word, i in tqdm(word_index.items()):
        for candidate in [word, word.lower()]:
            if candidate in embedding_index:
                embedding_matrix[i] = embedding_index[candidate]
                break
    return embedding_matrix
```

6.1 Reading data

[14]:
```python
train_data = pd.read_csv('train/train.csv')
test_df = pd.read_csv('test/test.csv')
```

[15]:
```python
for column in IDENTITY_COLUMNS + [TARGET_COLUMN]:
    train_data[column] = np.where(train_data[column] >= 0.5, 1, 0)
```

6.2 Train test split (80% - 20%)

using stratified sampling to avoid bias while splitting data

[16]:
```python
train_data, cv_df = train_test_split(train_data, test_size=0.2,␣
↪stratify=train_data.target.values, random_state=2020)
print(train_data.shape)
print(cv_df.shape)
```

```
(1443899, 45)
(360975, 45)
```

Checking if test data is having approx same proportion of toxic comments compared to train data

[17]:
```python
neg_train = train_data[train_data['target'] == 1]
neg_train.shape
```

[17]: (115467, 45)

[18]:
```python
neg_validation = cv_df[cv_df['target'] == 1]
neg_validation.shape
```

[18]: (28867, 45)

[19]:
```
x_validation = cv_df[TEXT_COLUMN].astype(str)
y_validation = cv_df[TARGET_COLUMN].values
x_train = train_data[TEXT_COLUMN].astype(str)
y_train =train_data[TARGET_COLUMN].values
x_test = test_df[TEXT_COLUMN].astype(str)
```

6.3 Data preparation

[20]:
```
y_train = train_data[TARGET_COLUMN]
y_train = to_categorical(y_train)

y_validation = cv_df[TARGET_COLUMN]
y_validation = to_categorical(y_validation)
```

[21]:
```
sample_weights = np.ones(len(x_train), dtype=np.float32)
sample_weights += train_data[IDENTITY_COLUMNS].sum(axis=1)
sample_weights += train_data[TARGET_COLUMN] * (~train_data[IDENTITY_COLUMNS]).
↪sum(axis=1)
sample_weights += (~train_data[TARGET_COLUMN]) * train_data[IDENTITY_COLUMNS].
↪sum(axis=1) * 5
sample_weights /= sample_weights.mean()
```

[22]:
```
tokenizer = text.Tokenizer(filters=CHARS_TO_REMOVE, lower=False)
tokenizer.fit_on_texts(list(x_train) + list(x_test) + list(x_validation))

x_train = tokenizer.texts_to_sequences(x_train)
x_test = tokenizer.texts_to_sequences(x_test)
x_validation = tokenizer.texts_to_sequences(x_validation)

x_train = sequence.pad_sequences(x_train, maxlen=MAX_LEN)
x_test = sequence.pad_sequences(x_test, maxlen=MAX_LEN)
x_validation = sequence.pad_sequences(x_validation, maxlen=MAX_LEN)
```

[27]:
```
embedding_matrix = (build_matrix(tokenizer.word_index,␣
↪EMBEDDING_FILES[0])+build_matrix(tokenizer.word_index, EMBEDDING_FILES[1]))/2
```

```
100%|      | 424070/424070 [02:31<00:00, 2807.92it/s]
100%|      | 424070/424070 [02:36<00:00, 2709.57it/s]
```

6.4 Models

6.4.1 CNN Model

[28]:
```
input_text = Input(shape=(MAX_LEN,), dtype='float32')
embedding_layer = Embedding(len(tokenizer.word_index) + 1,
                            300,
                            weights=[embedding_matrix],
                            input_length=MAX_LEN,
                            trainable=False)
x = embedding_layer(input_text)
x = Conv1D(128, 2, activation='relu', padding='same')(x)
x = MaxPooling1D(5, padding='same')(x)
x = Conv1D(128, 3, activation='relu', padding='same')(x)
x = MaxPooling1D(5, padding='same')(x)
x = Conv1D(128, 4, activation='relu', padding='same')(x)
x = MaxPooling1D(40, padding='same')(x)
x = Flatten()(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
output = Dense(2, activation='softmax')(x)
```

```
WARNING:tensorflow:From /home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/resource_variable_ops.py:435: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Colocations handled automatically by placer.
```

[29]:
```
import keras
model = Model(inputs=[input_text], outputs=[output])
model.compile(loss='categorical_crossentropy',
                  optimizer='adam',
                  metrics=[keras.metrics.AUC()])
print(model.summary())
```

```
Model: "model_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 220)               0
_________________________________________________________________
embedding_1 (Embedding)      (None, 220, 300)          127221300
_________________________________________________________________
conv1d_1 (Conv1D)            (None, 220, 128)          76928
_________________________________________________________________
max_pooling1d_1 (MaxPooling1 (None, 44, 128)           0
_________________________________________________________________
```

```
conv1d_2 (Conv1D)            (None, 44, 128)           49280
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 9, 128)            0
_________________________________________________________________
conv1d_3 (Conv1D)            (None, 9, 128)            65664
_________________________________________________________________
max_pooling1d_3 (MaxPooling1 (None, 1, 128)            0
_________________________________________________________________
flatten_1 (Flatten)          (None, 128)               0
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 258
=================================================================
Total params: 127,429,942
Trainable params: 208,642
Non-trainable params: 127,221,300
_________________________________________________________________
None
```

[30]:

```
CNN_model = model.fit(
            x_train,
            y_train,
            batch_size=BATCH_SIZE,
            epochs=5
        )
```

```
WARNING:tensorflow:From /home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/5
1443899/1443899 [==============================] - 199s 138us/step - loss:
0.1380 - auc_1: 0.9879
Epoch 2/5
1443899/1443899 [==============================] - 199s 138us/step - loss:
0.1264 - auc_1: 0.9899
Epoch 3/5
1443899/1443899 [==============================] - 199s 138us/step - loss:
0.1230 - auc_1: 0.9905
Epoch 4/5
1443899/1443899 [==============================] - 200s 138us/step - loss:
0.1203 - auc_1: 0.9909
Epoch 5/5
```

```
1443899/1443899 [==============================] - 199s 138us/step - loss:
0.1184 - auc_1: 0.9912
```

[31]:
```
MODEL_NAME = 'cnn_model'
cv_df[MODEL_NAME] = model.predict(x_validation)[:, 1]
```

[42]:
```
bias_metrics_df = compute_bias_metrics_for_model(cv_df, identity_columns,␣
 ↪MODEL_NAME, TOXICITY_COLUMN)
```

[36]:
```
get_final_metric(bias_metrics_df, calculate_overall_auc(cv_df, MODEL_NAME))
```

[36]:
```
0.9098346247362036
```

[33]:
```
test_data = test_df
predicted_test = model.predict(x_test)[:, 1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/cnn_submission.csv', index=False)
```

[34]:
```
del model
```

6.4.2 Single layered LSTM

[35]:
```
import gc
gc.collect()
```

[35]:
```
26
```

[36]:
```
from keras.regularizers import l2
input_text = Input(shape=(MAX_LEN,), dtype='float32')
embedding_layer = Embedding(len(tokenizer.word_index) + 1,
                            300,
                            weights=[embedding_matrix],
                            input_length=MAX_LEN,
                            trainable=False)
x = embedding_layer(input_text)
x = LSTM(LSTM_UNITS, return_sequences=True, kernel_regularizer=l2(0.001),␣
 ↪dropout=0.5)(x)
x = Flatten()(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
output = Dense(2, activation='softmax')(x)
```

[37]:
```
model = Model(inputs=[input_text], outputs=[output])
model.compile(loss='categorical_crossentropy',
                  optimizer='adam',
                  metrics=[keras.metrics.AUC()])
```

```
print(model.summary())
```

```
Model: "model_2"

_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         (None, 220)               0

_________________________________________________________________
embedding_2 (Embedding)      (None, 220, 300)          127221300

_________________________________________________________________
lstm_1 (LSTM)                (None, 220, 128)          219648

_________________________________________________________________
flatten_2 (Flatten)          (None, 28160)             0

_________________________________________________________________
dropout_2 (Dropout)          (None, 28160)             0

_________________________________________________________________
dense_3 (Dense)              (None, 128)               3604608

_________________________________________________________________
dense_4 (Dense)              (None, 2)                 258
=================================================================
Total params: 131,045,814
Trainable params: 3,824,514
Non-trainable params: 127,221,300

_________________________________________________________________
None
```

[38]:
```
LSTM_1_layer_model = model.fit(
            x_train,
            y_train,
            batch_size=BATCH_SIZE,
            epochs=1
        )
```

```
Epoch 1/1
1443899/1443899 [==============================] - 2269s 2ms/step - loss: 0.1985
- auc_2: 0.9794
```

[47]:
```
MODEL_NAME = 'LSTM_1_layer_model'
cv_df[MODEL_NAME] = LSTM_1_layer_model.model.predict(x_validation)[:, 1]
```

[41]:
```
bias_metrics_df = compute_bias_metrics_for_model(cv_df, identity_columns,␣
 ↪MODEL_NAME, TOXICITY_COLUMN)
```

[49]:
```
get_final_metric(bias_metrics_df, calculate_overall_auc(cv_df, MODEL_NAME))
```

[49]: 0.8869887233187211

[39]:
```
predicted_test = model.predict(x_test)[:, 1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/lstm_1_layer_submission.csv', index=False)
```

[40]:
```
del model
gc.collect()
```

[40]: 606

6.4.3 Two layered Bi-Directional LSTM

[41]:
```
from keras.regularizers import l2
input_text = Input(shape=(MAX_LEN,), dtype='float32')
embedding_layer = Embedding(len(tokenizer.word_index) + 1,
                            300,
                            weights=[embedding_matrix],
                            input_length=MAX_LEN,
                            trainable=False)
x = embedding_layer(input_text)
x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True,␣
 ↪kernel_regularizer=l2(0.001), dropout=0.5))(x)
x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True,␣
 ↪kernel_regularizer=l2(0.001), dropout=0.5))(x)
x = GlobalMaxPooling1D()(x)
x = Dense(128, activation='relu')(x)
x = Dropout(0.5)(x)
x = Dense(128, activation='relu')(x)
output = Dense(2, activation='softmax')(x)
```

[42]:
```
model = Model(inputs=[input_text], outputs=[output])
model.compile(loss='categorical_crossentropy',
                optimizer='adam',
                metrics=[keras.metrics.AUC()])
print(model.summary())
```

```
Model: "model_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         (None, 220)               0
_________________________________________________________________
embedding_3 (Embedding)      (None, 220, 300)          127221300
_________________________________________________________________
bidirectional_1 (Bidirection (None, 220, 256)          439296
_________________________________________________________________
bidirectional_2 (Bidirection (None, 220, 256)          394240
```

```
_________________________________________________________________
global_max_pooling1d_1 (Glob (None, 256)               0
_________________________________________________________________
dense_5 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_6 (Dense)              (None, 128)               16512
_________________________________________________________________
dense_7 (Dense)              (None, 2)                 258
=================================================================
Total params: 128,104,502
Trainable params: 883,202
Non-trainable params: 127,221,300
_________________________________________________________________
None
```

[43]:

```
bi_dir_LSTM_2_layer_model = model.fit(
            x_train,
            y_train,
            batch_size=BATCH_SIZE,
            epochs=1
        )
```

```
WARNING:tensorflow:From /home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math_grad.py:102: div (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Deprecated in favor of operator or tf.math.divide.
Epoch 1/1
1443899/1443899 [==============================] - 8428s 6ms/step - loss: 0.1993
- auc_3: 0.9806
```

[56]:

```
MODEL_NAME = 'bi_dir_LSTM_2_layer_model'
cv_df[MODEL_NAME] = model.predict(x_validation)[:, 1]
```

[57]:

```
bias_metrics_df = compute_bias_metrics_for_model(cv_df, identity_columns,␣
 ↪MODEL_NAME, TOXICITY_COLUMN)
bias_metrics_df
```

[57]:

	subgroup	subgroup_size	…	bpsn_auc	bnsp_auc
7	white	5016	…	0.809932	0.945186
2	homosexual_gay_or_lesbian	2184	…	0.792816	0.948477
5	muslim	4205	…	0.881415	0.907155
6	black	3054	…	0.815275	0.943441
8	psychiatric_or_mental_illness	1002	…	0.916938	0.879761

```
4                           jewish           1583  …  0.884846  0.913397
0                             male           9049  …  0.871653  0.942291
1                           female          10791  …  0.889218  0.935191
3                        christian           8189  …  0.927190  0.906267

[9 rows x 5 columns]
```

[58]:
```
get_final_metric(bias_metrics_df, calculate_overall_auc(cv_df, MODEL_NAME))
```

[58]: 0.8877852468005003

[44]:
```
predicted_test = model.predict(x_test)[:, 1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/lstm_2_layer_submission.csv', index=False)
```

[45]:
```
del model
gc.collect()
```

[45]: 523

6.4.4 Research paper approach

https://www.theseus.fi/bitstream/handle/10024/226938/Quan_Do.pdf

[46]:
```
input_text = Input(shape=(MAX_LEN,), dtype='float32')
embedding_layer = Embedding(len(tokenizer.word_index) + 1,
                                    300,
                                    weights=[embedding_matrix],
                                    input_length=MAX_LEN,
                                    trainable=False)
x = embedding_layer(input_text)
x = SpatialDropout1D(0.2)(x)
x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True))(x)
x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True))(x)

hidden = concatenate([
        GlobalMaxPooling1D()(x),
        GlobalAveragePooling1D()(x),
    ])
hidden = add([hidden, Dense(DENSE_HIDDEN_UNITS, activation='relu')(hidden)])
hidden = add([hidden, Dense(DENSE_HIDDEN_UNITS, activation='relu')(hidden)])
result = Dense(2, activation='sigmoid')(hidden)
```

[47]:
```
model = Model(inputs=input_text, outputs=[result])
model.compile(loss='categorical_crossentropy',
                  optimizer='adam',
```

```
                 metrics=[keras.metrics.AUC()])
print(model.summary())
```

```
Model: "model_4"
__________________________________________________________________________________
__________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================
==================
input_4 (InputLayer)            (None, 220)          0

__________________________________________________________________________________
__________________
embedding_4 (Embedding)         (None, 220, 300)     127221300   input_4[0][0]

__________________________________________________________________________________
__________________
spatial_dropout1d_1 (SpatialDro (None, 220, 300)     0
embedding_4[0][0]

__________________________________________________________________________________
__________________
bidirectional_3 (Bidirectional) (None, 220, 256)     439296
spatial_dropout1d_1[0][0]

__________________________________________________________________________________
__________________
bidirectional_4 (Bidirectional) (None, 220, 256)     394240
bidirectional_3[0][0]

__________________________________________________________________________________
__________________
global_max_pooling1d_2 (GlobalM (None, 256)          0
bidirectional_4[0][0]

__________________________________________________________________________________
__________________
global_average_pooling1d_1 (Glo (None, 256)          0
bidirectional_4[0][0]

__________________________________________________________________________________
__________________
concatenate_1 (Concatenate)     (None, 512)          0
global_max_pooling1d_2[0][0]
global_average_pooling1d_1[0][0]

__________________________________________________________________________________
__________________
dense_8 (Dense)                 (None, 512)          262656
concatenate_1[0][0]

__________________________________________________________________________________
__________________
add_1 (Add)                     (None, 512)          0
concatenate_1[0][0]
                                                                 dense_8[0][0]
```

```
--------------------------------------------------------------------------------
------------------
dense_9 (Dense)                 (None, 512)          262656      add_1[0][0]

--------------------------------------------------------------------------------
------------------
add_2 (Add)                     (None, 512)          0           add_1[0][0]
                                                                 dense_9[0][0]

--------------------------------------------------------------------------------
------------------
dense_10 (Dense)                (None, 2)            1026        add_2[0][0]
================================================================================
==================
Total params: 128,581,174
Trainable params: 1,359,874
Non-trainable params: 127,221,300

--------------------------------------------------------------------------------
------------------
None
```

[36]:

```
plot_model(model, show_shapes=True, to_file='research_paper_model.png')
```

[36]:

[48]:
```
research_paper_model = model.fit(
            x_train,
            y_train,
            batch_size=BATCH_SIZE,
            epochs=1)
```

```
Epoch 1/1
1443899/1443899 [==============================] - 8081s 6ms/step - loss: 0.1329
- auc_4: 0.9861
```

[38]:
```
MODEL_NAME = 'research_paper_model'
cv_df[MODEL_NAME] = model.predict(x_validation)[:, 1]
```

[39]:
```
bias_metrics_df = compute_bias_metrics_for_model(cv_df, identity_columns,␣
↪MODEL_NAME, TOXICITY_COLUMN)
bias_metrics_df
```

[39]:
```
                      subgroup  subgroup_size  subgroup_auc  bpsn_auc  \
6                        black           2956      0.839738  0.829836
2     homosexual_gay_or_lesbian          2148      0.844528  0.831435
5                       muslim           4133      0.857721  0.866696
7                        white           5001      0.858279  0.833863
4                       jewish           1543      0.894097  0.899702
8  psychiatric_or_mental_illness          990      0.916345  0.900627
1                       female          10652      0.925286  0.922746
0                         male           8998      0.926840  0.918693
3                    christian           8029      0.931650  0.949586

   bnsp_auc
6  0.971977
2  0.971242
5  0.965435
7  0.974571
4  0.964022
8  0.969396
1  0.966645
0  0.968962
3  0.951175
```

[40]:
```
get_final_metric(bias_metrics_df, calculate_overall_auc(cv_df, MODEL_NAME))
```

[40]: 0.9228624083847328

[49]:
```
predicted_test = model.predict(x_test)[:, 1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/research_paper_submission.csv', index=False)
```

[50]:
```
del model
gc.collect()
```

[50]: 165

6.4.5 Research paper with attention layer

[51]:
```
# https://www.kaggle.com/takuok/bidirectional-lstm-and-attention-lb-0-043
from keras.layers import Layer
from keras import initializers, regularizers, constraints
class Attention(Layer):
    def __init__(self, step_dim,
```

```python
                 W_regularizer=None, b_regularizer=None,
                 W_constraint=None, b_constraint=None,
                 bias=True, **kwargs):
        self.supports_masking = True
        self.init = initializers.get('glorot_uniform')

        self.W_regularizer = regularizers.get(W_regularizer)
        self.b_regularizer = regularizers.get(b_regularizer)

        self.W_constraint = constraints.get(W_constraint)
        self.b_constraint = constraints.get(b_constraint)

        self.bias = bias
        self.step_dim = step_dim
        self.features_dim = 0
        super(Attention, self).__init__(**kwargs)

    def build(self, input_shape):
        assert len(input_shape) == 3

        self.W = self.add_weight(shape=(input_shape[-1],),
                                initializer=self.init,
                                name=f'{self.name}_W',
                                regularizer=self.W_regularizer,
                                constraint=self.W_constraint)
        self.features_dim = input_shape[-1]

        if self.bias:
            self.b = self.add_weight(shape=(input_shape[1],),
                                    initializer='zero',
                                    name='{}_b'.format(self.name),
                                    regularizer=self.b_regularizer,
                                    constraint=self.b_constraint)
        else:
            self.b = None

        self.built = True

    def compute_mask(self, input, input_mask=None):
        return None

    def call(self, x, mask=None):
        features_dim = self.features_dim
        step_dim = self.step_dim

        eij = K.reshape(K.dot(K.reshape(x, (-1, features_dim)),
                        K.reshape(self.W, (features_dim, 1))), (-1, step_dim))
```

```
        if self.bias:
            eij += self.b

        eij = K.tanh(eij)

        a = K.exp(eij)

        if mask is not None:
            a *= K.cast(mask, K.floatx())

        a /= K.cast(K.sum(a, axis=1, keepdims=True) + K.epsilon(), K.floatx())

        a = K.expand_dims(a)
        weighted_input = x * a
        return K.sum(weighted_input, axis=1)

    def compute_output_shape(self, input_shape):
        return input_shape[0],  self.features_dim
```

[52]:
```
input_text = Input(shape=(MAX_LEN,), dtype='float32')
embedding_layer = Embedding(len(tokenizer.word_index) + 1,
                                    300,
                                    weights=[embedding_matrix],
                                    input_length=MAX_LEN,
                                    trainable=False)
x = embedding_layer(input_text)
x = SpatialDropout1D(0.2)(x)
x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True))(x)
x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True))(x)
att = Attention(MAX_LEN)(x)
x = Conv1D(64, kernel_size = 3, padding = "valid", kernel_initializer =␣
 ↪"he_uniform")(x)
hidden = concatenate([att,
        GlobalMaxPooling1D()(x),
        GlobalAveragePooling1D()(x),
    ])
hidden = add([hidden, Dense(384, activation='relu')(hidden)])
hidden = Dropout(0.5)(hidden)
hidden = add([hidden, Dense(384, activation='relu')(hidden)])
result = Dense(2, activation='sigmoid')(hidden)
#     aux_result = Dense(num_aux_targets, activation='sigmoid')(hidden)
```

[53]:
```
model = Model(inputs=input_text, outputs=[result])
model.compile(loss='categorical_crossentropy',
                  optimizer='adam',
                  metrics=[keras.metrics.AUC()])
```

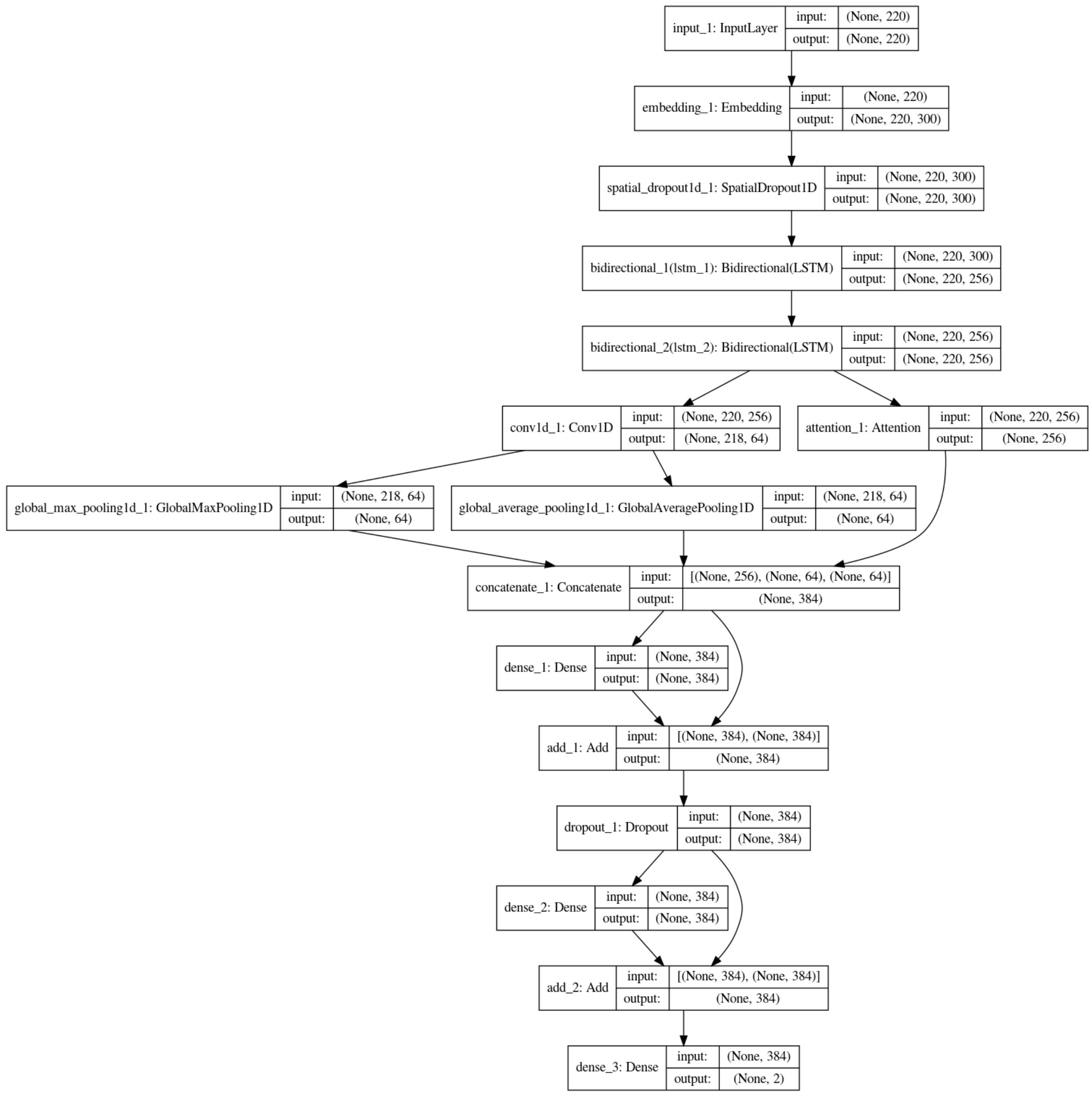
```python
print(model.summary())
```

```
Model: "model_5"
__________________________________________________________________________________
________________
Layer (type)                    Output Shape         Param #     Connected to
==================================================================================
================
input_5 (InputLayer)            (None, 220)          0

__________________________________________________________________________________
________________
embedding_5 (Embedding)         (None, 220, 300)     127221300   input_5[0][0]
__________________________________________________________________________________
________________
spatial_dropout1d_2 (SpatialDro (None, 220, 300)     0
embedding_5[0][0]
__________________________________________________________________________________
________________
bidirectional_5 (Bidirectional) (None, 220, 256)     439296
spatial_dropout1d_2[0][0]
__________________________________________________________________________________
________________
bidirectional_6 (Bidirectional) (None, 220, 256)     394240
bidirectional_5[0][0]
__________________________________________________________________________________
________________
conv1d_4 (Conv1D)               (None, 218, 64)      49216
bidirectional_6[0][0]
__________________________________________________________________________________
________________
attention_1 (Attention)         (None, 256)          476
bidirectional_6[0][0]
__________________________________________________________________________________
________________
global_max_pooling1d_3 (GlobalM (None, 64)           0           conv1d_4[0][0]
__________________________________________________________________________________
________________
global_average_pooling1d_2 (Glo (None, 64)           0           conv1d_4[0][0]
__________________________________________________________________________________
________________
concatenate_2 (Concatenate)     (None, 384)          0
attention_1[0][0]
global_max_pooling1d_3[0][0]
global_average_pooling1d_2[0][0]
__________________________________________________________________________________
________________
dense_11 (Dense)                (None, 384)          147840
```

```
concatenate_2[0][0]
__________________________________________________________________________________
add_3 (Add)                     (None, 384)          0
concatenate_2[0][0]
                                                                 dense_11[0][0]
__________________________________________________________________________________
dropout_4 (Dropout)             (None, 384)          0           add_3[0][0]
__________________________________________________________________________________
dense_12 (Dense)                (None, 384)          147840      dropout_4[0][0]
__________________________________________________________________________________
add_4 (Add)                     (None, 384)          0           dropout_4[0][0]
                                                                 dense_12[0][0]
__________________________________________________________________________________
dense_13 (Dense)                (None, 2)            770         add_4[0][0]
==================================================================================
Total params: 128,400,978
Trainable params: 1,179,678
Non-trainable params: 127,221,300
__________________________________________________________________________________
None
```

[21]:
```
plot_model(model, show_shapes=True,
 to_file='research_paper_with_attention_model.png')
```

[21]:



[54]:

```
research_paper_model = model.fit(
            x_train,
            y_train,
            batch_size=BATCH_SIZE,
            epochs=4)
```

```
Epoch 1/4
1443899/1443899 [==============================] - 8155s 6ms/step - loss: 0.1360
- auc_5: 0.9835
Epoch 2/4
1443899/1443899 [==============================] - 8184s 6ms/step - loss: 0.1201
- auc_5: 0.9855
Epoch 3/4
```

```
1443899/1443899 [==============================] - 8136s 6ms/step - loss: 0.1143
- auc_5: 0.9849
Epoch 4/4
1443899/1443899 [==============================] - 8136s 6ms/step - loss: 0.1102
- auc_5: 0.9846
```

[23]:
```
MODEL_NAME = 'research_paper_with_attention'
cv_df[MODEL_NAME] = model.predict(x_validation)[:, 1]
```

[24]:
```
bias_metrics_df = compute_bias_metrics_for_model(cv_df, identity_columns,␣
↪MODEL_NAME, TOXICITY_COLUMN)
bias_metrics_df
```

[24]:
```
                        subgroup  subgroup_size  subgroup_auc  bpsn_auc  \
5                         muslim           4187      0.850103  0.879523
6                          black           3017      0.850858  0.827608
2      homosexual_gay_or_lesbian           2227      0.851779  0.850920
7                          white           4932      0.863925  0.849635
4                         jewish           1540      0.888502  0.920189
8  psychiatric_or_mental_illness            989      0.915460  0.921929
3                      christian           7955      0.925814  0.952348
1                         female          10754      0.931927  0.934992
0                           male           8883      0.933275  0.929630

   bnsp_auc
5  0.962804
6  0.976094
2  0.970679
7  0.974505
4  0.955366
8  0.964872
3  0.949032
1  0.966422
0  0.969869
```

[25]:
```
get_final_metric(bias_metrics_df, calculate_overall_auc(cv_df, MODEL_NAME))
```

[25]: 0.9269571528954396

[55]:
```
predicted_test = model.predict(x_test)[:, 1]
test_data['prediction'] = predicted_test
test_data.to_csv('test_preds/research_paper_with_attan_submission.csv',␣
↪index=False)
```

6.5 Using Transfer Learning (BERT)

[64]:
```
# https://www.kaggle.com/prithvi1029/unprocessed-comments-worked-well
from __future__ import absolute_import
from __future__ import division
from __future__ import print_function
import sys
package_dir = "ppbert/pytorch-pretrained-bert/pytorch-pretrained-BERT"
sys.path.append(package_dir)
import torch.utils.data
import numpy as np
import pandas as pd
from tqdm import tqdm
import os
import warnings
from pytorch_pretrained_bert import BertTokenizer,␣
↪BertForSequenceClassification, BertAdam
from pytorch_pretrained_bert import BertConfig
import gc
from sklearn import metrics
from sklearn.model_selection import train_test_split

warnings.filterwarnings(action='once')
device = torch.device('cuda')
```

[2]:
```
IDENTITY_COLUMNS = [
    'transgender', 'female', 'homosexual_gay_or_lesbian', 'muslim', 'hindu',
    'white', 'black', 'psychiatric_or_mental_illness', 'jewish'
    ]
TARGET_COLUMN = 'target'
```

[4]:
```
for column in IDENTITY_COLUMNS + [TARGET_COLUMN]:
    train_df[column] = np.where(train_df[column] >=0.5, True, False)
```

[43]:
```
# cv_df.to_csv('cv_df.csv')
# train_data.to_csv('train_data.csv')
cv_df = pd.read_csv('cv_df.csv')
train_data = pd.read_csv('train_data.csv')
```

6.5.1 Bert Small And Large with fine tuned models

Data Preparation

[7]:
```
def convert_lines(example, max_seq_length,tokenizer):
    max_seq_length -=2
    all_tokens = []
```

```
    longer = 0
    for text in tqdm(example):
        tokens_a = tokenizer.tokenize(text)
        if len(tokens_a)>max_seq_length:
            tokens_a = tokens_a[:max_seq_length]
            longer += 1
        one_token = tokenizer.
↪convert_tokens_to_ids(["[CLS]"]+tokens_a+["[SEP]"])+[0] * (max_seq_length -␣
↪len(tokens_a))
        all_tokens.append(one_token)
    return np.array(all_tokens)
```

[8]:
```
MAX_SEQUENCE_LENGTH = 220
SEED = 1234
BATCH_SIZE = 32
BERT_MODEL_PATH = 'bert-pretrained-models/uncased_l-12_h-768_a-12/
↪uncased_L-12_H-768_A-12/'
LARGE_BERT_MODEL_PATH = 'bert-pretrained-models/uncased_l-24_h-1024_a-16/
↪uncased_L-24_H-1024_A-16/'
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed(SEED)
torch.backends.cudnn.deterministic = True
```

[9]:
```
# Pretrained BERT models - Google's pretrained BERT model
BERT_SMALL_PATH = 'bert-pretrained-models/uncased_l-12_h-768_a-12/
↪uncased_L-12_H-768_A-12/'
BERT_LARGE_PATH = 'bert-pretrained-models/uncased_l-24_h-1024_a-16/
↪uncased_L-24_H-1024_A-16/'
```

[10]:
```
# JIGSAW fine-tuned BERT models
JIGSAW_BERT_SMALL_MODEL_PATH =␣
↪'finetuned-bert-for-jigsaw-toxicity-classification/bert_pytorch.bin'
JIGSAW_BERT_LARGE_MODEL_PATH = 'pretrained-b-j/
↪jigsaw-bert-large-uncased-len-220-fp16/epoch-1/pytorch_model.bin'
JIGSAW_BERT_SMALL_JSON_PATH =␣
↪'finetuned-bert-for-jigsaw-toxicity-classification/bert_config.json'
JIGSAW_BERT_LARGE_JSON_PATH = 'pretrained-b-j/
↪jigsaw-bert-large-uncased-len-220-fp16/epoch-1/config.json'
NUM_BERT_MODELS = 2
INFER_BATCH_SIZE = 64
```

[11]:
```
cv_preds = np.zeros((cv_df.shape[0],NUM_BERT_MODELS))
np.random.seed(SEED)
torch.manual_seed(SEED)
torch.cuda.manual_seed(SEED)
```

```
torch.backends.cudnn.deterministic = True
```

Predicting BERT large model

```
[12]: # Prepare data
bert_config = BertConfig(JIGSAW_BERT_LARGE_JSON_PATH)
tokenizer = BertTokenizer.from_pretrained(BERT_LARGE_PATH,␣
 ↪cache_dir=None,do_lower_case=True)
X_cv = convert_lines(cv_df["comment_text"].fillna("DUMMY_VALUE"),␣
 ↪MAX_SEQUENCE_LENGTH, tokenizer)
cv = torch.utils.data.TensorDataset(torch.tensor(X_cv, dtype=torch.long))
```

```
100%|      | 360975/360975 [03:47<00:00, 1589.46it/s]
```

```
[44]: # Load fine-tuned BERT model
gc.collect()
model = BertForSequenceClassification(bert_config, num_labels=1)
model.load_state_dict(torch.load(JIGSAW_BERT_LARGE_MODEL_PATH))
model.to(device)
for param in model.parameters():
    param.requires_grad = False
model.eval()
```

```
[14]: # Predicting
gc.collect()
model_preds = np.zeros((len(X_cv)))
cv_loader = torch.utils.data.DataLoader(cv, batch_size=INFER_BATCH_SIZE,␣
 ↪shuffle=False)
tk0 = tqdm(cv_loader)
for i, (x_batch,) in enumerate(tk0):
        pred = model(x_batch.to(device), attention_mask=(x_batch > 0).
 ↪to(device), labels=None)
        model_preds[i * INFER_BATCH_SIZE:(i + 1) * INFER_BATCH_SIZE] = pred[:,␣
 ↪0].detach().cpu().squeeze().numpy()

cv_preds[:,0] = torch.sigmoid(torch.tensor(model_preds)).numpy().ravel()
del model
gc.collect()
```

```
100%|      | 5641/5641 [5:23:34<00:00,  3.44s/it]
```

```
[14]: 0
```

Predicting BERT small model

[15]:
```
bert_config = BertConfig(JIGSAW_BERT_SMALL_JSON_PATH)
tokenizer = BertTokenizer.from_pretrained(BERT_SMALL_PATH,␣
↪cache_dir=None,do_lower_case=True)
X_cv = convert_lines(cv_df["comment_text"].fillna("DUMMY_VALUE"),␣
↪MAX_SEQUENCE_LENGTH, tokenizer)
cv = torch.utils.data.TensorDataset(torch.tensor(X_cv, dtype=torch.long))
```

```
100%|      | 360975/360975 [03:47<00:00, 1584.12it/s]
```

[45]:
```
# # # Load fine-tuned BERT model
model = BertForSequenceClassification(bert_config, num_labels=1)
model.load_state_dict(torch.load(JIGSAW_BERT_SMALL_MODEL_PATH))
model.to(device)
for param in model.parameters():
    param.requires_grad = False
model.eval()
```

[17]:
```
# Predicting
model_preds = np.zeros((len(X_cv)))
cv_loader = torch.utils.data.DataLoader(cv, batch_size=INFER_BATCH_SIZE,␣
↪shuffle=False)
tk0 = tqdm(cv_loader)
for i, (x_batch,) in enumerate(tk0):
        pred = model(x_batch.to(device), attention_mask=(x_batch > 0).
↪to(device), labels=None)
        model_preds[i * INFER_BATCH_SIZE:(i + 1) * INFER_BATCH_SIZE] = pred[:,␣
↪0].detach().cpu().squeeze().numpy()

cv_preds[:,1] = torch.sigmoid(torch.tensor(model_preds)).numpy().ravel()

del model
gc.collect()
```

```
100%|      | 5641/5641 [1:45:48<00:00,  1.13s/it]
```

[17]: 0

[18]:
```
# Sub-model prediction
bert_submission = pd.DataFrame.from_dict({
'id': cv_df['id'],
'prediction': cv_preds.mean(axis=1)})
bert_submission.to_csv('bert_submission.csv')
```

[16]:
```
bert_submission = pd.read_csv('bert_submission.csv')
bert_submission.head()
```

[16]:
```
        id  prediction
0  6182394    0.174450
1  5328597    0.000077
2  4980998    0.051977
3  5520712    0.000070
4  5214775    0.000070
```

6.5.2 Research paper implementation

[39]:
```
from keras.preprocessing import text, sequence
from keras import backend as K
from keras.models import Model
from keras.layers import Input, Dense, Embedding, SpatialDropout1D, add,␣
↪concatenate
from keras.layers import CuDNNLSTM, Bidirectional, GlobalMaxPooling1D,␣
↪GlobalAveragePooling1D, LSTM, Conv1D
from keras.preprocessing import text, sequence
from keras.callbacks import LearningRateScheduler
from keras.engine.topology import Layer
from keras import initializers, regularizers, constraints, optimizers, layers
from tqdm._tqdm_notebook import tqdm_notebook as tqdm
import pickle
tqdm.pandas()
import gc
```

[4]:
```
EMBEDDING_PATHS = [
    '../convolutional_model/crawl-300d-2M.gensim',
    '../convolutional_model/glove.840B.300d.gensim'
]


NUM_MODELS = 2 # The number of classifiers we want to train
BATCH_SIZE = 512 # can be tuned
LSTM_UNITS = 128 # can be tuned
DENSE_HIDDEN_UNITS = 4*LSTM_UNITS # can betuned
EPOCHS = 4 # The number of epoches we want to train for each classifier
MAX_LEN = 220 # can ben tuned


IDENTITY_COLUMNS = [
    'transgender', 'female', 'homosexual_gay_or_lesbian', 'muslim', 'hindu',
    'white', 'black', 'psychiatric_or_mental_illness', 'jewish'
    ]

AUX_COLUMNS = ['target',␣
↪'severe_toxicity','obscene','identity_attack','insult','threat']
```

```
TEXT_COLUMN = 'comment_text'
TARGET_COLUMN = 'target'
```

Embedding

[5]:
```
def get_coefs(word, *arr):
    """
    Get word, word_embedding from a pretrained embedding file
    """
    return word, np.asarray(arr,dtype='float32')

def load_embeddings(path):
    if path.split('.')[-1] in ['txt','vec']: # for original pretrained␣
 ↪embedding files (extension .text, .vec)
        with open(path,'rb') as f:
            return dict(get_coefs(*line.strip().split(' ')) for line in f)
    if path.split('.')[-1] =='pkl': # for pickled pretrained embedding files␣
 ↪(extention pkl). Loading pickeled embeddings is faster than texts
        with open(path,'rb') as f:
            return pickle.load(f)



def build_matrix(word_index, path):
    embedding_index = KeyedVectors.load(path, mmap='r')
    embedding_matrix = np.zeros((len(word_index) + 1, 300))
    for word, i in tqdm(word_index.items()):
        for candidate in [word, word.lower()]:
            if candidate in embedding_index:
                embedding_matrix[i] = embedding_index[candidate]
                break
    return embedding_matrix
```

Defining model architecture

[6]:
```
def build_model(embedding_matrix, num_aux_targets):#, loss_weight):
    """
    embedding layer
    dropout layer
    2 * bidirectional LSTM layers
    2 * pooling layers
    2 dense layers
    1 softmax layer
    """
    words = Input(shape=(MAX_LEN,))
```

```
    x = Embedding(*embedding_matrix.shape, weights = [embedding_matrix],␣
↪trainable=False)(words)
    x = SpatialDropout1D(0.1)(x)
    x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True))(x)
    x = Bidirectional(LSTM(LSTM_UNITS, return_sequences=True))(x)
    hidden = concatenate([
        GlobalMaxPooling1D()(x),
        GlobalAveragePooling1D()(x)
        ])
    hidden = add([hidden, Dense(DENSE_HIDDEN_UNITS, activation='relu')(hidden)])
    hidden = add([hidden, Dense(DENSE_HIDDEN_UNITS, activation='relu')(hidden)])
    hidden = add([hidden, Dense(DENSE_HIDDEN_UNITS, activation='relu')(hidden)])
    hidden = add([hidden, Dense(DENSE_HIDDEN_UNITS, activation='relu')(hidden)])
    result = Dense(1, activation='sigmoid')(hidden)
    aux_result =Dense(num_aux_targets, activation='sigmoid')(hidden)

    model = Model(inputs =words, outputs =[result, aux_result])
    model.compile(loss='binary_crossentropy', optimizer='adam')

    return model
```

Text Tokanization

[7]:
```
x_train = train_data[TEXT_COLUMN].astype(str)
y_train = train_data[TARGET_COLUMN].values
y_aux_train = train_data[AUX_COLUMNS].values
x_cv = cv_df[TEXT_COLUMN].astype(str)
```

[8]:
```
# Return a Keras tokenizer class
CHARS_TO_REMOVE = '!"#$%&()*+,-./:;<=>?@[\\]^_`{|}~\t\n""'\'∞÷•à− ³ ‘ ´°£€\×√²−
'
tokenizer = text.Tokenizer(filters = CHARS_TO_REMOVE)
tokenizer.fit_on_texts(list(x_train)+ list(x_cv))
# Turn text to sequences of tokens
x_train = tokenizer.texts_to_sequences(x_train)
x_cv = tokenizer.texts_to_sequences(x_cv)
#Pad sequences to the same length
x_train = sequence.pad_sequences(x_train,maxlen=MAX_LEN)
x_cv= sequence.pad_sequences(x_cv, maxlen=MAX_LEN)
```

[9]:
```
x_train.shape
```

[9]:
```
(1443899, 220)
```

[10]:
```
# Initialize weights
sample_weights = np.ones(len(x_train), dtype=np.float32)
# Add all the values of the identities along rows
```

```
sample_weights += train_data[IDENTITY_COLUMNS].sum(axis=1)
#Add all values of targets*~identity
sample_weights += train_data[TARGET_COLUMN]*(~train_data[IDENTITY_COLUMNS]).
 ↪sum(axis=1)
#Add all values ~targets*identity
sample_weights += (~train_data[TARGET_COLUMN])*train_data[IDENTITY_COLUMNS].
 ↪sum(axis=1)
#Normalize them
sample_weights/=sample_weights.mean()
```

[40]:
```
from gensim.models import KeyedVectors
embedding_matrix = np.concatenate([build_matrix(tokenizer.word_index,f) for f␣
 ↪in EMBEDDING_PATHS], axis =-1)
print("Embedding matrix shape:", embedding_matrix.shape)
del train_data, tokenizer
gc.collect()
```

Model Training

[12]:
```
checkpoint_predictions = []
weights = []
NUM_MODELS = 1
for model_idx in range(NUM_MODELS):
    model = build_model(embedding_matrix, y_aux_train.shape[-1])
    for global_epoch in range(EPOCHS):
        model.fit(
            x_train,
            [y_train, y_aux_train],
            batch_size=BATCH_SIZE,
            epochs=1,
            sample_weight=[sample_weights.values, np.ones_like(sample_weights)],
            callbacks = [
                LearningRateScheduler(lambda _: 1e-3*(0.55**global_epoch)) #␣
 ↪Decayed learning rate
                ]
        )
        checkpoint_predictions.append(model.predict(x_cv, batch_size=2048)[0].
 ↪flatten())
        weights.append(2 ** global_epoch)
    del model
    gc.collect()
```

```
WARNING:tensorflow:From /home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/resource_variable_ops.py:435: colocate_with (from
tensorflow.python.framework.ops) is deprecated and will be removed in a future
version.
Instructions for updating:
```

```
Colocations handled automatically by placer.
```

```
/home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/framework/tensor_util.py:573: DeprecationWarning:
np.asscalar(a) is deprecated since NumPy v1.16, use a.item() instead
  append_fn(tensor_proto, proto_values)
```

```
WARNING:tensorflow:From /home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Use tf.cast instead.
WARNING:tensorflow:From /home/user/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math_grad.py:102: div (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
Deprecated in favor of operator or tf.math.divide.
Epoch 1/1
1443899/1443899 [==============================] - 1703s 1ms/step - loss: 0.3804
- dense_5_loss: 0.2900 - dense_6_loss: 0.0904
Epoch 1/1
1443899/1443899 [==============================] - 1712s 1ms/step - loss: 0.3337
- dense_5_loss: 0.2499 - dense_6_loss: 0.0839
Epoch 1/1
1443899/1443899 [==============================] - 1728s 1ms/step - loss: 0.3123
- dense_5_loss: 0.2303 - dense_6_loss: 0.0820
Epoch 1/1
1443899/1443899 [==============================] - 1707s 1ms/step - loss: 0.2943
- dense_5_loss: 0.2135 - dense_6_loss: 0.0807
```

[13]:
```python
predictions = np.average(checkpoint_predictions, weights=weights, axis=0)
predictions.shape
```

[13]:
```
(360975,)
```

[14]:
```python
lstm_submission = pd.DataFrame.from_dict({
    'id': cv_df.id,
    'prediction': predictions
})
lstm_submission.to_csv('lstm_submission.csv')
```

[44]:
```python
bert_submission = pd.read_csv('bert_submission.csv')
lstm_submission = pd.read_csv('lstm_submission.csv')
```

[45]:
```python
lstm_submission.head()
```

[45]:

	Unnamed: 0	id	prediction
0	0	6005154	0.000086
1	1	851365	0.093943
2	2	892430	0.000834
3	3	5752256	0.997884
4	4	5590246	0.002142

[46]:
```
bert_submission.head()
```

[46]:

	Unnamed: 0	id	prediction
0	1538593	6005154	0.003758
1	495446	851365	0.016163
2	530578	892430	0.000078
3	1339353	5752256	0.997755
4	1206486	5590246	0.000212

[47]:
```
# https://www.kaggle.com/prithvi1029/unprocessed-comments-worked-well
submission = pd.DataFrame.from_dict({
'id': cv_df['id'],
'prediction': lstm_submission['prediction'].rank(pct=True)*0.3 +␣
↪bert_submission['prediction'].rank(pct=True)*0.7})
submission.to_csv('submission.csv')
```

Metric calculation

[75]:
```
identity_columns = [
    'male', 'female', 'homosexual_gay_or_lesbian', 'christian', 'jewish',
    'muslim', 'black', 'white', 'psychiatric_or_mental_illness']
# https://www.kaggle.com/c/jigsaw-unintended-bias-in-toxicity-classification/
↪discussion/90986#latest-527331
SUBGROUP_AUC = 'subgroup_auc'
BPSN_AUC = 'bpsn_auc'  # stands for background positive, subgroup negative
BNSP_AUC = 'bnsp_auc'  # stands for background negative, subgroup positive
TOXICITY_COLUMN = 'target'

def compute_auc(y_true, y_pred):
    try:
        return metrics.roc_auc_score(y_true, y_pred)
    except ValueError:
        return np.nan

def compute_subgroup_auc(df, subgroup, label, model_name):
    subgroup_examples = df[df[subgroup] != np.nan]
    return compute_auc(subgroup_examples[label], subgroup_examples[model_name])

def compute_bpsn_auc(df, subgroup, label, model_name):
```

```
    """Computes the AUC of the within-subgroup negative examples and the␣
↪background positive examples."""
    subgroup_negative_examples = df[(df[subgroup] == True) & (df[label] ==␣
↪False)]
    non_subgroup_positive_examples = df[(df[subgroup] == False) & (df[label] ==␣
↪True)]
    examples = subgroup_negative_examples.append(non_subgroup_positive_examples)
    return compute_auc(examples[label], examples[model_name])

def compute_bnsp_auc(df, subgroup, label, model_name):
    """Computes the AUC of the within-subgroup positive examples and the␣
↪background negative examples."""
    subgroup_positive_examples = df[(df[subgroup] == True) & (df[label] ==␣
↪True)]
    non_subgroup_negative_examples = df[(df[subgroup] == False) & (df[label] ==␣
↪False)]
    examples = subgroup_positive_examples.append(non_subgroup_negative_examples)
    return compute_auc(examples[label], examples[model_name])

def compute_bias_metrics_for_model(dataset,
                                   subgroups,
                                   model,
                                   label_col,
                                   include_asegs=False):
    """Computes per-subgroup metrics for all subgroups and one model."""
    records = []
    for subgroup in subgroups:
        record = {
            'subgroup': subgroup,
            'subgroup_size': len(dataset[dataset[subgroup] != np.nan])
        }
        record[SUBGROUP_AUC] = compute_subgroup_auc(dataset, subgroup,␣
↪label_col, model)
        record[BPSN_AUC] = compute_bpsn_auc(dataset, subgroup, label_col, model)
        record[BNSP_AUC] = compute_bnsp_auc(dataset, subgroup, label_col, model)
        records.append(record)
    return pd.DataFrame(records).sort_values('subgroup_auc', ascending=True)
```

[76]:
```
def calculate_overall_auc(df, model_name):
    true_labels = df[TOXICITY_COLUMN]
    predicted_labels = df[model_name]
    return metrics.roc_auc_score(true_labels, predicted_labels)

def power_mean(series, p):
    total = sum(np.power(series, p))
    return np.power(total / len(series), 1 / p)
```

```python
def get_final_metric(bias_df, overall_auc, POWER=-5, OVERALL_MODEL_WEIGHT=0.25):
    bias_score = np.average([
        power_mean(bias_df[SUBGROUP_AUC], POWER),
        power_mean(bias_df[BPSN_AUC], POWER),
        power_mean(bias_df[BNSP_AUC], POWER)
    ])
    return (OVERALL_MODEL_WEIGHT * overall_auc) + ((1 - OVERALL_MODEL_WEIGHT) *␣
↪bias_score)
```

[51]:
```python
MODEL_NAME = 'research_paper_with_bert'
cv_df[MODEL_NAME] = submission['prediction'].values
```

[38]:
```python
bias_metrics_df = compute_bias_metrics_for_model(cv_df, identity_columns,␣
↪MODEL_NAME, TOXICITY_COLUMN)
```

[78]:
```python
get_final_metric(bias_metrics_df, calculate_overall_auc(cv_df, MODEL_NAME))
```

[78]: 0.9667060455662488

7 Result Summary

7.1 Machine Learning Simple models

[14]:
```python
from prettytable import PrettyTable
x = PrettyTable()

column_names = ["model_names", "hyper_params", "train_metric_score",␣
↪"test_metric_score", "kaggle_submission_score"]
model_names = ['Naive Bayes', 'Logistic Regression', 'SVM', 'XG-Boost', 'Random␣
↪Forest', 'Stacking']
hyper_params = ['alpha=1','alpha=1e-5', 'apha=1e-5', 'scale_pos_weight=99,\n␣
↪n_estimators=2000', 'n_estimators=1500,\n max_depth=12', 'params got from \n␣
↪others']
train_metric_scores = [85.3, 88.72, 88.97, 88.05, 80.51, 89.68]
test_metric_scores = [84.24, 87.84, 87.9, 86.73, 78.90, 87.57]
kaggle_scores = [83.52, 87.80, 88.03, 73.40, 68.30, 75.35]
x.add_column(column_names[0], model_names)
x.add_column(column_names[1], hyper_params)
x.add_column(column_names[2], train_metric_scores)
x.add_column(column_names[3], test_metric_scores)
x.add_column(column_names[4], kaggle_scores)
print(x.get_string(sortby="kaggle_submission_score", reversesort = True))
```

```
# results_summary = pd.DataFrame({'model_names':model_names, 'hyper_params':
↪hyper_params, 'train_metric_score':train_metric_scores, 'test_metric_score':
↪test_metric_scores, 'kaggle_submission_score':kaggle_scores})
# results_summary.sort_values(by=['kaggle_submission_score'], ascending=False)
```

```
+---------------------+----------------------+--------------------+-------------
------+------------------------+
|     model_names     |     hyper_params     | train_metric_score |
test_metric_score | kaggle_submission_score |
+---------------------+----------------------+--------------------+-------------
------+------------------------+
|         SVM         |      apha=1e-5       |       88.97        |         87.9
|          88.03          |
| Logistic Regression |      alpha=1e-5      |       88.72        |        87.84
|           87.8          |
|     Naive Bayes     |       alpha=1        |        85.3        |        84.24
|          83.52          |
|       Stacking      |   params got from    |       89.68        |        87.57
|          75.35          |
|                     |        others        |                    |
|                         |
|       XG-Boost      | scale_pos_weight=99, |       88.05        |        86.73
|           73.4          |
|                     |   n_estimators=2000  |                    |
|                         |
|    Random Forest    |  n_estimators=1500,  |       80.51        |         78.9
|           68.3          |
|                     |     max_depth=12     |                    |
|                         |
+---------------------+----------------------+--------------------+-------------
------+------------------------+
```

7.2 Deep Learning Models

[16]:
```
column_names = ["model_names", "epochs", "test_metric_score",␣
↪"kaggle_submission_score"]
model_names = ['CNN', 'Single layer LSTM', 'Two Layered \n Bi-Directional␣
↪LSTM', 'LSTM', 'LSTM \n with Attention', '(LSTM + \n BERT small + \n BERT␣
↪large)']
epochs = ['5','1', '1', '1', '4', '-']
test_metric_scores = [90.98, 88.70, 88.78, 92.28, 92.70, 96.67]
kaggle_scores = [91.14, 87.66, 88.47, 92.14, 92.63, 94.17]

x = PrettyTable()

x.add_column(column_names[0], model_names)
```

```python
x.add_column(column_names[1], epochs)
x.add_column(column_names[2], test_metric_scores)
x.add_column(column_names[3], kaggle_scores)
print(x.get_string(sortby="kaggle_submission_score", reversesort = True))
```

```
+----------------------+--------+-------------------+-------------------------+
|     model_names      | epochs | test_metric_score | kaggle_submission_score |
+----------------------+--------+-------------------+-------------------------+
|       (LSTM +        |   -    |       96.67       |          94.17          |
|     BERT small +     |        |                   |                         |
|      BERT large)     |        |                   |                         |
|         LSTM         |   4    |        92.7       |          92.63          |
|    with Attention    |        |                   |                         |
|         LSTM         |   1    |       92.28       |          92.14          |
|         CNN          |   5    |       90.98       |          91.14          |
|     Two Layered      |   1    |       88.78       |          88.47          |
|  Bi-Directional LSTM |        |                   |                         |
|  Single layer LSTM   |   1    |        88.7       |          87.66          |
+----------------------+--------+-------------------+-------------------------+
```

7.3 Conclusion

- We are getting best result from the combination of BERT small, BERT large and LSTM.
- The weight initialization also helped us in LSTM model as we were able to inculcate some information about the identities.
- We are using weighted average for prediction in LSTM model
- We are using pct ranking for for both bert as well as lstm predictions and given 30% and 70% weightage to lstm and bert predicted values respectively. This approach has scope of experimentation.
- We must note that we are getting decent score with simple CNN for just 5 epochs. So there may be a scope of improvement there.

[ ]: