AIML CAPSTONE PROJECT

FINAL REPORT
AUTOMATIC TICKET ASSIGNMENT

Group C NLP 1
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1. Problem statement

To provide a fix or solution for the Incident Management process that would resolve the interruption and ensure no business impact. In organizations, incidents are created by the IT Users, End Users/Vendors through ticketing systems. The Ticket assignment to appropriate IT groups is still a manual process in many IT organizations. Since the manual assignment of incidents is time-consuming and requires human efforts, there might be human errors and often misaddresses resulting in poor customer services.

2. As-Is support process

In the support process, incoming incidents are analysed and assessed by the organization's support teams to fulfil the request. In many organizations, better allocation and effective usage of the valuable support resources will directly result in substantial cost savings.

Currently, the incidents are created by various stakeholders (Business Users, IT Users and Monitoring Tools) within the IT Service Management Tool and are assigned to Service Desk teams (L1 / L2 teams). This team will review the incidents for right ticket categorization, priorities and then carry out an initial diagnosis to see if they can resolve them. Around ~54% of the incidents are resolved by L1 / L2 teams. In case L1 / L2 is unable to resolve, they will then escalate/assign the tickets to Functional teams from Applications and Infrastructure (L3 teams). Some portions of incidents are directly assigned to L3 teams by either Monitoring tools or Callers / Requestors. L3 teams will carry out detailed diagnoses and resolve the incidents. Around ~56% of incidents are resolved by Functional / L3 teams. In case if vendor support is needed, they will reach out for their support towards incident closure.

L1 / L2 needs to spend time reviewing Standard Operating Procedures (SOPs) before assigning to Functional teams (Minimum ~25-30% of incidents needs to be reviewed for SOPs before ticket assignment). 15 min is being spent for SOP review for each incident. Minimum of ~1 FTE effort needed only for incident assignment to L3 teams.

During the process of incident assignments by L1 / L2 teams to functional groups, there were multiple instances of incidents getting assigned to the wrong functional groups. Around ~25% of Incidents are wrongly assigned to functional teams. The additional effort is needed for Functional teams to re-assign to the right functional groups. During this process, some of the incidents are in the queue and not addressed in a timely manner resulting in poor customer service.

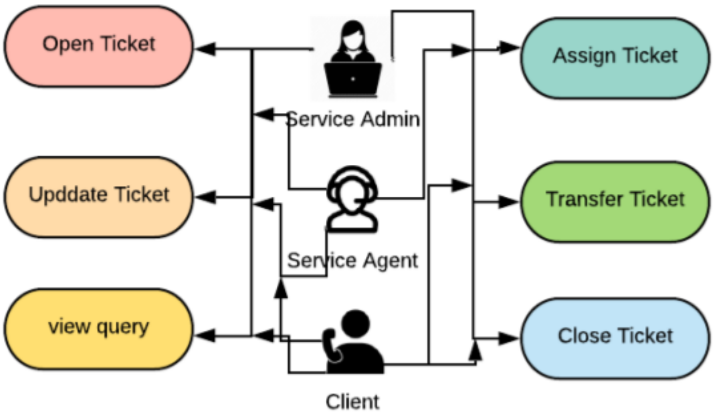


Figure 1: Use case diagram of IT service industry

3. To-Be process

To build an AI-driven solution to mine the unstructured text using cutting edge algorithms that can classify the tickets by analysing text and assigning it to the correct group.

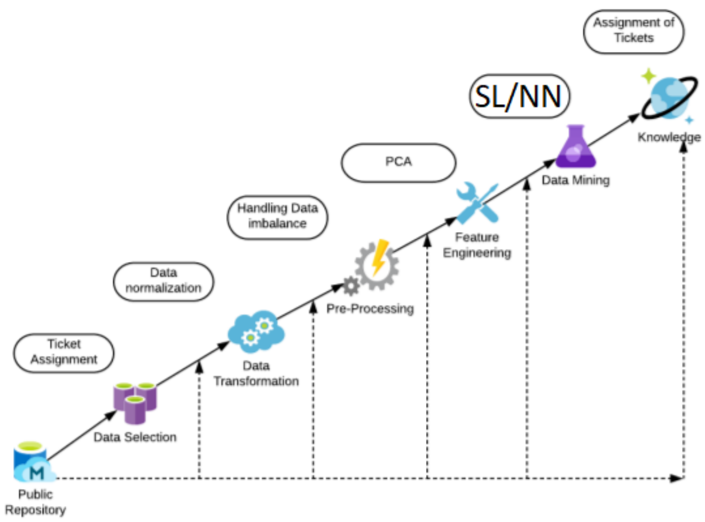


Figure 2: Automatic Ticket Assignment Methodology

SL - Supervised Learning Classifier, NN - Neural Network Classifier

4. Data and findings

The data was provided by ©Great Learning.

Details about the data and dataset files are given in the below link,
https://drive.google.com/open?id=1OZNJm81JXucV3HmZroMq6qCT2m7ez7IJ

The data is in Microsoft Excel Worksheet (.xlsx) format with a size of 977 KB (10,01,307 bytes).

4.1. Exploring the data and findings

In the first look into data, we found that the dataset contains 8500 rows/observations and 4 columns/attributes/features. The 4 columns/attributes/features are Short description, Description, Caller, Assignment group.

Short description – contains shorthand description of the ticket.
Description – long description of what the IT User/End User is facing.
Caller – unique ID created for that particular IT User/End User.
Assignment group – To what group the ticket should be assigned.

Observation in the dataset

1. The total number of incidents reported in the dataset is 8500.
2. Caller names are random (may not be useful for training data).
3. The dataset has English and German Language words.
4. Email/chat format found in the description.
5. There are a total number of 8 null records in the Short Description column and there is 1 null record in the Description column. There are no null records in the Caller and Assignment Group columns.
6. There are a total of 74 different groups for the Assignment Group column.
7. Approximately 50% of the dataset comprises complaints that are corresponding to GRP_0.
8. There are a few rows of data that have the same text for the Short Description and the Description column.
9. Few words were combined.
10. Spelling mistakes and typo errors are found.

4.2. Benchmark

In real world scenario:

1. With the 60% of assignment work automated, it will save a lot of time and effort for L1/L2.

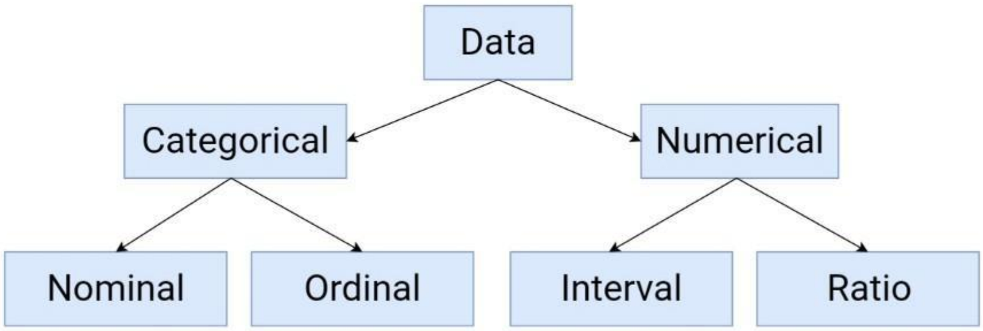
2. This will improve assignment accuracy, and faster issue resolution.

3. Time and effort saved translates to cost savings and customer ratification

5. Overview of the final process

In exploratory data analysis, we discover patterns and spot anomalies, also to test hypotheses and check assumptions with the help of summary statistics and graphical representation of the given data.

Here data in the sense, records, points, vectors, patterns, events, cases, samples, observations, or entities.



Here the data is Categorical, that is this data may be grouped according to the variables as 'GRP_0', 'GRP_1', etc.

Understand the data and try to gather as many insights from it. EDA is all about making sense of data that we already have in hand before we get into pre-processing and model building.

After the process of EDA comes a pre-processing step, this is the step where data gets transformed or encoded, in this process the data features can easily be interpreted by the algorithm.

Here are features in the sense, variables, characteristics, fields, attributes, or dimensions.

Below are major steps followed to implement the solution

1. Understanding the problem.
2. EDA (Exploratory Data Analysis) and Data Pre Processing of the given dataset.
3. Model building.
4. Model evaluation.
5. Final model.
6. Enhance the solution.

Importing necessary libraries

```
#!pip install wordcloud

#!pip install nlpaug

#!pip install textblob
```

Install additional libraries [eg: Run !pip install wordcloud in the code cell]. If you get an error even after you have installed additional libraries that did not come with anaconda, please restart the kernel or re-run the below cell.

```
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
sns.set(color_codes=True)
%matplotlib inline
import warnings
warnings.filterwarnings('ignore', category=DeprecationWarning)
warnings.simplefilter('ignore')
import numpy as np
import copy
import re
import string
import nltk
nltk.download('wordnet', quiet=True)
nltk.download('stopwords', quiet=True)
from nltk.corpus import stopwords
nltk.download('words', quiet=True)
nltk.download('averaged_perceptron_tagger', quiet=True)
from nltk import WordNetLemmatizer
from wordcloud import WordCloud
from keras.preprocessing.text import Tokenizer
from sklearn import preprocessing
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report
from sklearn.naive_bayes import MultinomialNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
```

```
from keras.models import Sequential
from keras.layers import Dense, LSTM, Bidirectional, BatchNormalization, Dropout, GRU
from keras.layers.embeddings import Embedding
from keras.preprocessing.sequence import pad_sequences
import tensorflow as tf
import random as python_random
import nlpaug.augmenter.word as naw
from sklearn.utils import resample
import math
from sklearn.decomposition import LatentDirichletAllocation
from keras.optimizers import SGD
from keras.callbacks import ModelCheckpoint
from keras.callbacks import EarlyStopping
```

Read the csv file as a data frame

```
df = pd.read_csv("input_data.csv")
```

Check shape of data

```
Out[5]: (8500, 4)
```

The dataset has 8500 rows/observations and 4 columns/attributes

View first 5 rows of data

```
df.head(5)
```

Out[6]:

	Short description	Description	Caller	Assignment group
0	login issue	-verified user details.(employee# & manager na...	spxjnwir pjlcoqds	GRP_0
1	outlook	\n\nreceived from: hmjdrvpb.komuaywn@gmail.com...	hmjdrvpb komuaywn	GRP_0
2	cant log in to vpn	\n\nreceived from: eylqgodm.ybqkwiam@gmail.com...	eylqgodm ybqkwiam	GRP_0
3	unable to access hr_tool page	unable to access hr_tool page	xbkucsvz gcpydteq	GRP_0
4	skype error	skype error	owlgqjme qhcozdfx	GRP_0

View last 5 rows of data

```
df.tail(5)
```

Out[7]:

	Short description	Description	Caller	Assignment group
8495	emails not coming in from zz mail	\n\nreceived from: avglmrts.vhqmtiua@gmail.com...	avglmrts vhqmtiua	GRP_29
8496	telephony_software issue	telephony_software issue	rbozivdq gmlhrtvp	GRP_0
8497	vip2: windows password reset for tifpdchb pedx...	vip2: windows password reset for tifpdchb pedx...	oybwdsgx oxyhwrfz	GRP_0
8498	machine nÃ£o estÃ¡ funcionando	i am unable to access the machine utilities to...	ufawcgob aowhxjky	GRP_62
8499	an mehreren pc`s lassen sich verschiedene prgr...	an mehreren pc`s lassen sich verschiedene prgr...	kqvbrspl jyzoklfx	GRP_49

5.1 Understanding the structure of data

Get information about the data along with the data type of each attribute

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8500 entries, 0 to 8499
Data columns (total 4 columns):
Short description    8498 non-null object
Description          8499 non-null object
Caller               8500 non-null object
Assignment group     8500 non-null object
dtypes: object(4)
memory usage: 265.7+ KB
```

The count of data types (object(4)) and memory usage are provided

The data type of the 4 columns/attributes/features is an object and there are null values in Short description and Description.

Unique values of Assignment group attribute

```
df['Assignment group'].unique()
```

```
Out[9]: array(['GRP_0', 'GRP_1', 'GRP_3', 'GRP_4', 'GRP_5', 'GRP_6', 'GRP_7',
               'GRP_8', 'GRP_9', 'GRP_10', 'GRP_11', 'GRP_12', 'GRP_13', 'GRP_14',
               'GRP_15', 'GRP_16', 'GRP_17', 'GRP_18', 'GRP_19', 'GRP_2',
               'GRP_20', 'GRP_21', 'GRP_22', 'GRP_23', 'GRP_24', 'GRP_25',
               'GRP_26', 'GRP_27', 'GRP_28', 'GRP_29', 'GRP_30', 'GRP_31',
               'GRP_33', 'GRP_34', 'GRP_35', 'GRP_36', 'GRP_37', 'GRP_38',
               'GRP_39', 'GRP_40', 'GRP_41', 'GRP_42', 'GRP_43', 'GRP_44',
               'GRP_45', 'GRP_46', 'GRP_47', 'GRP_48', 'GRP_49', 'GRP_50',
               'GRP_51', 'GRP_52', 'GRP_53', 'GRP_54', 'GRP_55', 'GRP_56',
               'GRP_57', 'GRP_58', 'GRP_59', 'GRP_60', 'GRP_61', 'GRP_32',
               'GRP_62', 'GRP_63', 'GRP_64', 'GRP_65', 'GRP_66', 'GRP_67',
               'GRP_68', 'GRP_69', 'GRP_70', 'GRP_71', 'GRP_72', 'GRP_73'],
              dtype=object)
```

In the assignment group, there are 74 unique classes found.

Percentage form value counts of Assignment group

```
df["Assignment group"].value_counts(normalize=True)
```

```
Out[10]: GRP_0     0.467765
         GRP_8     0.077765
         GRP_24    0.034000
         GRP_12    0.030235
         GRP_9     0.029647
         GRP_2     0.028353
         GRP_19    0.025294
         GRP_3     0.023529
         GRP_6     0.021647
         GRP_13    0.017059
         GRP_10    0.016471
         GRP_5     0.015176
         GRP_14    0.013882
         GRP_25    0.013647
         GRP_33    0.012588
         GRP_4     0.011765
         GRP_29    0.011412
         GRP_18    0.010353
         GRP_16    0.010000
         GRP_17    0.009529
         GRP_31    0.008118
         GRP_7     0.008000
         GRP_34    0.007294
         GRP_26    0.006588
         GRP_40    0.005294
         GRP_28    0.005176
         GRP_41    0.004706
         GRP_30    0.004588
         GRP_15    0.004588
         GRP_42    0.004353
                     ...
```

```
              ...
GRP_36     0.001765
GRP_44     0.001765
GRP_50     0.001647
GRP_53     0.001294
GRP_65     0.001294
GRP_52     0.001059
GRP_55     0.000941
GRP_51     0.000941
GRP_49     0.000706
GRP_59     0.000706
GRP_46     0.000706
GRP_43     0.000588
GRP_32     0.000471
GRP_66     0.000471
GRP_68     0.000353
GRP_38     0.000353
GRP_56     0.000353
GRP_58     0.000353
GRP_63     0.000353
GRP_71     0.000235
GRP_69     0.000235
GRP_54     0.000235
GRP_57     0.000235
GRP_72     0.000235
GRP_35     0.000118
GRP_70     0.000118
GRP_64     0.000118
GRP_73     0.000118
GRP_61     0.000118
GRP_67     0.000118
Name: Assignment group, Length: 74, dtype: float64
```

Converting Description attribute to str type

```
df['Description'] = df['Description'].astype(str)
```

Create a word count attribute for Description

```
df['Description_word_count'] = df['Description'].apply(lambda text: len(text.split()))
```

Maximum word count of a Description

```
df['Description_word_count'].max()
```

```
Out[13]: 1625
```

Mean word count of a Description

```
df['Description_word_count'].mean()
```

```
Out[14]: 27.27423529411765
```

5.2 Missing points in data & finding inconsistencies in the data

Missing Points in the description column was filled with the values from the Short Description column. Since the ‘Caller’ column is irrelevant to determine the assignment group, that column is dropped. There were inconsistencies in the ‘Description’ column with just one word [eg: "complete"] and no information about the problem [eg: "please see attachment"]. Also, with less information than the ‘Short description’ column. So, copying ‘Short description’ to ‘Description’ helps avoid inconsistencies and have more information. The duplications were removed from ‘Description’ and ‘Assignment group’.

Removing Caller column which is not relevant to determine the Assignment group

```
df.drop(['Caller'],axis=1, inplace=True)
```

Get indexes of missing/nan value in Description attribute

```
idx_list = df[df['Description'].isnull()].index.tolist()
```

Copy value from Short Description attribute to Description attribute for missing values

```
for idx in idx_list:
    df.at[idx, 'Description'] = df.at[idx, 'Short description']
```

There are Inconsistencies in Description attribute such as holding only one word [eg:"complete"] and having no information about the problem[eg: "please see attachment"] and also less information than Short description attribute. Copying Short description to Description to avoid inconsistencies and have more information.

```
for idx, row in copy.deepcopy(df).iterrows():
    if(pd.notnull(row['Short description'])):
        if(row['Description_word_count'] < len(row['Short description'].split())):
            row['Description'] = row['Short description']
            df.at[idx, 'Description'] = df.at[idx, 'Short description']
```

Check for duplicate data that has same Description and Assignment group

```
df.duplicated(subset=['Description','Assignment group']).sum()
```

```
Out[19]: 623
```

Remove duplicate data that has same Description and Assignment group

```
df.drop_duplicates(['Description','Assignment group'], inplace=True)
df.shape
```

```
Out[20]: (7877, 4)
```

5.3 Text pre-processing

Description and Assignment groups are required for further processing. The approach to getting a good overview is to analyse the model with only base text and others with processed text.

df_base_txt_acc to use it for building a model with base text (lowercase and only remove punctuations/stop words).

df_process_txt_acc to use for building a model with complete pre-processed text (remove punctuations, stop words, spaces, special symbols, lemmatize etc). Delete df data frame to free up the memory.

```
df.drop(['Short description', 'Description_word_count'],axis=1, inplace=True)
df_base_txt_acc = copy.deepcopy(df)
df_process_txt_acc = copy.deepcopy(df)
del df
df_base_txt_acc.shape, df_process_txt_acc.shape
```

```
Out[23]:  ((7877, 2), (7877, 2))
```

5.3.1 Converting text to lowercase

Applying text_to_lower to remove any weight/value difference that could occur between lowercase and uppercase.

```
def text_to_lower(txt):
    return txt.lower()
```

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(text_to_lower)
df_process_txt_acc.head()
```

Out[25]:

	Description	Assignment group
0	-verified user details.(employee# & manager na...	GRP_0
1	\n\nreceived from: hmjdrvpb.komuaywn@gmail.com...	GRP_0
2	\n\nreceived from: eylqgodm.ybqkwiam@gmail.com...	GRP_0
3	unable to access hr_tool page	GRP_0
4	skype error	GRP_0

5.3.2 Removal of characters

Removal of characters and newline characters and "received from" string as these two pieces of information in the text does not add value to the problem description.

```
def remove_chars(txt, chars):
    return txt.replace(chars,'')
```

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(lambda text: remove_chars(text, '\n'))
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(lambda text: remove_chars(text, 'received from'))
df_process_txt_acc.head()
```

Out[27]:

	Description	Assignment group
0	-verified user details.(employee# & manager na...	GRP_0
1	: hmjdrvpb.komuaywn@gmail.comhello team,my mee...	GRP_0
2	: eylqgodm.ybqkwiam@gmail.comhii cannot log on...	GRP_0
3	unable to access hr_tool page	GRP_0
4	skype error	GRP_0

5.3.3 Removal of email ids

Applying txt_eml_rmv to remove email ids which is just a contact/from information related and no help with problem description.

```
def txt_eml_rmv(txt):
    return re.sub('\S+@\S+','',txt)
```

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(txt_eml_rmv)
df_process_txt_acc.head()
```

Out[29]:

	Description	Assignment group
0	-verified user details.(employee# & manager na...	GRP_0
1	: team,my meetings/skype meetings etc are not...	GRP_0
2	: cannot log on to vpnbest	GRP_0
3	unable to access hr_tool page	GRP_0
4	skype error	GRP_0

5.3.4 Removal of punctuation

Applying rem_punctuations to remove symbols that are not relevant for the ticket assignment classification. Some punctuations(!) might be helpful in the case of sentiment classification.

```
punctuations = set(string.punctuation)
def rem_punctuations(txt):
    return "".join(ltr if ltr not in punctuations else ' ' for ltr in txt)
```

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(rem_punctuations)
df_process_txt_acc.head()
```

Out[31]:

	Description	Assignment group
0	verified user details employee manager na...	GRP_0
1	team my meetings skype meetings etc are not...	GRP_0
2	cannot log on to vpnbest	GRP_0
3	unable to access hr tool page	GRP_0
4	skype error	GRP_0

5.3.5 Removal of special symbols and digits

Removal of special symbols, digits, etc with regular expression.
Applying text_to_alpha to convert the text in the Description attribute to recognizable characters.

```
def text_to_alpha(txt):
    return re.sub('[^a-zA-Z]', ' ', txt)
```

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(text_to_alpha)
df_process_txt_acc.head()
```

Out[33]:

	Description	Assignment group
0	verified user details employee manager na...	GRP_0
1	team my meetings skype meetings etc are not...	GRP_0
2	cannot log on to vpnbest	GRP_0
3	unable to access hr tool page	GRP_0
4	skype error	GRP_0

5.3.6 Removal of stop words

Applying rem_stpwrds to remove stopwords (this, is, had, will etc) which will not change the Description text important tokens/features that will be picked by the model to classify.

```
eng_stopwords = set(stopwords.words("english"))
def rem_stpwrds(txt):
    return " ".join(word for word in txt.split() if word not in eng_stopwords)
```

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(rem_stpwrds)
df_process_txt_acc.head()
```

Out[35]:

	Description	Assignment group
0	verified user details employee manager name ch...	GRP_0
1	team meetings skype meetings etc appearing out...	GRP_0
2	cannot log vpnbest	GRP_0
3	unable access hr tool page	GRP_0
4	skype error	GRP_0

5.3.7 Removal of whitespaces

Applying rem_whitespaces to remove whitespaces leading and trailing, replace multiple spaces with single spaces which will reduce the length of the text while keeping the words intact.

```
def rem_whitespaces(txt):
    txtstrp = txt.strip()
    return re.sub(r'\s+', ' ', txtstrp)
```

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(rem_whitespaces)
df_process_txt_acc.head()
```

Out[37]:

	Description	Assignment group
0	verified user details employee manager name ch...	GRP_0
1	team meetings skype meetings etc appearing out...	GRP_0
2	cannot log vpnbest	GRP_0
3	unable access hr tool page	GRP_0
4	skype error	GRP_0

5.3.8 Removal of two-letter characters

After removing the stop words, check if there are still words with two characters (hr, ad, sr etc) and remove them.

```
two_or_less_char_wrds = []
count = 0
for idx, row in copy.deepcopy(df_process_txt_acc).iterrows():
    for wrd in row['Description'].split():
        if len(wrd)<=2:
            two_or_less_char_wrds.append(wrd)
print(len(two_or_less_char_wrds))
```

```
12846
```

```
def rem_less_than_two_chars(txt):
    return ' '.join([wrd for wrd in txt.split() if len(wrd)>2])
```

```
df_process_txt_acc['Description'] = df_process_txt_acc['Description'].apply(rem_less_than_two_chars)
df_process_txt_acc.head()
```

Out[40]:

	Description	Assignment group
0	verified user details employee manager name ch...	GRP_0
1	team meetings skype meetings etc appearing out...	GRP_0
2	cannot log vpnbest	GRP_0
3	unable access tool page	GRP_0
4	skype error	GRP_0

5.3.9 Lemmatization

Lemmatize Words

```
lemmatz = WordNetLemmatizer()
def text_lemmatiz(txt):
    lmmtz_txt = []
    for wrd in txt.split():
        lmmtz_wrd = lemmatz.lemmatize(wrd)
        lmmtz_txt.append(lmmtz_wrd)
    return " ".join(lmmtz_txt)
```

Applying text_lemmatiz to convert words into base words which is an actual language word and we could get word embedding for it from pre-trained embeddings.

```
df_process_txt_acc["Description"] = df_process_txt_acc["Description"].apply(text_lemmatiz)
df_process_txt_acc.head()
```

Out[42]:

	Description	Assignment group
0	verified user detail employee manager name che...	GRP_0
1	team meeting skype meeting etc appearing outlo...	GRP_0
2	cannot log vpnbest	GRP_0
3	unable access tool page	GRP_0
4	skype error	GRP_0

After text preprocessing, check for duplicate data that has same Description and Assignment group

```
df_process_txt_acc.duplicated(subset=['Description','Assignment group']).sum()
```

Out[43]: 1291

Let's remove duplicate data that has same Description and Assignment group and empty Description

```
df_process_txt_acc.drop_duplicates(['Description','Assignment group'], inplace=True)
df_process_txt_acc = df_process_txt_acc[df_process_txt_acc['Description'].apply(lambda text: len(text.split())>0)]
df_process_txt_acc.shape
```

Out[44]: (6582, 2)

6. Walk through the solution

Define X(for features) and y(for target) variables. As our classes/targets are non numerical GRP_0, GRP_1 etc, using LabelEncoder to encode classes/targets to numerical with value between 0 and numberofclasses-1. Remove no longer required variables to free up memory.

```
X_base = df_base_txt_acc['Description']
lbl_enc_base = preprocessing.LabelEncoder()
y_base = lbl_enc_base.fit_transform(df_base_txt_acc['Assignment group'])
del df_base_txt_acc
```

Split X and y into training and test set in 75:25 ratio. Set random_state for the split to be able to generate the same sequence for every run.

```
X_train_base, X_test_base, y_train_base, y_test_base =train_test_split(X_base,y_base, random_state=7,
                                                        test_size = 0.20)
X_train_base.shape, X_test_base.shape
```

```
Out[59]: ((6176,), (1544,))
```

Using CountVectorizer to convert text documents(non numerical) to a matrix of token counts. Provides a way to extract and represent features from text documents.

```
cvt_base_unigram = CountVectorizer()
X_train_trnsfrm_base = cvt_base_unigram.fit_transform(X_train_base)
X_test_trnsfrm_base = cvt_base_unigram.transform(X_test_base)
```

Using Supervised learning algorithm: Multinomial logistic regression for our multi-class classification by having the multi_class argument as multinomial and supported solver lbfgs. We have seen in our analysis above there are many classes which have a single or two document samples. Multinomial logistic regression assigns more weight to features that helps it to distinguish between probable classes instead of trying to find class from all features.

```
lr_base = LogisticRegression(multi_class='multinomial', solver='lbfgs')
lr_base.fit(X_train_trnsfrm_base, y_train_base)
lr_base_predictions = lr_base.predict(X_test_trnsfrm_base)
print(accuracy_score(y_test_base, lr_base_predictions))
del cvt_base_unigram, X_train_trnsfrm_base, X_test_trnsfrm_base, X_base, lbl_enc_base, y_base, lr_base
del X_train_base, X_test_base, y_train_base, y_test_base, lr_base_predictions
```

```
0.6353626943005182
```

6.1. Building a supervised learning model architecture

Using processed text which have spaces removed, email ids removed, lemmatized etc in further steps down.

```
X = df_process_txt_acc['Description']
lbl_enc = preprocessing.LabelEncoder()
y = lbl_enc.fit_transform(df_process_txt_acc['Assignment group'])
```

Split X and y into training and test set in 80:20 ratio. Set random_state for the split.

```
X_train, X_test, y_train, y_test =train_test_split(X,y, random_state=6,
                                                    test_size = 0.2)
X_train.shape, X_test.shape
```

```
Out[63]:  ((5265,), (1317,))
```

Unigram features seen above (eg: password, ticket, failed, issue, reset etc) provides a good meaning/idea and possibly helps in good classification. Using unigram CountVectorizer.

```
cvt_process_uni = CountVectorizer(ngram_range = (1,1))
X_train_process_uni_trnsfrm = cvt_process_uni.fit_transform(X_train)
X_test_process_uni_trnsfrm = cvt_process_uni.transform(X_test)
```

We will use unigram features to train and test algorithm.

```
lr_process_uni = LogisticRegression(multi_class='multinomial', solver='lbfgs')
lr_process_uni.fit(X_train_process_uni_trnsfrm, y_train)
lr_process_uni_predictions = lr_process_uni.predict(X_test_process_uni_trnsfrm)
print(accuracy_score(y_test, lr_process_uni_predictions))
del cvt_process_uni, X_train_process_uni_trnsfrm, X_test_process_uni_trnsfrm, lr_process_uni, lr_process_uni_predictions
```

```
0.6378132118451025
```

The bottom features seen above contain many words with jumbled letters (rcpt, noif etc seen in our data) which provide no meaning. Will try to reduce the number of features to consider to train algorithm which also reduces training time and memory consumption. Tried with a different number of features to be considered.

```
cvt_process_uni_max = CountVectorizer(ngram_range = (1,1), max_features=7200)
X_train_trnsfrm_uni_max = cvt_process_uni_max.fit_transform(X_train)
X_test_trnsfrm_uni_max = cvt_process_uni_max.transform(X_test)
```

We will use reduced unigram features to train and test algorithm.

```
lr_uni_max = LogisticRegression(multi_class='multinomial', solver='lbfgs')
lr_uni_max.fit(X_train_trnsfrm_uni_max, y_train)
lr_uni_max_predictions = lr_uni_max.predict(X_test_trnsfrm_uni_max)
print(accuracy_score(y_test, lr_uni_max_predictions))
del cvt_process_uni_max, X_train_trnsfrm_uni_max, X_test_trnsfrm_uni_max, lr_uni_max, lr_uni_max_predictions
```

```
0.6332574031890661
```

The vocabulary size of unigrams was nearly 14000, and by considering nearly half of the features, we are still able to get the accuracy close to 64.

Bigram features (password reset, password management etc) provides more context which could help with good classification, but also possible the bigrams might mislead because of many jumbled letters words (rcpt, noif etc seen in our data) that could be part of bigrams. Using bigram CountVectorizer.

```
cvt_process_bi = CountVectorizer(ngram_range = (2,2))
X_train_process_bi_trnsfrm = cvt_process_bi.fit_transform(X_train)
X_test_process_bi_trnsfrm = cvt_process_bi.transform(X_test)
```

We will use bigram features to train and test algorithm.

```
lr_process_uni = LogisticRegression(multi_class='multinomial', solver='lbfgs')
lr_process_uni.fit(X_train_process_bi_trnsfrm, y_train)
lr_process_uni_predictions = lr_process_uni.predict(X_test_process_bi_trnsfrm)
print(accuracy_score(y_test, lr_process_uni_predictions))
del cvt_process_bi, X_train_process_bi_trnsfrm, X_test_process_bi_trnsfrm, lr_process_uni, lr_process_uni_predictions
```

```
0.5732725892179195
```

Using bigram features to train and test algorithm does bring down accuracy to some extent than using just unigram features

We will use the best(top) of unigram and bigram features by reducing the max features which could reduce the possibility of having jumbled letters words and it would help in both unigram and bigram features. Tried with a different number of features to be considered.

```
cvt_process_unibi_max = CountVectorizer(ngram_range = (1,2), max_features=24900)
X_train_trnsfrm_unibi_max = cvt_process_unibi_max.fit_transform(X_train)
X_test_trnsfrm_unibi_max = cvt_process_unibi_max.transform(X_test)
```

Input data to our model for train

```
X_train_trnsfrm_unibi_max, y_train
```

```
Out[71]: (<5265x24900 sparse matrix of type '<class 'numpy.int64'>'
         	with 122346 stored elements in Compressed Sparse Row format>,
          array([72,  5,  4, ..., 72,  0,  0]))
```

Input data to our model for test

```
X_test_trnsfrm_unibi_max, y_test
```

```
Out[72]: (<1317x24900 sparse matrix of type '<class 'numpy.int64'>'
         	with 24106 stored elements in Compressed Sparse Row format>,
          array([ 0,  8, 17, ...,  0, 15,  0]))
```

Check the unique group values available in train and test data

```
print(len(np.unique(y_train))), print(len(np.unique(y_test)))
print(np.unique(y_train))
print(np.unique(y_test))
```

```
73
59
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48
 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72
 73]
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 33 34 35 36 37 39 40 41 42 43 44 45 46 47 48 49 51
 53 54 55 56 57 59 60 66 67 72 73]
```

We will use reduced unigram and bigram features to train and test algorithm.

```
lr_unibi_max = LogisticRegression(multi_class='multinomial', solver='lbfgs')
lr_unibi_max.fit(X_train_trnsfrm_unibi_max, y_train)
lr_unibi_max_predictions = lr_unibi_max.predict(X_test_trnsfrm_unibi_max)
print(accuracy_score(y_test, lr_unibi_max_predictions))
del cvt_process_unibi_max, lr_unibi_max
```

```
0.6340167046317388
```

We will use the best(top) of unigram, bigram, and trigram features by reducing the max features which could reduce the possibility of having jumbled letters words. Tried with a different number of features to be considered.

```
cvt_process_unibitri_max = CountVectorizer(ngram_range = (1,3), max_features=35000)
X_train_trnsfrm_unibitri_max = cvt_process_unibitri_max.fit_transform(X_train)
X_test_trnsfrm_unibitri_max = cvt_process_unibitri_max.transform(X_test)
```

We will use reduced unigram, bigram and trigram features to train and test algorithm.

```
lr_unibitri_max = LogisticRegression(multi_class='multinomial', solver='lbfgs')
lr_unibitri_max.fit(X_train_trnsfrm_unibitri_max, y_train)
lr_unibitri_max_predictions = lr_unibitri_max.predict(X_test_trnsfrm_unibitri_max)
print(accuracy_score(y_test, lr_unibitri_max_predictions))
del cvt_process_unibitri_max, X_train_trnsfrm_unibitri_max, X_test_trnsfrm_unibitri_max, lr_unibitri_max
```

```
0.6302201974183751
```

Using top unigram, bigram, and trigram features accuracy remains almost same, but max features considered increases as well.

Let us check the classification_report. The predictions of the model which used top unigram and bigram features for training.

```
print(classification_report(y_test, lr_unibi_max_predictions, digits=2))
```

	precision	recall	f1-score	support
0	0.66	0.94	0.78	642
1	0.50	0.25	0.33	4
2	0.50	0.09	0.15	22
3	0.00	0.00	0.00	6
4	0.71	0.54	0.62	46
5	0.55	0.44	0.49	27
6	0.64	0.36	0.46	25

7	1.00	0.33	0.50	6
8	0.50	0.20	0.29	20
9	1.00	0.86	0.92	7
10	0.55	0.40	0.46	15
11	0.30	0.20	0.24	35
12	0.55	0.37	0.44	43
13	1.00	0.14	0.25	7
14	0.00	0.00	0.00	6
15	1.00	0.25	0.40	4
16	0.50	0.17	0.25	6
17	0.93	0.74	0.82	50
18	0.56	0.32	0.41	28
19	0.60	0.33	0.43	9
20	0.00	0.00	0.00	5
21	0.00	0.00	0.00	10
22	0.67	0.35	0.46	23
23	0.53	0.34	0.42	47
24	0.00	0.00	0.00	2
25	1.00	0.11	0.20	9
26	0.00	0.00	0.00	1
27	0.46	0.40	0.43	15
28	0.33	0.25	0.29	8
29	0.00	0.00	0.00	1
30	0.50	0.25	0.33	4
31	0.00	0.00	0.00	0
33	1.00	0.50	0.67	2
34	0.33	0.21	0.26	19
35	0.25	0.22	0.24	9
36	0.00	0.00	0.00	8
37	0.00	0.00	0.00	1
39	0.00	0.00	0.00	3
40	0.00	0.00	0.00	5
41	0.00	0.00	0.00	4
42	0.67	0.40	0.50	5
43	0.00	0.00	0.00	1
44	0.00	0.00	0.00	2
45	0.33	0.15	0.21	13
46	0.00	0.00	0.00	2
47	0.00	0.00	0.00	1
48	0.00	0.00	0.00	4
49	0.00	0.00	0.00	3
51	0.00	0.00	0.00	1
53	0.00	0.00	0.00	1
54	1.00	1.00	1.00	1
55	0.00	0.00	0.00	2
56	0.41	0.58	0.48	12
57	0.00	0.00	0.00	1
59	0.00	0.00	0.00	7
60	0.00	0.00	0.00	1
66	0.00	0.00	0.00	1
67	0.50	0.20	0.29	15

72	0.55	0.67	0.60	48
73	0.57	0.33	0.42	12
accuracy			0.63	1317
macro avg	0.35	0.22	0.25	1317
weighted avg	0.59	0.63	0.58	1317

Let us check the classification_report. The predictions of the model which used top unigram, bigram and trigram features for training.

```
print(classification_report(y_test, lr_unibitri_max_predictions, digits=2))
del lr_unibi_max_predictions, lr_unibitri_max_predictions
```

	precision	recall	f1-score	support
0	0.66	0.93	0.77	642
1	0.50	0.25	0.33	4
2	0.50	0.09	0.15	22
3	0.00	0.00	0.00	6
4	0.69	0.52	0.59	46
5	0.58	0.52	0.55	27
6	0.62	0.32	0.42	25
7	1.00	0.17	0.29	6
8	0.67	0.20	0.31	20
9	1.00	0.86	0.92	7
10	0.45	0.33	0.38	15
11	0.29	0.20	0.24	35
12	0.53	0.40	0.45	43
13	1.00	0.14	0.25	7
14	1.00	0.17	0.29	6
15	0.00	0.00	0.00	4
16	0.50	0.17	0.25	6
17	0.92	0.72	0.81	50
18	0.59	0.36	0.44	28
19	0.60	0.33	0.43	9
20	0.00	0.00	0.00	5
21	0.00	0.00	0.00	10
22	0.75	0.39	0.51	23
23	0.57	0.36	0.44	47
24	0.00	0.00	0.00	2
25	1.00	0.11	0.20	9
26	0.00	0.00	0.00	1
27	0.43	0.40	0.41	15
28	0.50	0.38	0.43	8
29	0.00	0.00	0.00	1
30	0.50	0.25	0.33	4
31	0.00	0.00	0.00	0

33	1.00	0.50	0.67	2
34	0.31	0.21	0.25	19
35	0.33	0.33	0.33	9
36	0.00	0.00	0.00	8
37	0.00	0.00	0.00	1
39	0.00	0.00	0.00	3
40	0.00	0.00	0.00	5
41	0.00	0.00	0.00	4
42	0.50	0.20	0.29	5
43	0.00	0.00	0.00	1
44	0.00	0.00	0.00	2
45	0.33	0.15	0.21	13
46	0.00	0.00	0.00	2
47	0.00	0.00	0.00	1
48	0.00	0.00	0.00	4
49	0.00	0.00	0.00	3
51	0.00	0.00	0.00	1
53	0.00	0.00	0.00	1
54	1.00	1.00	1.00	1
55	0.00	0.00	0.00	2
56	0.39	0.58	0.47	12
57	0.00	0.00	0.00	1
59	0.00	0.00	0.00	7
60	0.00	0.00	0.00	1
66	0.00	0.00	0.00	1
67	0.50	0.20	0.29	15
72	0.53	0.65	0.58	48
73	0.50	0.25	0.33	12
accuracy			0.63	1317
macro avg	0.35	0.21	0.24	1317
weighted avg	0.59	0.63	0.58	1317

The Model(Model_Uni_Bigram) which was trained on combination of unigram and bigram with max_features=24900 was able to perform slightly better (63.40 vs 63.02) than the Model(Model_Uni_Bi_Trigram) which was trained on combination of unigram, bigram, and trigram with max_features=35000. Also, bigram features could be helpful after performing text augmentation. We also have the additional advantage of reduced number of features in a Model_Uni_Bigram which will help to compute faster and occupy less memory while accuracy remains good.

6.1.1 Build different models

We will use reduced unigram and bigram features vectorized data that gave good accuracy to test supervised learning models [RandomForestClassifier, MultinomialNB, SVC]

Score RandomForestClassifier

```
rf_unibi_max = RandomForestClassifier()
rf_unibi_max.fit(X_train_trnsfrm_unibi_max, y_train)
rf_unibi_max_predictions = rf_unibi_max.predict(X_test_trnsfrm_unibi_max)
print(accuracy_score(y_test, rf_unibi_max_predictions))
del rf_unibi_max
```

```
0.5968109339407744
```

Score Naive Bayes Classifier.

```
nb_unibi_max = MultinomialNB()
nb_unibi_max.fit(X_train_trnsfrm_unibi_max, y_train)
nb_unibi_max_predictions = nb_unibi_max.predict(X_test_trnsfrm_unibi_max)
print(accuracy_score(y_test, nb_unibi_max_predictions))
del nb_unibi_max
```

```
0.6044039483675019
```

Score Support Vector Classifier

```
svm_unibi_max = SVC()
svm_unibi_max.fit(X_train_trnsfrm_unibi_max, y_train)
svm_unibi_max_predictions = svm_unibi_max.predict(X_test_trnsfrm_unibi_max)
print(accuracy_score(y_test, svm_unibi_max_predictions))
del svm_unibi_max
```

```
0.5725132877752468
```

The Naive Bayes is the one which performs better than RandomForestClassifier and Support Vector Classifier, but still falls behind the LogisticRegression Classifier.

Let us check the classification_report of Naive Bayes.

```
print(classification_report(y_test, nb_unibi_max_predictions, digits=2))
del X, y, X_train, X_test, y_train, y_test, X_train_trnsfrm_unibi_max, X_test_trnsfrm_unibi_max
del rf_unibi_max_predictions, nb_unibi_max_predictions, svm_unibi_max_predictions
```

	precision	recall	f1-score	support
0	0.59	0.98	0.74	642
1	0.00	0.00	0.00	4
2	0.00	0.00	0.00	22
3	0.00	0.00	0.00	6
4	0.65	0.48	0.55	46
5	0.53	0.37	0.43	27
6	0.60	0.24	0.34	25
7	0.00	0.00	0.00	6
8	0.00	0.00	0.00	20
9	0.00	0.00	0.00	7
10	0.60	0.20	0.30	15
11	0.80	0.11	0.20	35
12	0.55	0.40	0.46	43
13	0.00	0.00	0.00	7
14	0.00	0.00	0.00	6
15	0.00	0.00	0.00	4
16	0.00	0.00	0.00	6
17	0.85	0.80	0.82	50
18	1.00	0.07	0.13	28
19	0.00	0.00	0.00	9
20	0.00	0.00	0.00	5
21	0.00	0.00	0.00	10
22	1.00	0.09	0.16	23
23	1.00	0.13	0.23	47
24	0.00	0.00	0.00	2
25	0.00	0.00	0.00	9
26	0.00	0.00	0.00	1
27	0.64	0.47	0.54	15
28	0.00	0.00	0.00	8
29	0.00	0.00	0.00	1
30	0.00	0.00	0.00	4
33	0.00	0.00	0.00	2
34	1.00	0.11	0.19	19
35	0.00	0.00	0.00	9
36	0.00	0.00	0.00	8
37	0.00	0.00	0.00	1
39	0.00	0.00	0.00	3
40	0.00	0.00	0.00	5
41	0.00	0.00	0.00	4
42	0.00	0.00	0.00	5
43	0.00	0.00	0.00	1
44	0.00	0.00	0.00	2

45	0.00	0.00	0.00	13
46	0.00	0.00	0.00	2
47	0.00	0.00	0.00	1
48	0.00	0.00	0.00	4
49	0.00	0.00	0.00	3
51	0.00	0.00	0.00	1
53	0.00	0.00	0.00	1
54	0.00	0.00	0.00	1
55	0.00	0.00	0.00	2
56	0.40	0.33	0.36	12
57	0.00	0.00	0.00	1
59	0.00	0.00	0.00	7
60	0.00	0.00	0.00	1
66	0.00	0.00	0.00	1
67	0.00	0.00	0.00	15
72	0.58	0.79	0.67	48
73	1.00	0.08	0.15	12
accuracy			0.60	1317
macro avg	0.20	0.10	0.11	1317
weighted avg	0.54	0.60	0.50	1317

The classification report above shows that the overall accuracy is lesser and also the number of individual classes does not have any accuracy compared to LogisticRegression Classifier. The LogisticRegression Classifier performs better than other supervised learning models [RandomForestClassifier, MultinomialNB, SVC]

6.2. Building a Neural Network model architecture

The documents/texts are sequential. It is a sequence of words following grammatical structure. We will use the Sequential Model after creating the features by tokenizing the text, converting to vector and applying padding

Initialize the random state

```
def reset_seeds(sed):
    np.random.seed(sed)
    python_random.seed(sed)
    tf.set_random_seed(sed)
reset_seeds(9)
```

Defining params top_num_words for most frequent words from dataset, embedding_dim for the output dimension of our embedding layer, oov_char for words that were cut out because of the top_num_words, pad_type to append 0 at beginning or end of a text which is shorter than maximum length text, trunc_type for removing the words from beginning or end of a text which exceeds maximum length text. The documents/texts are of various lengths. The mean length is around 30. There are many outliers. We will consider max length of 35 in our tokenizer's pad sequences to add up some deviation.

```
top_num_words = 5000
embedding_dim = 300
oov_char = "<OOV>"
pad_type = "pre"
trunc_type = "pre"
max_length = 35
loss_fn = 'categorical_crossentropy'
optimizer_alg='adam'
metric_eval = 'accuracy'
```

Fit tokenizer on texts to break the sentences to individual tokens and rank them based on the frequency of appearance.

```
tknzr = Tokenizer(num_words=top_num_words, oov_token=oov_char)
tknzr.fit_on_texts(df_process_txt_acc['Description'])
```

Creating the features by converting our text to sequences. Truncate the ones which are more than max_length, and apply padding (add 0) to the sequences which are shorter until it is of max_length size.

```
X_seq = tknzr.texts_to_sequences(df_process_txt_acc['Description'])
X_seq_pad = pad_sequences(X_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)
```

Using get dummies function to convert categorical variables into dummy variables that can be understood by model

```
y_seq = pd.get_dummies(df_process_txt_acc['Assignment group']).values
```

Get the vocabulary size. We will add +1 to the word index as zero is reserved for padding.

```
tknz_vocabsize =len(tknzr.word_index)+1
print(tknz_vocabsize)
```

```
13290
```

Split text and class data into training and test set in 80:20 ratio.

```
X_train_Seq, X_test_Seq, y_train_Seq, y_test_Seq = train_test_split(X_seq_pad, y_seq, test_size=0.20, random_state=6)
X_train_Seq.shape, X_test_Seq.shape
```

```
Out[89]: ((5265, 35), (1317, 35))
```

Input data to our model for train

```
X_train_Seq, y_train_Seq
```

```
Out[90]: (array([[   0,    0,    0, ..., 2862, 4165,    1],
                 [  11,   26,  156, ...,  795,  276,   41],
                 [   0,    0,    0, ...,   22,   22,  365],
                 ...,
                 [   0,    0,    0, ...,  381,   28,   33],
                 [   0,    0,    0, ...,  255,  246, 3885],
                 [   0,    0,    0, ...,    1,  621,    1]], dtype=int32),
          array([[0, 0, 0, ..., 0, 1, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 ...,
                 [0, 0, 0, ..., 0, 1, 0],
                 [1, 0, 0, ..., 0, 0, 0],
                 [1, 0, 0, ..., 0, 0, 0]], dtype=uint8))
```

Input data to our model for test

```
X_test_Seq, y_test_Seq
```

```
Out[91]: (array([[   0,    0,    0, ...,    0,   20,   25],
                 [   0,    0,    0, ..., 2619,    2,  262],
                 [   0,    0,    0, ...,  408, 2874, 2875],
                 ...,
                 [   0,    0,    0, ...,   30,   95,   91],
                 [   0,    0,    0, ...,    1,    1,  102],
                 [   0,    0,    0, ...,    1,  513,   86]], dtype=int32),
          array([[1, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 ...,
                 [1, 0, 0, ..., 0, 0, 0],
                 [0, 0, 0, ..., 0, 0, 0],
                 [1, 0, 0, ..., 0, 0, 0]], dtype=uint8))
```

6.2.1 Build different models

Sequential model with LSTM (Long Short-Term Memory) to train and classify our documents. LSTM (Long Short-Term Memory) network is a type of RNN (Recurrent Neural Network). It can memorize patterns. It uses a series of gates(input gate, output gate and forget gate) to control how the information in a sequence of data comes in, how it is stored and leaves the network.

Build a Sequential model with LSTM layer

```
model_lstm = Sequential()
model_lstm.add(Embedding(input_dim=tknz_vocabsize, output_dim=embedding_dim, input_length=max_length))
model_lstm.add(LSTM(100))
model_lstm.add(Dense(100, activation = "relu"))
model_lstm.add(Dense(74,activation='softmax'))
```

Compile and fit the model

```
model_lstm.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
model_lstm.fit(X_train_Seq, y_train_Seq, epochs = 5, batch_size=128, verbose = 0,validation_split=0.25)
```

```
Out[93]: <keras.callbacks.History at 0x142693f28>
```

Loss and accuracy

```
model_lstm.evaluate(X_test_Seq, y_test_Seq)
```

```
         1317/1317 [==============================] - 0s 331us/step
Out[94]: [2.18423331879085, 0.5292331056334163]
```

Save the weights

```
model_lstm.save_weights("model_lstm.h5")
```

The Bidirectional LSTM propagates the input forwards and backwards through the LSTM layer, and concatenates the outputs. It increase the amount of information available to the network by knowing the words that follow and precede a word in a sentence

Build a Sequential model with Bidirectional LSTM layer

```
model_lstmbi = Sequential()
model_lstmbi.add(Embedding(input_dim=tknz_vocabsize, output_dim=embedding_dim, input_length=max_length))
model_lstmbi.add(Bidirectional(LSTM(10)))
model_lstmbi.add(Dense(100, activation = "relu"))
model_lstmbi.add(Dense(74,activation='softmax'))
```

Compile and fit the model

```
model_lstmbi.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
model_lstmbi.fit(X_train_Seq, y_train_Seq, epochs = 5, batch_size=32, verbose = 0,validation_split=0.25)
```

```
Out[97]: <keras.callbacks.History at 0x1423fab38>
```

Loss and accuracy

```
model_lstmbi.evaluate(X_test_Seq, y_test_Seq)
```

```
1317/1317 [==============================] - 0s 279us/step
Out[98]: [2.0970806782229343, 0.5466970387470025]
```

Save the weights

```
model_lstmbi.save_weights("model_lstmbi.h5")
del tknzr, X_seq, X_seq_pad, y_seq, tknz_vocabsize
del model_lstm, X_train_Seq, y_train_Seq, model_lstmbi, X_test_Seq, y_test_Seq
```

6.3. Build Train-Test data having all unique groups

In the above train-test splits we could not have all unique group values available in both train and test split as it is an imbalanced data which you can see below.

Check number of documents in the groups

```
df_process_txt_acc["Assignment group"].value_counts()
```

GRP_0	3065
GRP_24	277
GRP_2	240
GRP_12	238
GRP_8	234
GRP_19	213
GRP_3	200
GRP_13	142
GRP_14	118
GRP_25	116
GRP_33	106
GRP_29	97
GRP_4	91
GRP_16	85
GRP_18	84
GRP_10	82
GRP_9	78
GRP_6	70

```
GRP_7     67
GRP_17    63
GRP_34    62
GRP_26    56
GRP_31    55
GRP_5     50
GRP_40    45
GRP_28    44
GRP_41    39
GRP_15    38
GRP_42    37
GRP_20    36
          ...
GRP_50    14
GRP_60    11
GRP_65    11
GRP_53    11
GRP_52     9
GRP_51     8
GRP_55     8
GRP_48     7
GRP_49     6
GRP_46     6
GRP_59     6
GRP_43     5
GRP_32     4
GRP_63     3
GRP_38     3
GRP_56     3
GRP_66     3
GRP_68     3
GRP_58     3
GRP_71     2
GRP_54     2
GRP_69     2
GRP_57     2
GRP_72     2
GRP_64     1
GRP_67     1
GRP_35     1
GRP_70     1
GRP_73     1
GRP_61     1
Name: Assignment group, Length: 74, dtype: int64
```

Let's create documents for the groups[GRP_64, GRP_73, GRP_35, GRP_61, GRP_67, GRP_70] by augmenting data with synonyms. Divide the data frame into three parts(greater than 2 counts, equal to 2 counts, lesser than 2 counts) and finally prepare the train test split to have all unique group values available in both train side and test side data.

Filter the dataframe to get the groups with more than 2 counts

```
df_process_txt_acc_cpc = copy.deepcopy(df_process_txt_acc)
df_process_grtr_2 = df_process_txt_acc_cpc.groupby("Assignment group").filter(lambda x: len(x) > 2)
df_process_grtr_2.shape
```

```
Out[101]: (6566, 2)
```

Filter the dataframe to get the groups equal to 2 counts

```
df_process_eql2 = df_process_txt_acc_cpc.groupby("Assignment group").filter(lambda x: len(x) == 2)
df_process_eql2.shape
```

```
Out[102]: (10, 2)
```

Filter the dataframe to get the groups with less than 2 counts

```
df_process_lssr2 = df_process_txt_acc_cpc.groupby("Assignment group").filter(lambda x: len(x) < 2)
df_process_lssr2.shape
```

```
Out[103]: (6, 2)
```

SynonymAug Augmenter that leverage semantic meaning to substitute word from wordnet(WordNet is a lexical database of semantic relations between words. It links words into semantic relations including synonyms)

```
syno_aug = naw.SynonymAug(aug_p=0.5)
def aug_syno_text(text):
    try:
        return syno_aug.augment(text)
    except:
        return text
```

Apply text augmentation through SynonymAug Augmenter for data frame containing groups with less than 2 counts

```
df_process_lssr2_cpc = copy.deepcopy(df_process_lssr2)
df_process_lssr2_cpc["Description"] = df_process_lssr2_cpc["Description"].apply(aug_syno_text)
df_process_lssr2_cpc.shape
```

```
Out[105]: (6, 2)
```

Concatenating data frame containing groups with less than 2 counts and it's synonym text augmented data

```
df_process_txt_lss2_aug = pd.concat([df_process_lssr2, df_process_lssr2_cpc])
df_process_txt_lss2_aug.shape
```

```
Out[106]: (12, 2)
```

Start to prepare for the train and test split. First consider values from dataframe which has groups with more than 2 counts Stratify on y ('Assignment group')

```
X_strat = df_process_grtr_2['Description']
y_strat = df_process_grtr_2['Assignment group']

X_train_strat, X_test_strat, y_train_strat, y_test_strat =train_test_split(X_strat,y_strat, random_state=6,
                                                            test_size = 0.25, stratify=y_strat)
print(len(np.unique(y_train_strat)))
print(len(np.unique(y_test_strat)))
del df_process_txt_acc_cpc, df_process_grtr_2, df_process_lssr2, df_process_lssr2_cpc
```

```
63
63
```

Manually add groups from dataframe which has groups equal to 2 counts into train and test data

```
for idx, row in copy.deepcopy(df_process_eql2).iterrows():
    if not np.isin(row['Assignment group'], y_train_strat):
        X_train_strat = X_train_strat.append(pd.Series(row['Description'], index=[idx]))
        y_train_strat = np.append(y_train_strat, row['Assignment group'])
    elif not np.isin(row['Assignment group'], y_test_strat):
            X_test_strat = X_test_strat.append(pd.Series(row['Description'], index=[idx]))
            y_test_strat = np.append(y_test_strat, row['Assignment group'])
print(len(np.unique(y_train_strat)))
print(len(np.unique(y_test_strat)))
del X_strat, y_strat, df_process_eql2
```

```
68
68
```

Manually add groups from dataframe which has groups with less than 2 counts and it's synonym text augmented data into train and test data. Remove no longer required variables to free up memory.

```
for idx, row in copy.deepcopy(df_process_txt_lss2_aug).iterrows():
    if not np.isin(row['Assignment group'], y_train_strat):
        X_train_strat = X_train_strat.append(pd.Series(row['Description'], index=[idx]))
        y_train_strat = np.append(y_train_strat, row['Assignment group'])
    elif not np.isin(row['Assignment group'], y_test_strat):
            X_test_strat = X_test_strat.append(pd.Series(row['Description'], index=[idx]))
            y_test_strat = np.append(y_test_strat, row['Assignment group'])
print(len(np.unique(y_train_strat)))
print(len(np.unique(y_test_strat)))
del df_process_txt_lss2_aug
```

```
74
74
```

All unique groups['GRP_0' to 'GRP_73'] available in both train and test data

```
print(X_train_strat.shape), print(X_test_strat.shape)
print(np.unique(y_train_strat))
print(np.unique(y_test_strat))
```

```
(4935,)
(1653,)
['GRP_0' 'GRP_1' 'GRP_10' 'GRP_11' 'GRP_12' 'GRP_13' 'GRP_14' 'GRP_15'
 'GRP_16' 'GRP_17' 'GRP_18' 'GRP_19' 'GRP_2' 'GRP_20' 'GRP_21' 'GRP_22'
 'GRP_23' 'GRP_24' 'GRP_25' 'GRP_26' 'GRP_27' 'GRP_28' 'GRP_29' 'GRP_3'
 'GRP_30' 'GRP_31' 'GRP_32' 'GRP_33' 'GRP_34' 'GRP_35' 'GRP_36' 'GRP_37'
 'GRP_38' 'GRP_39' 'GRP_4' 'GRP_40' 'GRP_41' 'GRP_42' 'GRP_43' 'GRP_44'
 'GRP_45' 'GRP_46' 'GRP_47' 'GRP_48' 'GRP_49' 'GRP_5' 'GRP_50' 'GRP_51'
 'GRP_52' 'GRP_53' 'GRP_54' 'GRP_55' 'GRP_56' 'GRP_57' 'GRP_58' 'GRP_59'
 'GRP_6' 'GRP_60' 'GRP_61' 'GRP_62' 'GRP_63' 'GRP_64' 'GRP_65' 'GRP_66'
 'GRP_67' 'GRP_68' 'GRP_69' 'GRP_7' 'GRP_70' 'GRP_71' 'GRP_72' 'GRP_73'
 'GRP_8' 'GRP_9']
['GRP_0' 'GRP_1' 'GRP_10' 'GRP_11' 'GRP_12' 'GRP_13' 'GRP_14' 'GRP_15'
 'GRP_16' 'GRP_17' 'GRP_18' 'GRP_19' 'GRP_2' 'GRP_20' 'GRP_21' 'GRP_22'
 'GRP_23' 'GRP_24' 'GRP_25' 'GRP_26' 'GRP_27' 'GRP_28' 'GRP_29' 'GRP_3'
 'GRP_30' 'GRP_31' 'GRP_32' 'GRP_33' 'GRP_34' 'GRP_35' 'GRP_36' 'GRP_37'
 'GRP_38' 'GRP_39' 'GRP_4' 'GRP_40' 'GRP_41' 'GRP_42' 'GRP_43' 'GRP_44'
 'GRP_45' 'GRP_46' 'GRP_47' 'GRP_48' 'GRP_49' 'GRP_5' 'GRP_50' 'GRP_51'
 'GRP_52' 'GRP_53' 'GRP_54' 'GRP_55' 'GRP_56' 'GRP_57' 'GRP_58' 'GRP_59'
 'GRP_6' 'GRP_60' 'GRP_61' 'GRP_62' 'GRP_63' 'GRP_64' 'GRP_65' 'GRP_66'
 'GRP_67' 'GRP_68' 'GRP_69' 'GRP_7' 'GRP_70' 'GRP_71' 'GRP_72' 'GRP_73'
 'GRP_8' 'GRP_9']
```

We will use the CountVectorizer with uni bigram features that we selected above after analysis. Using LabelEncoder to encode classes/target to numerical with value between 0 and numberofclasses-1 Function to use the CountVectorizer.

```
def lr_cvt_unibi_eval(X_train_strat_parm, y_train_strat_parm, X_test_strat_parm, y_test_strat_parm):
    cvt_process_strat_unibi_max = CountVectorizer(ngram_range = (1,2), max_features=24900)
    X_train_strat_unibi_max = cvt_process_strat_unibi_max.fit_transform(X_train_strat_parm)
    X_test_strat_unibi_max = cvt_process_strat_unibi_max.transform(X_test_strat_parm)

    lbl_enc_strat = preprocessing.LabelEncoder()
    y_train_enc_strat = lbl_enc_strat.fit_transform(y_train_strat_parm)
    y_test_enc_strat = lbl_enc_strat.fit_transform(y_test_strat_parm)

    lr_unibi_max_strat = LogisticRegression(multi_class='multinomial', solver='lbfgs')
    lr_unibi_max_strat.fit(X_train_strat_unibi_max, y_train_enc_strat)
    lr_unibi_max_strat_predictions = lr_unibi_max_strat.predict(X_test_strat_unibi_max)
    return accuracy_score(y_test_enc_strat, lr_unibi_max_strat_predictions)
```

We will use Logistic Regression with reduced unigram, bigram features to train and test algorithm.

```
print("Accuracy:{}".format(lr_cvt_unibi_eval(X_train_strat, y_train_strat, X_test_strat, y_test_strat)))
```

```
Accuracy:0.6134301270417423
```

Performance of Model Uni_bigram considering all unique groups for train and test is at closer range to earlier performance.

Function to build a Sequential model with Bidirectional LSTM layer and keras Embedding layer, compile, fit and evaluate

```
def seq_lstm_bi_eval(X_train_strat_parm, y_train_strat_parm, X_test_strat_parm, y_test_strat_parm):
    tknzr_strat = Tokenizer(num_words=top_num_words, oov_token=oov_char)
    tknzr_strat.fit_on_texts(X_train_strat_parm.append(X_test_strat_parm))
    tknz_strat_vocabsize =len(tknzr_strat.word_index)+1

    X_train_strat_seq = tknzr_strat.texts_to_sequences(X_train_strat_parm)
    X_train_strat_seq_pad = pad_sequences(X_train_strat_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)
    X_test_strat_seq = tknzr_strat.texts_to_sequences(X_test_strat_parm)
    X_test_strat_seq_pad = pad_sequences(X_test_strat_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)

    lbl_enc_tknzr_strat = preprocessing.LabelEncoder()
    y_train_strat_tknzr = pd.get_dummies(lbl_enc_tknzr_strat.fit_transform(y_train_strat_parm)).values
    y_test_strat_tknzr = pd.get_dummies(lbl_enc_tknzr_strat.fit_transform(y_test_strat_parm)).values

    model_strat = Sequential()
    model_strat.add(Embedding(input_dim=tknz_strat_vocabsize, output_dim=embedding_dim, input_length=max_length))
    model_strat.add(Bidirectional(LSTM(10)))
    model_strat.add(Dense(100, activation = "relu"))
    model_strat.add(Dense(74,activation='softmax'))

    model_strat.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
    model_strat.fit(X_train_strat_seq_pad, y_train_strat_tknzr, epochs = 5, batch_size=32, verbose = 0,validation_split=0.25)

    return model_strat.evaluate(X_test_strat_seq_pad, y_test_strat_tknzr)
```

We will use a Sequential model with Bidirectional LSTM layer to train and test algorithm.

```
print("Accuracy:{}".format(seq_lstm_bi_eval(X_train_strat, y_train_strat, X_test_strat, y_test_strat)))
```

```
1653/1653 [==============================] - 0s 301us/step
Accuracy:[2.2823932567511047, 0.516636418795052]
```

Performance of Sequential Model with Bidirectional LSTM layer considering all unique groups for train and test is at closer range to earlier performance.

Function to create glove embedding matrix to use it in Neural Network Sequential Model

```
def weight_matrx_glv_embed(glove_embd_path, embedding_dim, tknzr_parm):
    embeddings_word_val = {}
    lowrds=[]

    f = open(glove_embd_path)
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embeddings_word_val[word] = coefs
    f.close()

    tknzr_parm_vocabsize = len(tknzr_parm.word_index)+1
    embedding_matrix=np.zeros((tknzr_parm_vocabsize,embedding_dim))
    for word,idx in tknzr_parm.word_index.items():
        try:
            embedding_vector=embeddings_word_val[word]
            embedding_matrix[idx]=embedding_vector
        except:
            lowrds.append(word)
    return embedding_matrix
```

Function to build a Sequential model with Bidirectional LSTM layer and Glove Embedding layer, compile, fit and evaluate

```
def seq_lstm_bi_glv_eval(X_train_strat_parm, y_train_strat_parm, X_test_strat_parm,
                     y_test_strat_parm, glv_embed_path, dimension_parm, last_dense_layer=74):
    tknzr_strat = Tokenizer(num_words=top_num_words, oov_token=oov_char)
    tknzr_strat.fit_on_texts(X_train_strat_parm.append(X_test_strat_parm))
    tknz_strat_vocabsize =len(tknzr_strat.word_index)+1

    X_train_strat_seq = tknzr_strat.texts_to_sequences(X_train_strat_parm)
    X_train_strat_seq_pad = pad_sequences(X_train_strat_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)
    X_test_strat_seq = tknzr_strat.texts_to_sequences(X_test_strat_parm)
    X_test_strat_seq_pad = pad_sequences(X_test_strat_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)

    lbl_enc_tknzr_strat = preprocessing.LabelEncoder()
    y_train_strat_tknzr = pd.get_dummies(lbl_enc_tknzr_strat.fit_transform(y_train_strat_parm)).values
    y_test_strat_tknzr = pd.get_dummies(lbl_enc_tknzr_strat.fit_transform(y_test_strat_parm)).values

    embedding_matrix_strat = weight_matrx_glv_embed(glv_embed_path, dimension_parm, tknzr_strat)

    model_strat = Sequential()
    model_strat.add(Embedding(input_dim=tknz_strat_vocabsize, output_dim=dimension_parm, weights=[embedding_matrix_strat],
                          input_length=max_length, trainable=True))
    model_strat.add(Bidirectional(LSTM(10)))
    model_strat.add(Dense(100, activation = "relu"))
    model_strat.add(Dense(last_dense_layer,activation='softmax'))

    model_strat.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
    model_strat.fit(X_train_strat_seq_pad, y_train_strat_tknzr, epochs = 5, batch_size=32, verbose = 0,validation_split=0.25)

    return model_strat.evaluate(X_test_strat_seq_pad, y_test_strat_tknzr)
```

We will use a Sequential model with Bidirectional LSTM layer and Glove 300 dimensional embedding to train and test algorithm.

```
print("Accuracy:{}".format(seq_lstm_bi_glv_eval(X_train_strat, y_train_strat,
                                                 X_test_strat, y_test_strat, './glove.6B.300d.txt', 300)))
```

```
1653/1653 [==============================] - 1s 320us/step
Accuracy:[2.070863858180845, 0.5402298852197344]
```

Performance of Sequential Model with Bidirectional LSTM layer and Glove 300 dimensional embedding considering all unique groups for train and test holds out at closer range to earlier performance.

The initial performance of LogisticRegression and Sequential Model where we did not focus on having all unique groups/target available in train, test data and later performance of LogisticRegression and Sequential Model where we made sure to have all unique groups/target available in train, test data and the one where we used Glove pre trained embedding remains almost at same range 61-63 percent and 51-54 percent accuracy respectively.

We will try to handle class imbalance using sklearn resample which creates a random resampling with(default=True)/without replacement of data and evaluate the performance of models. We will be using the train and test data that has all unique groups available in them

6.4. Build model with resampled train data

Create random resample with replacement for groups/target with counts less than 150. Using the train data and upsampling it. Tried with a different number of random samples.

```
resampl_df = pd.DataFrame({ 'Assignment group': y_train_strat, 'Description': X_train_strat })
df_grt_150_rl = resampl_df.groupby("Assignment group").filter(lambda x: len(x) > 150)
df_lssr_150_rl = resampl_df.groupby("Assignment group").filter(lambda x: len(x) <= 150)
df_lssr_150_rl_upsampl = resample(df_lssr_150_rl, n_samples=len(df_grt_150_rl), random_state=6)
df_rl_upsampld = pd.concat([df_grt_150_rl, df_lssr_150_rl_upsampl])
df_grt_150_rl.shape, df_lssr_150_rl.shape, df_lssr_150_rl_upsampl.shape
```

```
Out[118]:  ((3200, 2), (1735, 2), (3200, 2))
```

We will use Logistic Regression with reduced unigram, bigram features to train and test algorithm. Using the train data that is random upsampled and evaluating performance

```
print("Accuracy:{}".format(lr_cvt_unibi_eval(df_rl_upsampld['Description'], df_rl_upsampld['Assignment group'],
                                              X_test_strat, y_test_strat)))
del resampl_df, df_grt_150_rl, df_lssr_150_rl, df_lssr_150_rl_upsampl
```

```
Accuracy:0.6158499697519662
```

We will use a Sequential model with Bidirectional LSTM layer and Glove 300 dimensional embedding to train and test the algorithm. Using the train data that is random upsampled and evaluating performance

```
print("Accuracy:{}".format(seq_lstm_bi_glv_eval(df_rl_upsampld['Description'], df_rl_upsampld['Assignment group'],
                                                 X_test_strat, y_test_strat, './glove.6B.300d.txt', 300)))
del df_rl_upsampld
```

```
1653/1653 [==============================] - 1s 324us/step
Accuracy:[2.153939386749729, 0.5589836661879106]
```

The performance of LogisticRegression and Sequential Model with Glove pretrained embedding layer using the upsampled train data, evaluating performance is at range 61-63 percent and 51-55 percent accuracy respectively.

6.5. Build model on augmented train data

We will try to handle class imbalance using various text augmentation techniques on groups with less or equal to 100 counts/documents and evaluate the performance of models. We will be using the train and test data that has all unique groups available in them

Translate text augmentation technique to generate documents/text by converting text in english to different language[Here: German(de)] then back to english. This could help us get the documents which give similar context/meaning with different words.

```
def translt_text(text):
    try:
        txt_blb = TextBlob(text)
        txt_blb_trans = txt_blb.translate(from_lang='en', to='de')
        txt_blb_bck = txt_blb_trans.translate(from_lang='de', to='en')
        return txt_blb_bck
    except:
        return text
```

Using the train data and performing text augmentation on groups with less than the number of documents that is passed as argument to function. Removing any duplicates and returning the data frame with non augmented [groups with more than number of documents that is passed as argument] and text augmented data.

```
def aug_text_data(X_train_strat_parm, y_train_strat_parm, no_of_docs, text_aug_fn):

    df_aug = pd.DataFrame({ 'Description': X_train_strat_parm, 'Assignment group': y_train_strat_parm })
    df_grt_no_of_docs = df_aug.groupby("Assignment group").filter(lambda x: len(x) > no_of_docs)

    new_aug_dfs_lst = []
    grouped_trgts = df_aug.groupby('Assignment group')
    for key, item in grouped_trgts:
        df_grp_trgt = grouped_trgts.get_group(key)
        if len(df_grp_trgt) <= no_of_docs:
            sampls_size_2_increase = (no_of_docs - len(df_grp_trgt))
            if sampls_size_2_increase < len(df_grp_trgt):
                df_lssr_aug_grptrgt = copy.deepcopy(df_grp_trgt.sample(n=sampls_size_2_increase))
                df_lssr_aug_grptrgt["Description"] = df_lssr_aug_grptrgt["Description"].apply(text_aug_fn)
                new_aug_dfs_lst.append(pd.concat([df_grp_trgt,df_lssr_aug_grptrgt]))
            else:
                rng = math.ceil(sampls_size_2_increase/len(df_grp_trgt))
                df_grt_ln_aug_grptrgt = copy.deepcopy(df_grp_trgt)
                lssr_div_aug_dfs_lst = []
                for i in range(0, rng):
                    if i==0:
                        df_grt_ln_aug_grptrgt["Description"] = df_grt_ln_aug_grptrgt["Description"].apply(text_aug_fn)
                    else:
                        df_grt_ln_aug_grptrgt = copy.deepcopy(lssr_div_aug_dfs_lst[i-1])
                        df_grt_ln_aug_grptrgt["Description"] = df_grt_ln_aug_grptrgt["Description"].apply(text_aug_fn)
                    lssr_div_aug_dfs_lst.append(df_grt_ln_aug_grptrgt)
                lssr_div_aug_dfs_lst.append(df_grp_trgt)
                new_aug_dfs_lst.append(pd.concat(lssr_div_aug_dfs_lst))
    new_aug_df = pd.concat(new_aug_dfs_lst)

    df_grtr_lssr_aug = pd.concat([df_grt_no_of_docs, new_aug_df])
    df_grtr_lssr_aug.drop_duplicates(['Description','Assignment group'], inplace=True)
    return df_grtr_lssr_aug
```

We will use Logistic Regression with reduced unigram, bigram features to train and test algorithms. Using the train data that is translated augmentative and evaluating performance.

```
df_translt_aug = aug_text_data(X_train_strat, y_train_strat, 100, translt_text)
print("Accuracy:{}".format(lr_cvt_unibi_eval(df_translt_aug['Description'], df_translt_aug['Assignment group'],
                                              X_test_strat, y_test_strat)))
```

```
Accuracy:0.6134301270417423
```

We will use a Sequential model with Bidirectional LSTM layer and Glove 300 dimensional embedding to train and test the algorithm. Using the train data that is random upsampled and evaluating performance.

```
print("Accuracy:{}".format(seq_lstm_bi_glv_eval(df_translt_aug['Description'], df_translt_aug['Assignment group'],
                                                X_test_strat, y_test_strat, './glove.6B.300d.txt', 300)))
del df_translt_aug
```

```
1653/1653 [==============================] - 1s 320us/step
Accuracy:[4.083550006637989, 0.5511191774157416]
```

The performance of LogisticRegression and Sequential Model with Glove pre-trained embedding layer using the translate argumentative train data, evaluating performance is at range 61-63 percent and 51-55 percent accuracy respectively.

We will use Logistic Regression with reduced unigram, bigram features to train and test algorithm. Using the train data that is synonym augmentative and evaluating performance.

```
df_synonm_aug = aug_text_data(X_train_strat, y_train_strat, 100, aug_syno_text)
print("Accuracy:{}".format(lr_cvt_unibi_eval(df_synonm_aug['Description'], df_synonm_aug['Assignment group'],
                                              X_test_strat, y_test_strat)))
```

```
Accuracy:0.6212946158499697
```

We will use a Sequential model with Bidirectional LSTM layer and Glove 300 dimensional embedding to train and test the algorithm. Using the train data that is synonym augmentative and evaluating performance.

```
print("Accuracy:{}".format(seq_lstm_bi_glv_eval(df_synonm_aug['Description'], df_synonm_aug['Assignment group'],
                                                X_test_strat, y_test_strat, './glove.6B.300d.txt', 300)))
del df_synonm_aug
```

```
1653/1653 [==============================] - 1s 319us/step
Accuracy:[2.641554564760442, 0.5269207503135033]
```

The performance of LogisticRegression and Sequential Model with Glove pre-trained embedding layer using the synonym argumentative train data, evaluating performance is at range 61-63 percent and 51-55 percent accuracy respectively.

Word embedding Augmenter substitutes words from glove embedding. It links words with similar word embeddings

```
wrd_embd_aug = naw.WordEmbsAug(model_type='glove', model_path='./glove.6B.300d.txt', action="substitute", aug_p=0.5)
def sub_wrd_glv(text):
    try:
        return wrd_embd_aug.augment(text)
    except:
        return text
```

We will use Logistic Regression with reduced unigram, bigram features to train and test algorithms. Using the train data that is Word embeddings augmentative and evaluating performance

```
df_wrdembd_aug = aug_text_data(X_train_strat, y_train_strat, 100, sub_wrd_glv)
print("Accuracy:{}".format(lr_cvt_unibi_eval(df_wrdembd_aug['Description'], df_wrdembd_aug['Assignment group'],
                                            X_test_strat, y_test_strat)))
```

```
Accuracy:0.632183908045977
```

We will use a Sequential model with Bidirectional LSTM layer and Glove 300 dimensional embedding to train and test the algorithm. Using the train data that is Word embeddings augmentative and evaluating performance

```
print("Accuracy:{}".format(seq_lstm_bi_glv_eval(df_wrdembd_aug['Description'], df_wrdembd_aug['Assignment group'],
                                               X_test_strat, y_test_strat, './glove.6B.300d.txt', 300)))
del df_wrdembd_aug
```

```
1653/1653 [==============================] - 1s 309us/step
Accuracy:[2.705647482990281, 0.545069570640182]
```

The performance of LogisticRegression and Sequential Model with Glove pretrained embedding layer and word embed agumentated data on groups less or equal to 100 counts/documents, evaluating performance is at range 61-63 percent and 51-55 percent accuracy respectively.

6.6. LatentDirichletAllocation

LatentDirichletAllocation from sklearn helps us classify the documents into topics. We can use this to segregate documents belonging to GRP_0 class into 4 different classes which will reduce the difference ratio with other classes. First classify the documents into 4[can be any number] topics then assign a class for documents belonging to each topic. If this increases the accuracy at a reasonable rate, we can map these classes formed from topics to GRP_0 class and when any one of these classes is predicted, the result will be GRP_0 class.

Combine the train and test dataset which has all unique groups available in them to one dataframe.

```
df_train_all_grps = pd.DataFrame({ 'Description': X_train_strat, 'Assignment group': y_train_strat })
df_test_all_grps = pd.DataFrame({ 'Description': X_test_strat, 'Assignment group': y_test_strat })
```

Fetch the GRP_0 class documents available in train and test dataframe, use the selected CountVectorizer which has reduced unigram and bigram features to get vectorized data, fit on LatentDirichletAllocation to get the topics, loop the train and test data frame and assign the classes to each document based on the topic it belongs to.

```
df_trn_grp_0 =copy.deepcopy(df_train_all_grps[df_train_all_grps['Assignment group'].apply(lambda text: text=='GRP_0')].reset_ind
df_tst_grp_0 =copy.deepcopy(df_test_all_grps[df_test_all_grps['Assignment group'].apply(lambda text: text=='GRP_0')].reset_index

cvt_process_topcs_unibi_max = CountVectorizer(ngram_range = (1,2), max_features=24900)
X_train_topcs_unibi_max = cvt_process_topcs_unibi_max.fit_transform(df_trn_grp_0['Description'])
X_test_topcs_unibi_max = cvt_process_topcs_unibi_max.fit_transform(df_tst_grp_0['Description'])

lda_model = LatentDirichletAllocation(n_components=4, max_iter=100, random_state=6)
lda_train_topics = lda_model.fit_transform(X_train_topcs_unibi_max)
lda_test_topics = lda_model.fit_transform(X_test_topcs_unibi_max)

for idx, row in copy.deepcopy(df_trn_grp_0).iterrows():
    topic_doc = lda_train_topics[idx].argmax()
    df_trn_grp_0.at[idx, 'Assignment group'] = 'GRP_0'+ str(topic_doc)

for idx, row in copy.deepcopy(df_tst_grp_0).iterrows():
    topic_doc = lda_test_topics[idx].argmax()
    df_tst_grp_0.at[idx, 'Assignment group'] = 'GRP_0'+ str(topic_doc)

del cvt_process_topcs_unibi_max, X_train_topcs_unibi_max, X_test_topcs_unibi_max, lda_model
del lda_train_topics, lda_test_topics, topic_doc
```

Check the group value counts of train and test data

```
print("Train Group Value Counts")
print(df_trn_grp_0['Assignment group'].value_counts())
print("Test Group Value Counts")
print(df_tst_grp_0['Assignment group'].value_counts())
```

```
Train Group Value Counts
GRP_00    715
GRP_01    701
GRP_02    601
GRP_03    282
Name: Assignment group, dtype: int64
Test Group Value Counts
GRP_02    232
GRP_03    199
GRP_01    188
GRP_00    147
Name: Assignment group, dtype: int64
```

From our train and test dataframe where we selected GRP_0 class documents, let us now select all documents belonging to other group classes, concatenate it with dataframe holding four classes (GRP_00, GRP_01, GRP_02, GRP_03) in the train and test form respectively. Check all group values percentage ratio in train data

```
df_trn_grp_nt0 = copy.deepcopy(df_train_all_grps[df_train_all_grps['Assignment group'].apply(lambda text: text!='GRP_0')])
df_tst_grp_nt0 = copy.deepcopy(df_test_all_grps[df_test_all_grps['Assignment group'].apply(lambda text: text!='GRP_0')])

df_trn_grps_tpcs = pd.concat([df_trn_grp_0, df_trn_grp_nt0])
df_tst_grps_tpcs = pd.concat([df_tst_grp_0, df_tst_grp_nt0])

del df_trn_grp_0, df_trn_grp_nt0
del df_tst_grp_0, df_tst_grp_nt0

df_trn_grps_tpcs['Assignment group'].value_counts(normalize=True)
```

```
GRP_00    0.144883
GRP_01    0.142047
GRP_02    0.121783
GRP_03    0.057143
GRP_24    0.042148
GRP_2     0.036474
GRP_12    0.036069
GRP_8     0.035461
GRP_19    0.032421
GRP_3     0.030395
GRP_13    0.021479
GRP_14    0.017832
GRP_25    0.017629
GRP_33    0.016008
GRP_29    0.014792
GRP_4     0.013779
GRP_16    0.012969
GRP_18    0.012766
GRP_10    0.012361
GRP_9     0.011753
GRP_6     0.010740
GRP_7     0.010132
GRP_17    0.009524
GRP_34    0.009524
GRP_26    0.008511
GRP_31    0.008308
GRP_5     0.007700
GRP_40    0.006890
GRP_28    0.006687
GRP_15    0.005876
           ...
GRP_36    0.002229
GRP_65    0.001621
GRP_60    0.001621
GRP_53    0.001621
GRP_52    0.001418
```

```
GRP_55    0.001216
GRP_51    0.001216
GRP_59    0.001013
GRP_46    0.001013
GRP_48    0.001013
GRP_49    0.001013
GRP_43    0.000811
GRP_32    0.000608
GRP_68    0.000405
GRP_56    0.000405
GRP_66    0.000405
GRP_58    0.000405
GRP_38    0.000405
GRP_63    0.000405
GRP_35    0.000203
GRP_57    0.000203
GRP_64    0.000203
GRP_70    0.000203
GRP_69    0.000203
GRP_71    0.000203
GRP_72    0.000203
GRP_61    0.000203
GRP_54    0.000203
GRP_67    0.000203
GRP_73    0.000203
Name: Assignment group, Length: 77, dtype: float64
```

The percentage of difference between the groups is reduced, let's do word embedding text augmentation of the documents which are having count less than 100 to decrease the difference further. We will use a Sequential model to train and test data. Remove no longer required variables to free up memory.

```
df_trn_tpcs_wrdembd_aug = aug_text_data(df_trn_grps_tpcs['Description'], df_trn_grps_tpcs['Assignment group'],
                                        100, sub_wrd_glv)

print("Sequential-Accuracy:{}".format(seq_lstm_bi_glv_eval(df_trn_tpcs_wrdembd_aug['Description'],
                                                           df_trn_tpcs_wrdembd_aug['Assignment group'],
                                                           df_tst_grps_tpcs['Description'],
                                                           df_tst_grps_tpcs['Assignment group'],
                                                           './glove.6B.300d.txt', 300, 77)))

del df_trn_grps_tpcs
del df_tst_grps_tpcs
del df_trn_tpcs_wrdembd_aug
```

```
1653/1653 [==============================] - 1s 352us/step
Sequential-Accuracy:[3.501295832814553, 0.2667876588833094]
```

Using the LatentDirichletAllocation to reduce the major class to subclasses(by topics) to reduce difference ratio with other classes and word embedding augmenting lower documents classes, the performance of Sequential Model with Glove pretrained embedding layer goes down.

7. Model Evaluation

7.1. Build model to identify top 5 groups and common group

We will build two models after grouping classes. When there is a new dataset and prediction has to be done, the first model can be used to predict if the class belongs to major classes chosen or the common group and align the prediction against the dataset. Then, the second model can be used to predict which class in the common group the prediction refers to. But, first we have to prepare models and evaluate performances.

Combining all train and test data to one dataframe and checking the value counts for each group.

```
df_all_data = copy.deepcopy(df_process_txt_acc)
df_all_data['Assignment group'].value_counts()
```

```
GRP_0     3065
GRP_24     277
GRP_2      240
GRP_12     238
GRP_8      234
GRP_19     213
GRP_3      200
GRP_13     142
GRP_14     118
GRP_25     116
GRP_33     106
GRP_29      97
GRP_4       91
GRP_16      85
GRP_18      84
GRP_10      82
GRP_9       78
GRP_6       70
GRP_7       67
GRP_17      63
GRP_34      62
GRP_26      56
GRP_31      55
GRP_5       50
GRP_40      45
GRP_28      44
GRP_41      39
GRP_15      38
GRP_42      37
```

```
GRP_20    36
          ...
GRP_50    14
GRP_60    11
GRP_65    11
GRP_53    11
GRP_52     9
GRP_51     8
GRP_55     8
GRP_48     7
GRP_49     6
GRP_46     6
GRP_59     6
GRP_43     5
GRP_32     4
GRP_63     3
GRP_38     3
GRP_56     3
GRP_66     3
GRP_68     3
GRP_58     3
GRP_71     2
GRP_54     2
GRP_69     2
GRP_57     2
GRP_72     2
GRP_64     1
GRP_67     1
GRP_35     1
GRP_70     1
GRP_73     1
GRP_61     1
Name: Assignment group, Length: 74, dtype: int64
```

Tried with different numbers of groups. We will be having 6 groups. 5 major groups [GRP_0, GRP_24, GRP_2, GRP_12, GRP_8] and all other groups in one group [GRP_CMN]. GRP_CMN groups are the ones with groups having counts less than 230. Create a new column Assignment_group_cmn to hold this information.

```
less_val_grps = []
df_all_data_grouped = df_all_data.groupby('Assignment group')
for key, item in df_all_data_grouped:
    df_grp = df_all_data_grouped.get_group(key)
    if len(df_grp) <= 230:
        less_val_grps.append(key)

def cmn_labls(label):
    if label in less_val_grps:
        return 'GRP_CMN'
    else:
        return label

df_all_data['Assignment_group_cmn'] = df_all_data['Assignment group'].apply(cmn_labls)
del less_val_grps, df_all_data_grouped, df_grp
df_all_data['Assignment_group_cmn'].value_counts()
```

```
Out[186]: GRP_0      3065
          GRP_CMN    2528
          GRP_24      277
          GRP_2       240
          GRP_12      238
          GRP_8       234
          Name: Assignment_group_cmn, dtype: int64
```

Select features(X_all_grp) and target(y_all_grp) representing the classes GRP_0, GRP_24, GRP_2, GRP_12, GRP_8 and GRP_CMN. Perform train-test split and identify unique group values in them.

```
X_all_grp = df_all_data['Description']
y_all_grp = df_all_data['Assignment_group_cmn']

X_train_all_grp, X_test_all_grp, y_train_all_grp, y_test_all_grp =train_test_split(X_all_grp, y_all_grp, random_state=6,
                                                                   test_size = 0.25, stratify=y_all_grp)

np.unique(y_train_all_grp), np.unique(y_test_all_grp)
```

```
Out[187]: (array(['GRP_0', 'GRP_12', 'GRP_2', 'GRP_24', 'GRP_8', 'GRP_CMN'],
                 dtype=object),
           array(['GRP_0', 'GRP_12', 'GRP_2', 'GRP_24', 'GRP_8', 'GRP_CMN'],
                 dtype=object))
```

We will use Logistic Regression to train and test data.

```
print("LR-Accuracy:{}".format(lr_cvt_unibi_eval(X_train_all_grp, y_train_all_grp, X_test_all_grp, y_test_all_grp)))
```

```
LR-Accuracy:0.732685297691373
```

We will use Sequential model to get model reference to check the classification_report.

```
tknzr_cr = Tokenizer(num_words=top_num_words, oov_token=oov_char)
tknzr_cr.fit_on_texts(X_train_all_grp.append(X_test_all_grp))
tknzr_cr_vocabsize =len(tknzr_cr.word_index)+1

X_train_cr_seq = tknzr_cr.texts_to_sequences(X_train_all_grp)
X_train_cr_seq_pad = pad_sequences(X_train_cr_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)
X_test_cr_seq = tknzr_cr.texts_to_sequences(X_test_all_grp)
X_test_cr_seq_pad = pad_sequences(X_test_cr_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)

lbl_enc_tknzr_cr = preprocessing.LabelEncoder()
y_train_cr_tknzr = pd.get_dummies(lbl_enc_tknzr_cr.fit_transform(y_train_all_grp)).values
y_test_cr_tknzr = pd.get_dummies(lbl_enc_tknzr_cr.fit_transform(y_test_all_grp)).values

embedding_matrix_cr = weight_matrx_glv_embed('./glove.6B.300d.txt', 300, tknzr_cr)

model_cr = Sequential()
model_cr.add(Embedding(input_dim=tknzr_cr_vocabsize, output_dim=300, weights=[embedding_matrix_cr],
                       input_length=max_length, trainable=True))
model_cr.add(Bidirectional(LSTM(10)))
model_cr.add(Dense(100, activation = "relu"))
model_cr.add(Dense(6,activation='softmax'))

model_cr.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
model_cr.fit(X_train_cr_seq_pad, y_train_cr_tknzr, epochs = 5, batch_size=32, verbose = 0,validation_split=0.25)

print(model_cr.evaluate(X_test_cr_seq_pad, y_test_cr_tknzr))
del X_all_grp, y_all_grp
del X_train_all_grp, X_test_all_grp, y_train_all_grp, y_test_all_grp
```

```
1646/1646 [==============================] - 1s 415us/step
[0.8421598212252556, 0.7138517620641724]
```

Let us check the classification_report for the evaluation metrics and performance of model in the prediction of individual classes.

```
y_test_cr_tknzr_max = np.argmax(y_test_cr_tknzr, axis=1)
model_cr_predictions = model_cr.predict_classes(X_test_cr_seq_pad)
print(classification_report(y_test_cr_tknzr_max, model_cr_predictions))
```

```
              precision    recall  f1-score   support

           0       0.75      0.82      0.79       766
           1       0.41      0.52      0.46        60
           2       0.42      0.43      0.43        60
           3       0.92      0.87      0.90        69
           4       0.72      0.53      0.61        59
           5       0.70      0.63      0.66       632

    accuracy                           0.71      1646
   macro avg       0.66      0.63      0.64      1646
weighted avg       0.72      0.71      0.71      1646
```

The accuracy of both Logistic Regression and Sequential model in identifying GRP_0, GRP_24, GRP_2, GRP_12, GRP_8 and GRP_CMN has increased and around 70

Above classification report visualizer displays the main classification metrics. It lists out the precision, recall, F1 score and support scores for each class. The basis of metrics are defined in terms of true and false positives, and true and false negatives.

TN - True Negative: case is negative and predicted negative TP - True Positive: case is positive and predicted positive FN - False Negative: case is positive but predicted negative FP - False Positive: case is negative but predicted positive

Precision is the ability of a model not to make a false positive. It is defined as the ratio of true positives to the sum of true and false positives. Precision = TP/(TP + FP).

Recall gives the performance of the model to find all positives. It is defined as the ratio of true positives to the sum of true positives and false negatives. Recall = TP/(TP+FN).

Which metric to focus on is based on the problem we are trying to solve. If we are looking for a model which makes less false positives, precision metric would be preferred. On the other hand, if we are looking for a model which identifies a good number of positives or makes less false negatives, recall metric would be preferred. Here precision metric and accuracy would be the good indication of performance

7.2. Build model to identify common group's class

Let's check the classes that belongs to the common group ['GRP_CMN]

```
df_grp_cmn = df_all_data[df_all_data['Assignment_group_cmn'].apply(lambda text: text=='GRP_CMN')]
del df_all_data
df_grp_cmn['Assignment group'].value_counts()
```

GRP_19 213
GRP_3 200
GRP_13 142
GRP_14 118
GRP_25 116
GRP_33 106
GRP_29 97
GRP_4 91
GRP_16 85
GRP_18 84
GRP_10 82
GRP_9 78
GRP_6 70
GRP_7 67

```
GRP_17    63
GRP_34    62
GRP_26    56
GRP_31    55
GRP_5     50
GRP_40    45
GRP_28    44
GRP_41    39
GRP_15    38
GRP_42    37
GRP_20    36
GRP_22    31
GRP_11    30
GRP_45    28
GRP_21    28
GRP_1     27
          ...
GRP_50    14
GRP_53    11
GRP_65    11
GRP_60    11
GRP_52     9
GRP_55     8
GRP_51     8
GRP_48     7
GRP_49     6
GRP_46     6
GRP_59     6
GRP_43     5
GRP_32     4
GRP_68     3
GRP_58     3
GRP_38     3
GRP_66     3
GRP_63     3
GRP_56     3
GRP_54     2
GRP_71     2
GRP_57     2
GRP_72     2
GRP_69     2
GRP_64     1
GRP_35     1
GRP_70     1
GRP_73     1
GRP_67     1
GRP_61     1
Name: Assignment group, Length: 69, dtype: int64
```

Divide the common group dataframe to two groups one with more than 2 documents/counts and other with less than or equal to 2 documents/counts.

```
df_grp_cmn_grtr_2 = df_grp_cmn.groupby("Assignment group").filter(lambda x: len(x) > 2)
df_grp_cmn_lsseq_2 = df_grp_cmn.groupby("Assignment group").filter(lambda x: len(x) <= 2)

X_grp_cmn = df_grp_cmn_grtr_2['Description']
y_grp_cmn = df_grp_cmn_grtr_2['Assignment group']

X_train_cmn_grp, X_test_cmn_grp, y_train_cmn_grp, y_test_cmn_grp =train_test_split(X_grp_cmn, y_grp_cmn,
                                                                                    random_state=6, test_size = 0.25,
                                                                                    stratify=y_grp_cmn)

df_grp_cmn.shape, df_grp_cmn_grtr_2.shape, df_grp_cmn_lsseq_2.shape
```

```
((2528, 3), (2512, 3), (16, 3))
```

Manually add groups from dataframe which has groups equal to 2 or less counts into train and test data

```
for idx, row in copy.deepcopy(df_grp_cmn_lsseq_2).iterrows():
    if not np.isin(row['Assignment group'], y_train_cmn_grp):
        X_train_cmn_grp = X_train_cmn_grp.append(pd.Series(row['Description'], index=[idx]))
        y_train_cmn_grp = np.append(y_train_cmn_grp, row['Assignment group'])
    elif not np.isin(row['Assignment group'], y_test_cmn_grp):
            X_test_cmn_grp = X_test_cmn_grp.append(pd.Series(row['Description'], index=[idx]))
            y_test_cmn_grp = np.append(y_test_cmn_grp, row['Assignment group'])
del df_grp_cmn, df_grp_cmn_grtr_2, df_grp_cmn_lsseq_2
del X_grp_cmn, y_grp_cmn
```

We will use Logistic Regression to train and test data in identifying the proper GRP_CMN class

```
print("LR-Accuracy:{}".format(lr_cvt_unibi_eval(X_train_cmn_grp, y_train_cmn_grp, X_test_cmn_grp, y_test_cmn_grp)))
del X_train_cmn_grp, y_train_cmn_grp, X_test_cmn_grp, y_test_cmn_grp
```

```
LR-Accuracy:0.3570300157977883
```

The performance of both Logistic Regression and Sequential models in identifying the proper GRP_CMN class is not good. This shows the models are not able to predict the groups which have less number of documents even though all unique group values were made available in both train and test data. The classification reports above also indicate the same. This might be because of the groups with less number of documents holding such a kind of documents where there is no similarity between them and also has many jumbled letter words. For example when predicting the sentiment of a document is good or bad, two documents belonging to a good class holding words such as kind, love in one document and warm hearted, generous in another document can help model learn properly and predict the good class. However, if one of the documents holds words such as kind, love and the other holds words such as blue, food, some jumbled letters[jseritl] then the model will not be able to learn and may not predict correctly.

8. Enhanced Solution

No matter which model is considered and what are the good parameters, the data plays a very important role, without which model will not be able to learn properly. Data has to be collected in proper format while preparing the dataset and made sure to have documents that have some similarity when assigned to the group. Let's have some data augmented with word embeddings for groups having counts less than 600, evaluate the performance of the model and finally tune the parameters. More data is better, especially for neural networks. Let's generate documents with word embedding augmentation, split the data to train and test, evaluate the performance of the model.

```
df_wrdemds_aug = aug_text_data(df_process_txt_acc["Description"], df_process_txt_acc["Assignment group"], 600, sub_wrd_glv)

X_train_aug, X_test_aug, y_train_aug, y_test_aug =train_test_split(df_wrdemds_aug['Description'],
                                df_wrdemds_aug['Assignment group'],
                                                random_state=6, test_size = 0.25, stratify=df_wrdemds_aug['Assignment group'])
```

8.1. Build model

We will use Sequential model with Glove embedding layer to train and test data in identifying the proper classes

```
print("Sequential-Accuracy:{}".format(seq_lstm_bi_glv_eval(X_train_aug, y_train_aug, X_test_aug, y_test_aug,
                                                           './glove.6B.300d.txt', 300)))
del X_train_aug, X_test_aug, y_train_aug, y_test_aug

12066/12066 [==============================] - 6s 490us/step
Sequential-Accuracy:[1.7651926185012594, 0.5821316094811868]
```

8.2. Fine Tuning

Let's tokenize, perform the padding and have the glove embedding matrix prepared to use in our Sequential model while trying to tune the parameters. Remove no longer required variables to free up memory.

```
X_train_tune, X_test_tune, y_train_tune, y_test_tune =train_test_split(df_wrdemds_aug['Description'],
                                            df_wrdemds_aug['Assignment group'],
                                    random_state=6, test_size = 0.25,
                                                                         stratify=df_wrdemds_aug['Assignment group'])

tknzr_tune = Tokenizer(num_words=top_num_words, oov_token=oov_char)
tknzr_tune.fit_on_texts(X_train_tune)
tknz_tune_vocabsize =len(tknzr_tune.word_index)+1

X_train_tune_seq = tknzr_tune.texts_to_sequences(X_train_tune)
X_train_tune_seq_pad = pad_sequences(X_train_tune_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)
X_test_tune_seq = tknzr_tune.texts_to_sequences(X_test_tune)
X_test_tune_seq_pad = pad_sequences(X_test_tune_seq, padding=pad_type, truncating=trunc_type, maxlen=max_length)

lbl_enc_tknzr_tune = preprocessing.LabelEncoder()
y_train_tune_tknzr = pd.get_dummies(lbl_enc_tknzr_tune.fit_transform(y_train_tune)).values
y_test_tune_tknzr = pd.get_dummies(lbl_enc_tknzr_tune.fit_transform(y_test_tune)).values

embedding_matrix_tune = weight_matrx_glv_embed('./glove.6B.300d.txt', 300, tknzr_tune)
```

Let's tune the model with Bidirectional LSTM layers and Dense layers, compile, fit and evaluate. Tried with different number of layers

```
model_layrs = Sequential()
model_layrs.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                             input_length=max_length, trainable=True))
model_layrs.add(Bidirectional(LSTM(50, return_sequences=True)))
model_layrs.add(Bidirectional(LSTM(70, return_sequences=True)))
model_layrs.add(Bidirectional(LSTM(100)))
model_layrs.add(Dense(100, activation = "relu"))
model_layrs.add(Dense(85, activation = "relu"))
model_layrs.add(Dense(74,activation='softmax'))

model_layrs.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
model_layrs.fit(X_train_tune_seq_pad, y_train_tune_tknzr, epochs = 5, batch_size=128, verbose = 0,validation_split=0.25)

print(model_layrs.evaluate(X_test_tune_seq_pad, y_test_tune_tknzr))
del model_layrs
```

```
12066/12066 [==============================] - 23s 2ms/step
[1.6894413439290512, 0.55635670479032]
```

Build a Sequential model with GRU(Gated Recurrent Unit) layer and Glove Embedding layer. GRU is a type of recurrent neural network similar to an LSTM, but only has two gates: a reset gate and an update gate. Tried with different number of layers

```
model_gru = Sequential()
model_gru.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                             input_length=max_length, trainable=True))
model_gru.add(GRU(60, return_sequences=True))
model_gru.add(GRU(80, return_sequences=True))
model_gru.add(GRU(100))
model_gru.add(Dropout(0.2))
model_gru.add(Dense(100, activation = "relu"))
model_gru.add(Dense(85, activation = "relu"))
model_gru.add(Dense(74,activation='softmax'))

model_gru.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
model_gru.fit(X_train_tune_seq_pad, y_train_tune_tknzr, epochs = 5, batch_size=128, verbose = 0,validation_split=0.25)

print(model_gru.evaluate(X_test_tune_seq_pad, y_test_tune_tknzr))
del model_gru
```

```
12066/12066 [==============================] - 9s 705us/step
[1.8076826627725158, 0.539035305818001]
```

Let's tune the model with SGD optimizer and different learning rates, compile, fit and evaluate. Tried with different values

```
for k in range(0, 3):
    learn_rate = [0.01, 0.03, 0.05]

    optimizer_sgd = SGD(lr=learn_rate[k])

    model_optlr = Sequential()
    model_optlr.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                             input_length=max_length, trainable=True))
    model_optlr.add(Bidirectional(LSTM(50, return_sequences=True)))
    model_optlr.add(Bidirectional(LSTM(70, return_sequences=True)))
    model_optlr.add(Bidirectional(LSTM(100)))
    model_optlr.add(Dense(100, activation = "relu"))
    model_optlr.add(Dense(85, activation = "relu"))
    model_optlr.add(Dense(74,activation='softmax'))

    model_optlr.compile(loss = loss_fn, optimizer=optimizer_sgd,metrics = [metric_eval])
    model_optlr.fit(X_train_tune_seq_pad, y_train_tune_tknzr, epochs = 5, batch_size=128, verbose = 0,validation_split=0.25)

    print(model_optlr.evaluate(X_test_tune_seq_pad, y_test_tune_tknzr))
    del model_optlr
```

```
12066/12066 [==============================] - 14s 1ms/step
[4.255923758528431, 0.06348417039615448]
12066/12066 [==============================] - 14s 1ms/step
[3.8611896055443813, 0.0835405271009448]
12066/12066 [==============================] - 14s 1ms/step
[3.6083844422148013, 0.1037626388198243]
```

Let's tune the model with batch normalization layers. A layer that allows every layer of the network to learn independently. Normalize the output of the previous layers and kind of acts like a regularizer. Tried with different number of batch normalization layers

```
model_bachnrml = Sequential()
model_bachnrml.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                             input_length=max_length, trainable=True))
model_bachnrml.add(Bidirectional(LSTM(50, return_sequences=True)))
model_bachnrml.add(BatchNormalization())
model_bachnrml.add(Bidirectional(LSTM(70, return_sequences=True)))
model_bachnrml.add(BatchNormalization())
model_bachnrml.add(Bidirectional(LSTM(100)))
model_bachnrml.add(BatchNormalization())
model_bachnrml.add(Dense(100, activation = "relu"))
model_bachnrml.add(BatchNormalization())
model_bachnrml.add(Dense(85, activation = "relu"))
model_bachnrml.add(Dense(74,activation='softmax'))

model_bachnrml.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
model_bachnrml.fit(X_train_tune_seq_pad, y_train_tune_tknzr, epochs = 5, batch_size=128, verbose = 0,validation_split=0.25)

print(model_bachnrml.evaluate(X_test_tune_seq_pad, y_test_tune_tknzr))
del model_bachnrml
```

```
12066/12066 [==============================] - 14s 1ms/step
[1.444197908997259, 0.6504226752859275]
```

Let's tune the model with dropout layers. They are regularization techniques used to prevent overfitting in the model. Tried with different number of dropout layers and percentage

```
model_drpot = Sequential()
model_drpot.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                          input_length=max_length, trainable=True))
model_drpot.add(Bidirectional(LSTM(50, return_sequences=True)))
model_drpot.add(Dropout(0.2))
model_drpot.add(Bidirectional(LSTM(70, return_sequences=True)))
model_drpot.add(Dropout(0.2))
model_drpot.add(Bidirectional(LSTM(100)))
model_drpot.add(Dropout(0.2))
model_drpot.add(Dense(100, activation = "relu"))
model_drpot.add(Dropout(0.2))
model_drpot.add(Dense(85, activation = "relu"))
model_drpot.add(Dense(74,activation='softmax'))

model_drpot.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
model_drpot.fit(X_train_tune_seq_pad, y_train_tune_tknzr, epochs = 5, batch_size=128, verbose = 0,validation_split=0.25)

print(model_drpot.evaluate(X_test_tune_seq_pad, y_test_tune_tknzr))

del model_drpot
```

```
12066/12066 [==============================] - 13s 1ms/step
[1.7607451161005674, 0.5406928559588927]
```

Let's tune the model with the sparse_categorical_crossentropy loss function. Calculates cross-entropy loss, and does not need target variable to one hot encoded before training.

```
model_sparscategr = Sequential()
model_sparscategr.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                                input_length=max_length, trainable=True))
model_sparscategr.add(Bidirectional(LSTM(50, return_sequences=True)))
model_sparscategr.add(BatchNormalization())
model_sparscategr.add(Bidirectional(LSTM(70, return_sequences=True)))
model_sparscategr.add(BatchNormalization())
model_sparscategr.add(Bidirectional(LSTM(100)))
model_sparscategr.add(BatchNormalization())
model_sparscategr.add(Dense(100, activation = "relu"))
model_sparscategr.add(BatchNormalization())
model_sparscategr.add(Dense(85, activation = "relu"))
model_sparscategr.add(Dense(74,activation='softmax'))

model_sparscategr.compile(loss = 'sparse_categorical_crossentropy', optimizer=optimizer_alg,metrics = [metric_eval])
model_sparscategr.fit(X_train_tune_seq_pad, lbl_enc_tknzr_tune.fit_transform(y_train_tune), epochs = 5,
                      batch_size=128, verbose = 0,validation_split=0.25)

print(model_sparscategr.evaluate(X_test_tune_seq_pad, lbl_enc_tknzr_tune.fit_transform(y_test_tune)))
del model_sparscategr
```

```
12066/12066 [==============================] - 14s 1ms/step
[1.4552451920276175, 0.6524946129620421]
```

Let's tune the model with kullback_leibler_divergence loss function. Calculate Divergence Loss of how probability distribution differs from the baseline distribution.

```
model_kullbck = Sequential()
model_kullbck.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                                input_length=max_length, trainable=True))
model_kullbck.add(Bidirectional(LSTM(50, return_sequences=True)))
model_kullbck.add(BatchNormalization())
model_kullbck.add(Bidirectional(LSTM(70, return_sequences=True)))
model_kullbck.add(BatchNormalization())
model_kullbck.add(Bidirectional(LSTM(100)))
model_kullbck.add(BatchNormalization())
model_kullbck.add(Dense(100, activation = "relu"))
model_kullbck.add(BatchNormalization())
model_kullbck.add(Dense(85, activation = "relu"))
model_kullbck.add(Dense(74,activation='softmax'))

model_kullbck.compile(loss = 'kullback_leibler_divergence', optimizer=optimizer_alg,metrics = [metric_eval])
model_kullbck.fit(X_train_tune_seq_pad, y_train_tune_tknzr, epochs = 5, batch_size=128, verbose = 0,validation_split=0.25)

print(model_kullbck.evaluate(X_test_tune_seq_pad, y_test_tune_tknzr))
del model_kullbck
```

```
12066/12066 [==============================] - 15s 1ms/step
[1.492469321888205, 0.6415547820321564]
```

Let's tune the model with different epochs and batch size, compile, fit and evaluate.

```
for j in range(4, 6):
    for k in [32, 64]:

        model_epbach = Sequential()
        model_epbach.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                                   input_length=max_length, trainable=True))
        model_epbach.add(Bidirectional(LSTM(50, return_sequences=True)))
        model_epbach.add(Bidirectional(LSTM(70, return_sequences=True)))
        model_epbach.add(Bidirectional(LSTM(100)))
        model_epbach.add(Dense(100, activation = "relu"))
        model_epbach.add(Dense(85, activation = "relu"))
        model_epbach.add(Dense(74,activation='softmax'))

        model_epbach.compile(loss = loss_fn, optimizer=optimizer_alg,metrics = [metric_eval])
        model_epbach.fit(X_train_tune_seq_pad, y_train_tune_tknzr, epochs = j, batch_size=k, verbose = 0,validation_split=0.25)

        print(model_epbach.evaluate(X_test_tune_seq_pad, y_test_tune_tknzr))
        del model_epbach
```

```
12066/12066 [==============================] - 15s 1ms/step
[1.619255889604168, 0.5796452842698492]
12066/12066 [==============================] - 15s 1ms/step
[1.6982592033466533, 0.5532902370296702]
12066/12066 [==============================] - 15s 1ms/step
[1.553000250562949, 0.6055859439748053]
12066/12066 [==============================] - 15s 1ms/step
[1.6100360400420248, 0.5939002154815183]
```

Multiple Bidirectional lstm layers outperforms gru, adam optimizer which we have used initially performs better than SGD optimizer and batch normalizing layers yields better results than using the dropout layers. Also the loss function sparse_categorical_crossentropy helps model learn considerably better than other loss functions and batch size 32 seems to be good fit[earlier we had used 128 for same three layers bidirectional and accuracy is lesser] and model performs better with increase in the number of epochs. Will train the Sequential model using all these better performing parameters. Make use of ModelCheckpoint to save the best model which is the one with the max validation accuracy and use EarlyStopping to stop the training once the validation accuracy starts to go down after initial increase, but will provide the patience number indicating not to stop the training until a certain number of epochs after validation accuracy starts to decrease.

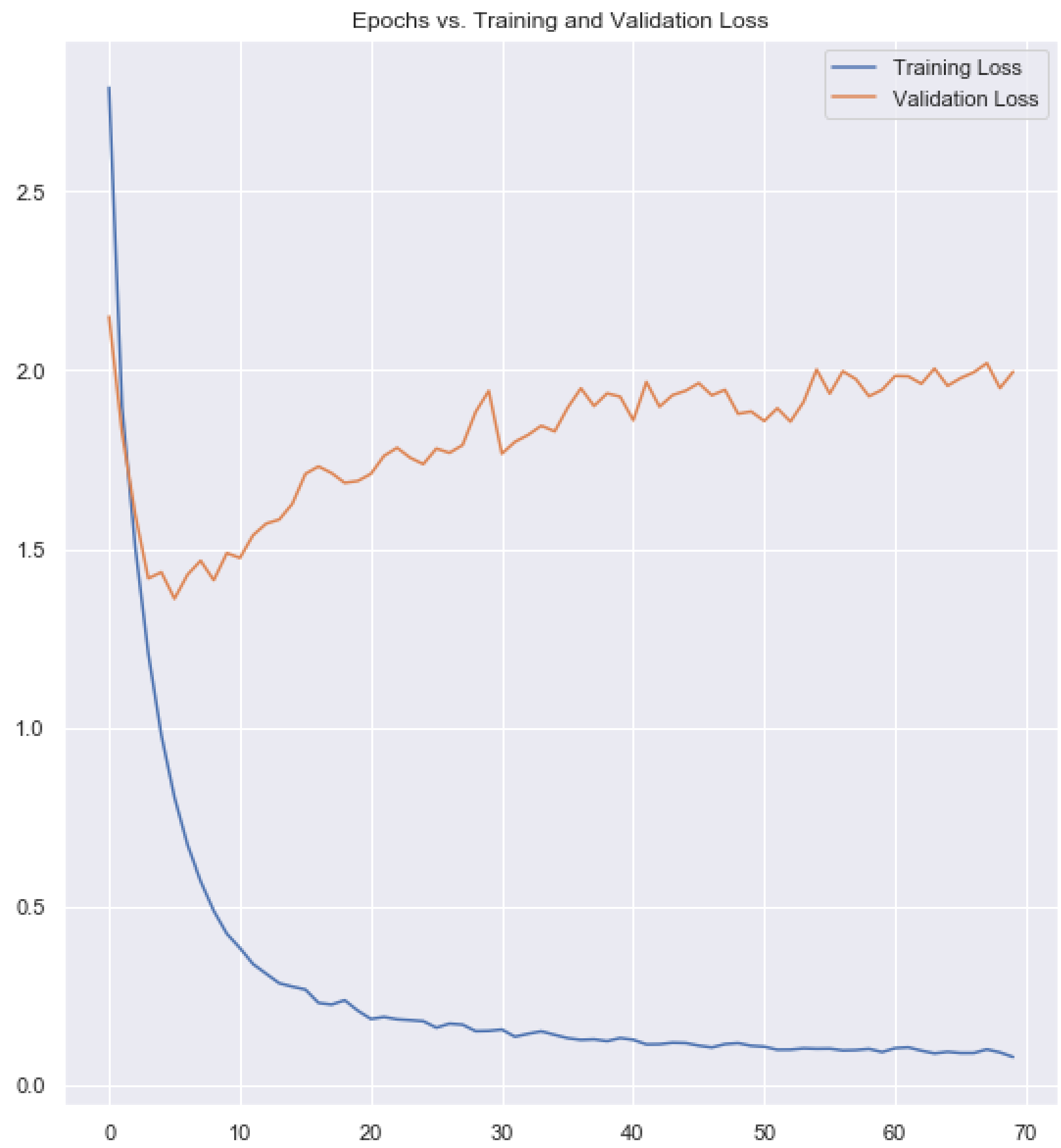
```
mc = ModelCheckpoint("model_lstmbi_tune.hdf5", monitor='val_acc', verbose=0, save_best_only=True, mode='max')
es = EarlyStopping(monitor='val_acc', verbose=0, mode='max', patience=30)
callbacks_list = [mc, es]

model_lstmbi_tune = Sequential()
model_lstmbi_tune.add(Embedding(input_dim=tknz_tune_vocabsize, output_dim=embedding_dim, weights=[embedding_matrix_tune],
                                input_length=max_length, trainable=True))
model_lstmbi_tune.add(Bidirectional(LSTM(50, return_sequences=True)))
model_lstmbi_tune.add(BatchNormalization())
model_lstmbi_tune.add(Bidirectional(LSTM(70, return_sequences=True)))
model_lstmbi_tune.add(BatchNormalization())
model_lstmbi_tune.add(Bidirectional(LSTM(100)))
model_lstmbi_tune.add(BatchNormalization())
model_lstmbi_tune.add(Dense(100, activation = "relu"))
model_lstmbi_tune.add(BatchNormalization())
model_lstmbi_tune.add(Dense(85, activation = "relu"))
model_lstmbi_tune.add(Dense(74,activation='softmax'))

model_lstmbi_tune.compile(loss = 'sparse_categorical_crossentropy', optimizer=optimizer_alg,metrics = [metric_eval])
model_lstmbi_tune_hist = model_lstmbi_tune.fit(X_train_tune_seq_pad, lbl_enc_tknzr_tune.fit_transform(y_train_tune),
                                               epochs = 70,
                                               callbacks=callbacks_list, batch_size=32, verbose = 0,
                                               validation_split=0.25)

print(model_lstmbi_tune.evaluate(X_test_tune_seq_pad, lbl_enc_tknzr_tune.fit_transform(y_test_tune)))
```

```
12066/12066 [==============================] - 17s 1ms/step
[2.057973738710964, 0.7181335985413558]
```

Plot training loss, validation loss vs number of epochs

```
train_loss = model_lstmbi_tune_hist.history['loss']
val_loss = model_lstmbi_tune_hist.history['val_loss']
plt.figure(figsize=(20, 10))
plt.subplot(1, 2, 1)
plt.plot(train_loss, label='Training Loss')
plt.plot(val_loss, label='Validation Loss')
plt.legend()
plt.title('Epochs vs. Training and Validation Loss')
```

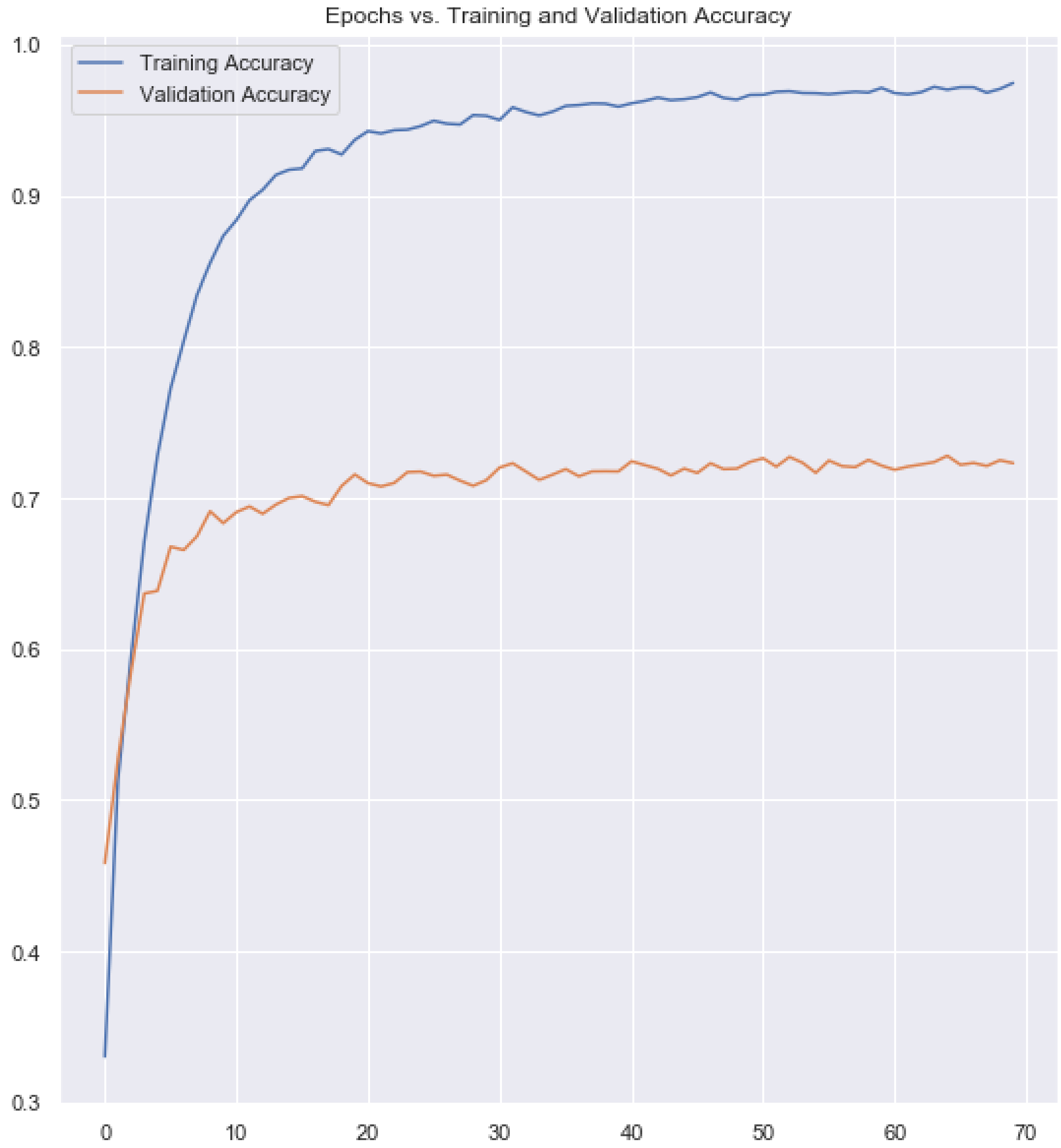
```
Out[165]: Text(0.5, 1.0, 'Epochs vs. Training and Validation Loss')
```



Plot training loss, validation loss vs number of epochs

```
train_acc = model_lstmbi_tune_hist.history['acc']
val_acc = model_lstmbi_tune_hist.history['val_acc']
plt.figure(figsize=(20, 10))
plt.subplot(1, 2, 1)
plt.plot(train_acc, label='Training Accuracy')
plt.plot(val_acc, label='Validation Accuracy')
plt.legend()
plt.title('Epochs vs. Training and Validation Accuracy')
```

```
Out[166]: Text(0.5, 1.0, 'Epochs vs. Training and Validation Accuracy')
```



Let us check the classification_report for the evaluation metrics and performance of the model in the prediction of individual classes.

	precision	recall	f1-score	support
0	0.72	0.64	0.68	766
1	0.65	0.57	0.61	155
2	0.54	0.62	0.58	164
3	0.58	0.53	0.56	150
4	0.43	0.55	0.48	177
5	0.56	0.57	0.56	178
6	0.49	0.58	0.53	177
7	0.45	0.64	0.53	152

8	0.52	0.52	0.52	170
9	0.55	0.57	0.56	157
10	0.77	0.49	0.60	168
11	0.41	0.41	0.41	160
12	0.48	0.43	0.45	180
13	0.55	0.60	0.57	153
14	0.71	0.61	0.66	154
15	0.48	0.62	0.54	155
16	0.71	0.67	0.69	150
17	0.64	0.76	0.69	206
18	0.46	0.53	0.49	173
19	0.64	0.62	0.63	154
20	0.75	0.56	0.64	153
21	0.60	0.47	0.52	154
22	0.38	0.59	0.46	170
23	0.38	0.30	0.34	150
24	0.65	0.76	0.70	144
25	0.37	0.49	0.42	146
26	1.00	0.99	0.99	150
27	0.63	0.50	0.56	158
28	0.51	0.41	0.45	153
29	0.99	0.97	0.98	150
30	0.71	0.94	0.81	129
31	0.83	0.79	0.81	152
32	0.95	0.97	0.96	150
33	0.69	0.78	0.73	152
34	0.54	0.47	0.50	159
35	0.57	0.55	0.56	157
36	0.62	0.57	0.60	156
37	0.76	0.70	0.73	153
38	0.99	0.94	0.96	150
39	0.71	0.81	0.76	150
40	0.67	0.68	0.68	154
41	0.94	0.91	0.93	150
42	0.77	0.69	0.73	155
43	0.80	0.83	0.81	127
44	0.99	0.98	0.98	150
45	0.70	0.52	0.60	150
46	0.72	0.69	0.71	150
47	0.95	0.93	0.94	150
48	0.81	0.87	0.84	151
49	0.86	0.76	0.81	151
50	0.99	0.97	0.98	150
51	0.79	0.83	0.81	150
52	0.99	0.99	0.99	150
53	0.99	0.95	0.97	150
54	0.99	0.97	0.98	150
55	0.79	0.95	0.86	150
56	0.63	0.46	0.53	158
57	0.87	0.90	0.89	151
58	0.98	1.00	0.99	150

59	0.60	0.69	0.64	150
60	0.97	0.94	0.95	150
61	0.99	1.00	0.99	150
62	0.94	0.82	0.88	151
63	0.97	0.99	0.98	150
64	1.00	1.00	1.00	150
65	0.98	0.99	0.98	150
66	1.00	0.99	1.00	150
67	0.45	0.47	0.46	151
68	0.99	1.00	0.99	150
69	0.99	0.99	0.99	150
70	0.92	0.94	0.93	150
71	0.99	0.97	0.98	150
72	0.64	0.62	0.63	176
73	0.54	0.50	0.52	156
accuracy			0.72	12066
macro avg	0.73	0.73	0.73	12066
weighted avg	0.73	0.72	0.72	12066

With the help of more observations, the model will be able to learn better. The company can keep check on groups with less number of documents, collect enough observations, reapply modeling and have the model achieve improved performance in classifying more individual classes accurately

9. Comparison to Benchmark

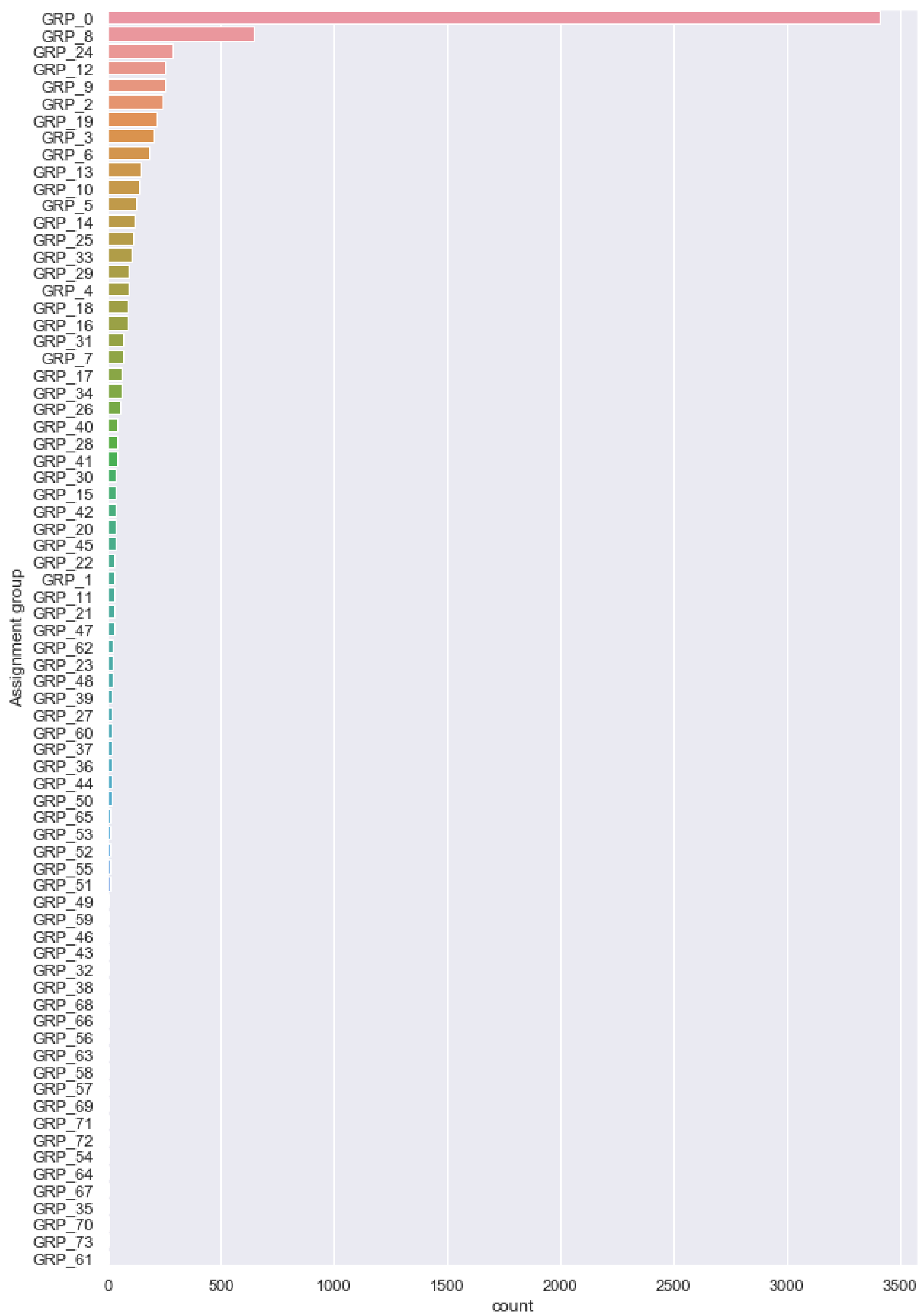
We have five classes [GRP_0, GRP_24, GRP_2, GRP_12, GRP_8] and other one GRP_CMN[classes which have counts/documents less than 230], built a LogisticRegression Uni-Bigram reduced features model and a Neural network Sequential model with Bidirectional LSTM layer and Glove embedding layer on this and were able to achieve around 70% precision and accuracy. This means, around 70% predictions are accurate that would help the company in reducing the manual routing of tickets. We started our project assuming that if we can automate 60% of the tasks, the company would benefit from it. With the application of Artificial Intelligence, we are able to get close to 70% automation. Also, one point on GRP_0 class which has maximum tickets is we were able to get around 75% precision. With this, we can say that we improved on the benchmark laid out at the outset.

10. Visualizations

10.1. Visualizing different patterns

Plot Assignment group values in increasing order

```
plt.figure(figsize = (10, 16))
sns.countplot(y= df['Assignment group'] ,data=df, order = df['Assignment group'].value_counts().index);
```



Majority of the Description/tickets belongs to Assignment groups GRP_0,GRP_8,GRP_24,GRP_12,GRP_9,GRP_2,GRP_19,GRP_3,GRP_6,GRP_13,GRP_10,GRP_5,GRP_14,GRP_25,GRP_33,GRP_29,GRP_4, GRP_18,GRP_16,GRP_31,GRP_7,GRP_34, and GRP_26. And, as we observe in the above plot, some reasonable number of Description/tickets belong to GRP_40 until GRP_52. There is bias in classes with close to 50% of the data belonging to GRP_0 class.

Plot Description word count against Assignment groups

```
plt.figure(figsize = (10, 16))
sns.boxplot(x = 'Description_word_count', y = 'Assignment group', data = df)
plt.xlabel("Description_word_count")
plt.ylabel("Assignment group")
plt.title("Description_word_count vs Assignment group")
plt.show()
```

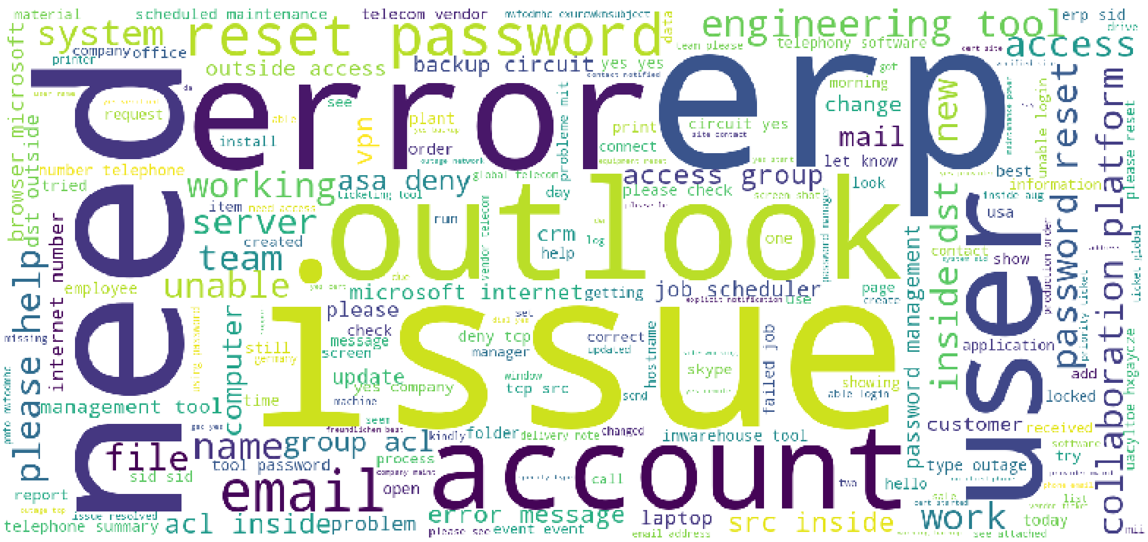
Almost every Assignment group has outliers at various lengths of Description word count. The average word count for every Assignment group seems to be almost under 30 words and covers most of the words for each class. This average word count will be helpful to decide the max length to be considered while converting text to sequence of numbers(vectors). And, during computation it will occupy less memory and training time will be lesser.

10.2 Visualization different text features

10.2.1 Word cloud

The visual representations of words portrayed below in different sizes are used in the model called word cloud which is after the removal of stopwords that give prominence to words on frequency.

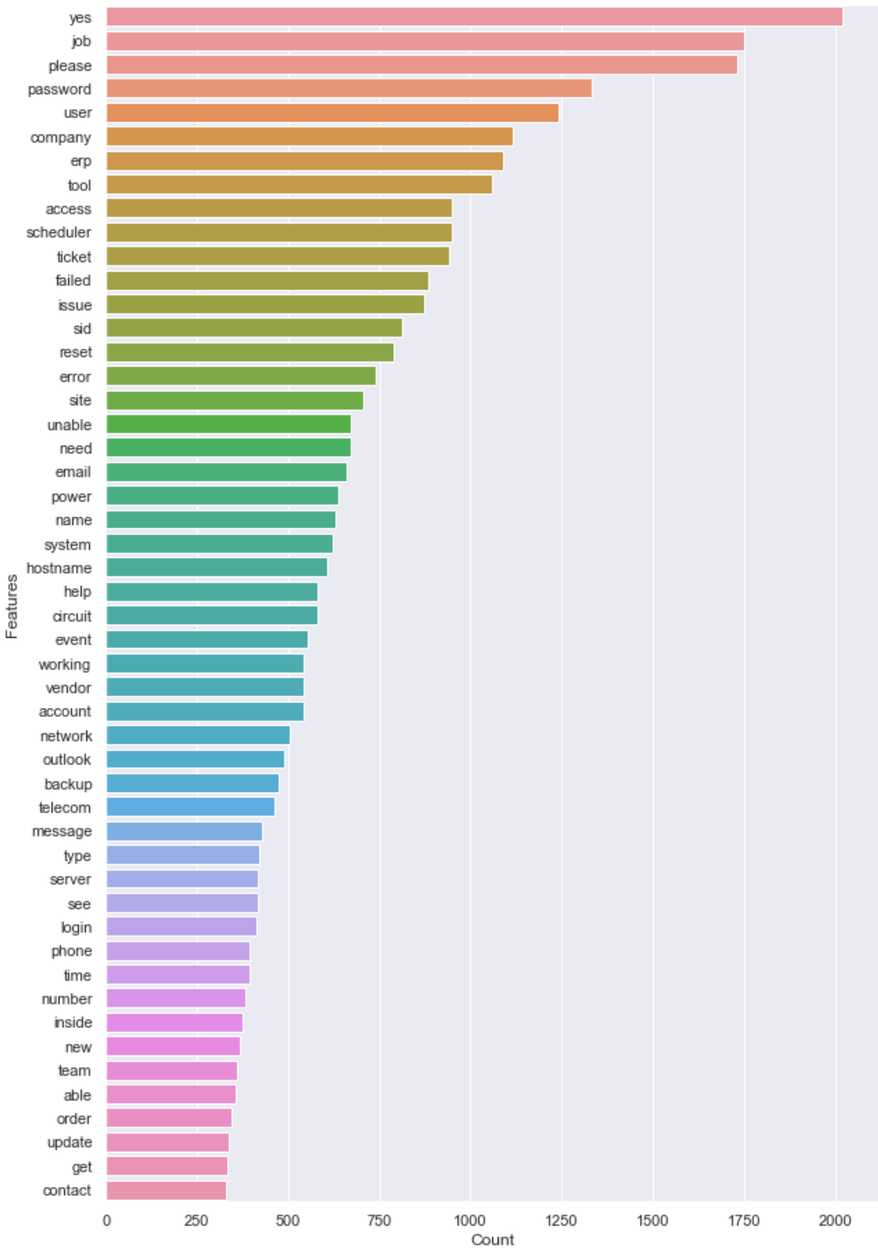
```
wordcld_inp = ' '.join(df_process_txt_acc['Description'].tolist())
wordcloud = WordCloud(background_color="white",width=1500, height=700).generate(wordcld_inp)
plt.figure(figsize=(14,16))
plt.imshow(wordcloud)
plt.axis("off")
plt.show()
```



10.2.2 Visualization of unigram and bigram

10.2.2.1 Representation of unigram (top 50 features)

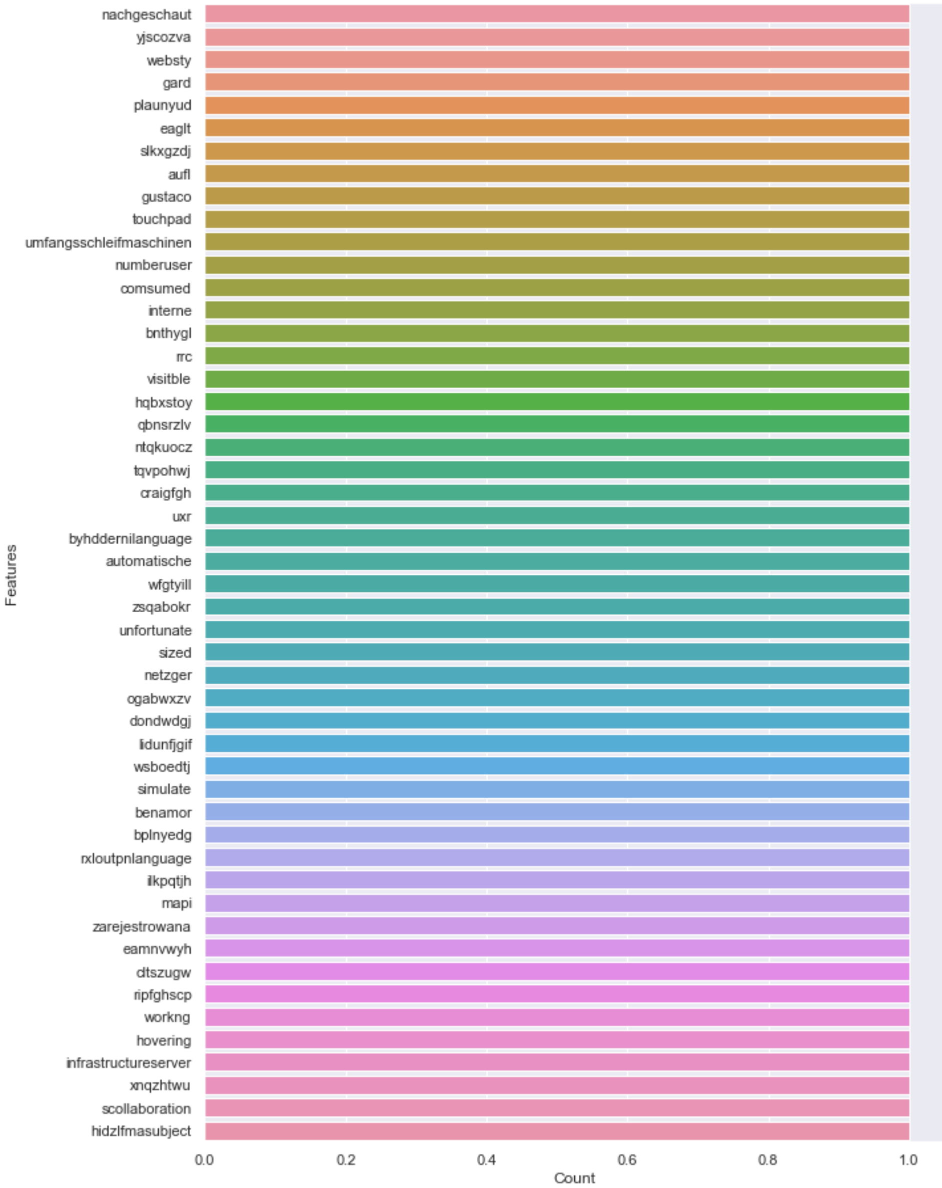
```
cvt_uni = CountVectorizer(ngram_range=(1, 1)).fit(df_process_txt_acc['Description'])
cvt_uni_wrds = cvt_uni.transform(df_process_txt_acc['Description'])
uni_sumtn_wrds = cvt_uni_wrds.sum(axis=0)
uni_wrds_occrnc = [(word, uni_sumtn_wrds[0, idx]) for word, idx in cvt_uni.vocabulary_.items()]
uni_wrds_occrnc =sorted(uni_wrds_occrnc, key = lambda x: x[1], reverse=True)
df_uni_top_50_featrs = pd.DataFrame(uni_wrds_occrnc[:50], columns = ['Features' , 'Count'])
plt.figure(figsize=(10,16))
sns.barplot(x="Count", y="Features", data=df_uni_top_50_featrs)
plt.show()
```



The top features here represent words that have meaning and are not just jumbled letters.

10.2.2.2 Representation of unigram (bottom 50 features)

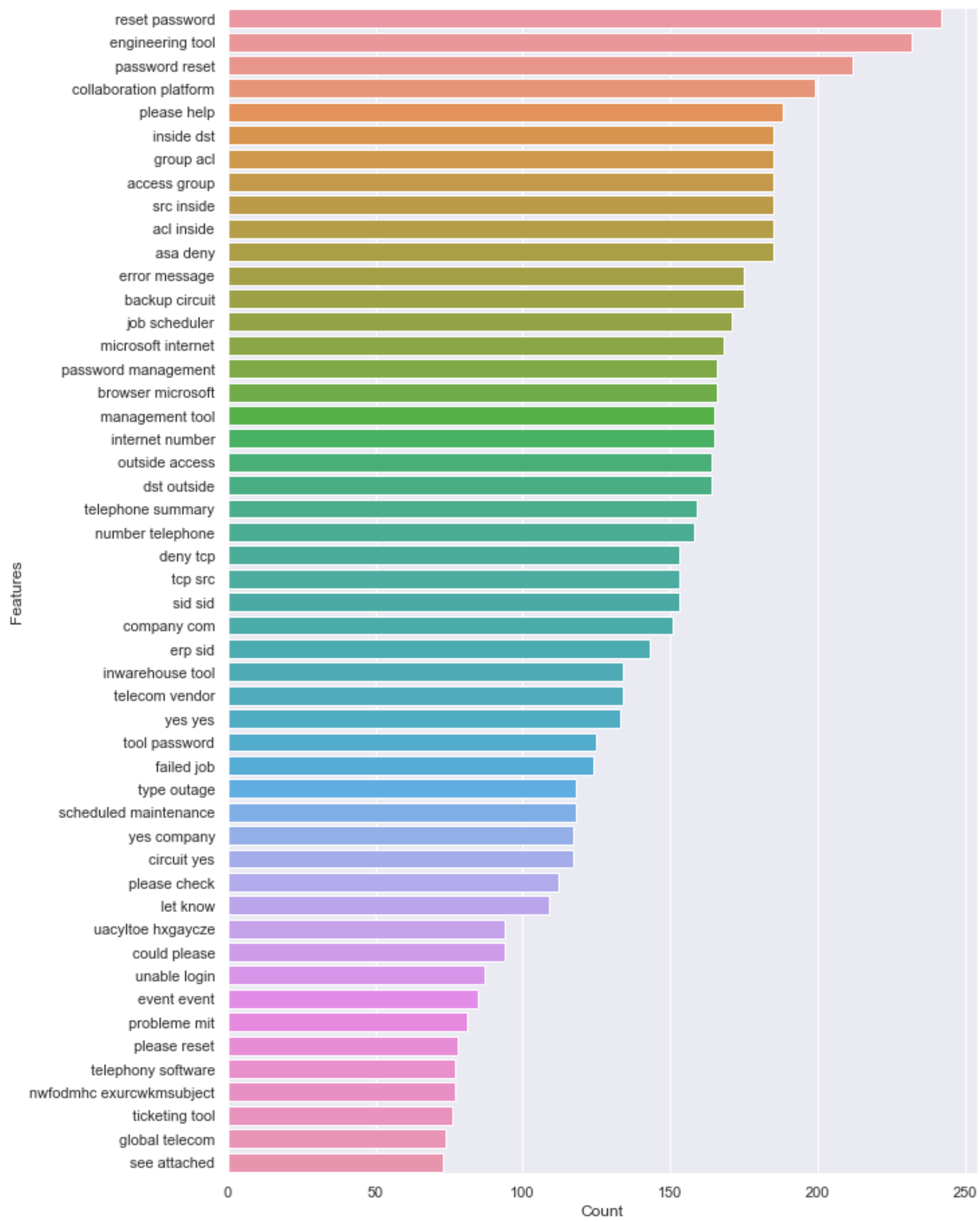
```
cvt_uni = CountVectorizer(ngram_range=(1, 1)).fit(df_process_txt_acc['Description'])
cvt_uni_wrds = cvt_uni.transform(df_process_txt_acc['Description'])
uni_sumtn_wrds = cvt_uni_wrds.sum(axis=0)
uni_wrds_occrnc = [(word, uni_sumtn_wrds[0, idx]) for word, idx in cvt_uni.vocabulary_.items()]
uni_wrds_occrnc =sorted(uni_wrds_occrnc, key = lambda x: x[1])
df_uni_bot_50_featrs = pd.DataFrame(uni_wrds_occrnc[:50], columns = ['Features' , 'Count'])
plt.figure(figsize=(10,16))
sns.barplot(x="Count", y="Features", data=df_uni_bot_50_featrs)
plt.show()
del wordcld_inp, wordcloud, cvt_uni, cvt_uni_wrds, uni_sumtn_wrds, uni_wrds_occrnc, df_uni_top_50_featrs, df_uni_bot_50_featrs
```



The bottom features here represent words that are mostly just jumbled[no meaning] letters.

10.2.2.3 Representation of bigram (top 50 features)

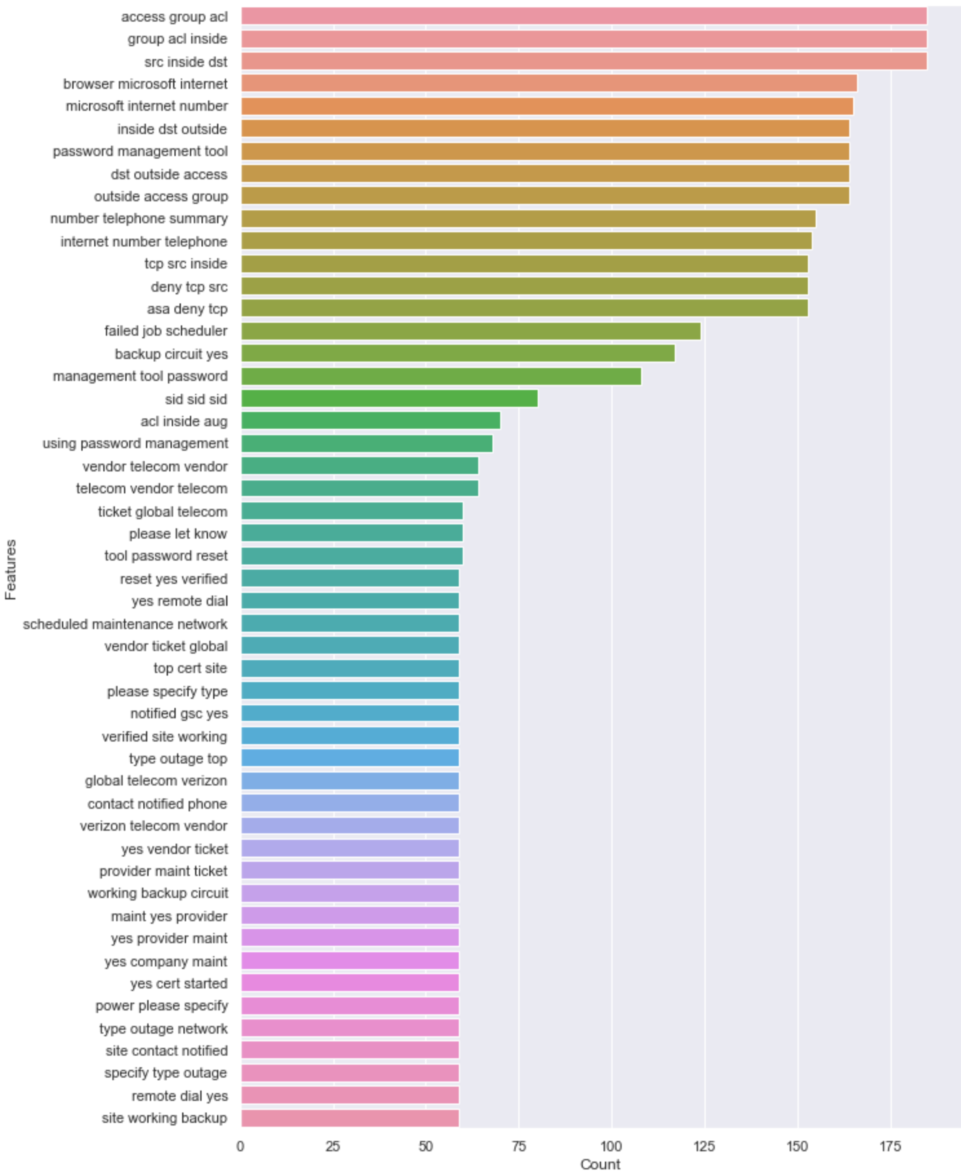
```
cvt_bi = CountVectorizer(ngram_range=(2, 2)).fit(df_process_txt_acc['Description'])
cvt_bi_wrds = cvt_bi.transform(df_process_txt_acc['Description'])
bi_sumtn_wrds = cvt_bi_wrds.sum(axis=0)
bi_wrds_occrnc = [(word, bi_sumtn_wrds[0, idx]) for word, idx in cvt_bi.vocabulary_.items()]
bi_wrds_occrnc =sorted(bi_wrds_occrnc, key = lambda x: x[1], reverse=True)
df_bi_top_50_featrs = pd.DataFrame(bi_wrds_occrnc[:50], columns = ['Features' , 'Count'])
plt.figure(figsize=(10,16))
sns.barplot(x="Count", y="Features", data=df_bi_top_50_featrs)
plt.show()
```



The top features in bigrams represent mostly words that have meaning and not just jumbled words/letters.

10.2.2.4 Representation of trigram (top 50 features)

```
cvt_tri = CountVectorizer(ngram_range=(3, 3)).fit(df_process_txt_acc['Description'])
cvt_tri_wrds = cvt_tri.transform(df_process_txt_acc['Description'])
tri_sumtn_wrds = cvt_tri_wrds.sum(axis=0)
tri_wrds_occrnc = [(word, tri_sumtn_wrds[0, idx]) for word, idx in cvt_tri.vocabulary_.items()]
tri_wrds_occrnc =sorted(tri_wrds_occrnc, key = lambda x: x[1], reverse=True)
df_tri_top_50_featrs = pd.DataFrame(tri_wrds_occrnc[:50], columns = ['Features' , 'Count'])
plt.figure(figsize=(10,16))
sns.barplot(x="Count", y="Features", data=df_tri_top_50_featrs)
plt.show()
del cvt_bi, cvt_bi_wrds, bi_sumtn_wrds, bi_wrds_occrnc, df_bi_top_50_featrs
del cvt_tri, cvt_tri_wrds, tri_sumtn_wrds, tri_wrds_occrnc, df_tri_top_50_featrs
```



The top features in trigrams represent mostly words that have meaning and not just jumbled words/letters.

11. Implications

Text classification is one of the important tasks in the IT world/Digital world as tickets would be raised frequently to the support team. Ticket assignment to the appropriate team was achieved through manual process in the earlier times which is a tedious and time consuming task. With the advancement in the field of AI and Machine Learning, the IT world now has a better option and should consider application of Natural Language Processing solutions which provides a reasonable accuracy in assigning tickets to proper support teams. This helps with the automation of redundant time consuming tasks thereby having the human effort available to much valued tasks. In our project, we were able to achieve automated classification of tickets to correct groups with an accuracy and precision around 70%. Considering traditional and deep learning models built which can be used for classification of tickets to correct groups, we can say we have a confidence interval of around 70%. Considering just the GRP_0, we are achieving even higher accuracy around 75% that helps with the automation of more than 35% of total tickets. Through our process, we will be able to automate the ticket assignment of more frequent issues even more accurately and that would benefit the IT world since top 5 groups cover 50 plus percent of tickets. Assuming each documents takes around 3 seconds to read, multiplied by number of documents say n, we will be able to save 70 % of n * 3 seconds as average precision and accuracy is around 70%.

12. Limitations

The dataset had only 8500 observations, was imbalanced, contained documents within a group with not much similar context and a lot of jumbled letter words. In the imbalanced part, out of 74 groups, one group constituted close to 50% and there were many groups with less than 0.001059% value counts. Many classes with very little observations and also having a problem of not having similar documents and no meaning words. We have a lot of groups with less than 150 documents, even a lot of groups with less than 50 documents, this limitation will make it difficult for any machine learning algorithm to learn the pattern, and classify accurately. In the real world, if more and more tickets start to arrive for these groups which had less counts/documents while building our model, the performance may fall short in correctly classifying the tickets to the groups. We came to know with the help of text augmentation, our model learning pattern would improve. It is better to keep a check on those less counted groups manually, and collect a good number of observations. Once we have collected a fair number of observations, we can apply text augmentation and model tuning techniques, and achieve improved performance in classifying more individual classes accurately.

13. Closing Reflections

Natural language processing (NLP) is a branch of linguistics and artificial intelligence(AI) that helps machines understand human language through the vocabulary, grammar, and context of the sentence. This will help in gaining valuable insights from the text. Grammar is what helps us form a sentence with proper arrangement of words. It is a set of rules. Every sentence includes words that fall into parts of speech which are nouns, pronouns, verbs, adjectives, adverbs, prepositions, conjunctions, articles/determiners, interjections, and some words can be part of more than one parts of speech. The probability of a word that will come before or after another word and even the context can be identified with the help of these concepts. Deep Learning and NLP help us achieve this and using it we can train machines to understand text/language. This helps us in automating many manual tasks, identifying customer sentiments, probability of a customer question and many other tasks. In this project, we learnt application of various NLP techniques to generate insights from text data, identified the problems associated with the dataset and then leverage multiple NLP and deep learning techniques to solve the problem. We could visualise the readable and top features, word counts of each document and class ratio which were useful insights. We converted the text to vector data using countvectorizer and also used glove embedding layers in our deep learning model. With the limitation in the dataset, this project gave us the opportunity to explore possible solutions to achieve the best with what data we have. Use of bidirectional lstms in Sequential seems to give reasonable results. Next time, we will try to explore even more at the data level and seek to come up with any new solutions, as no matter the model and tuning, the data is what matters the most.

14. References

Sejal Shah (2020), Automatic Ticket Assignment using Machine Learning and Deep Learning Techniques for *School of Computing National College of Ireland*.
URL: http://norma.ncirl.ie/4416/1/sejalshah.pdf