MCA Semester – IV Project

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A study on Automatic Ticket Allocation

Research Project submitted to Jain Online (Deemed-to-be University) In partial fulfillment of the requirements for the award of

Master of Computer Applications

Submitted by

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USN

211VMTR00912

Under the guidance of

Prof. Anil Shankar Phalle

DECLARATION

I, *Nishant Joshi,* hereby declare that the Research Project Report titled *"*Automatic Ticket Allocation*" has been* prepared by me under the guidance of Prof. Anil Shankar Phalle . I declare that this Project work is towards the partial fulfillment of the University Regulations for the award of degree of Master of Computer Applications by Jain University, Bengaluru. I have undergone a project for a period of Eight Weeks. I further declare that this Project is based on the original study undertaken by me and has not been submitted for the award of any degree/diploma from any other University
/ Institution.

Place: Bengaluru

Date:18/08/2023

Nishant Joshi
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CERTIFICATE

This is to certify that the Project report submitted by Mr. Nishant Joshi bearing 211VMTR00912 on the title *"Automatic Ticket Allocation"* is a record of project work done by him/ her during the academic year 2023-24 under my guidance and supervision in partial fulfillment of Master of Computer Applications.

Place: Bangalore

Date:18/08/2023

Faculty Guide

ACKNOWLEDGEMENT

I would like to express my heartfelt gratitude to the individuals and organizations that have played critical roles in guiding me towards the successful completion of my project. First and foremost, I would like to convey my heartfelt gratitude to my outstanding project mentor, Prof. Dr. Syed Naimatullah Hussain. Your advice, insight, and constant support have been invaluable in designing my project and broadening my knowledge in the industry. Your guidance has genuinely been a guiding light for me.

I am also grateful to the University administration for offering an enriching academic environment. Jain Deemed to be University (Online) has not only provided a learning platform, but it has also fostered an environment of creativity and academic success. The faculty members' consistent efforts have been amazing, and their passion to pass on information has been encouraging.

I'd like to convey my heartfelt gratitude to my faculty guide for their invaluable insights and constructive input during the project's progress. Your experience has been useful in developing my thoughts and approaches. In addition, I am grateful to my colleagues, who have always been friendly and eager to engage in interesting talks.

In addition, I want to thank my family for their constant support and understanding. Your unwavering confidence in my ability has been my driving force. Your sacrifices and affection have served as the foundation for my academic endeavors.

To summarize, I consider myself fortunate to have been a part of Jain Deemed to be University (Online) and to have received the advice and support that has propelled me to this accomplishment. My project guide, University officials, faculty guide, other faculty members, organization name, and my cherished family have all worked together to make this journey not just educational but also personally fulfilling.

Nishant Joshi
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Executive Summary

In any IT industry, Incident (an unplanned interruption to an IT service or reduction in the quality of an IT service that affects the Users and the Business) Management plays an important role in delivering quality support to customers.

The main goal of this management process is to provide a quick fix / workarounds or solutions that resolves the interruption and restores the service to its full capacity to ensure no business impact. Whenever an incident is created, it reaches the Service desk team and then it gets assigned to the respective teams to work on the incident.

The manual assignment of these incidents might have below disadvantages:

- Time consuming and requires human efforts
- Increases human errors and resource consumption, as it is carried out ineffectively because of the misaddressing.
- Increases the response and resolution times which result in user satisfaction deterioration / poor customer service

If this ticket assignment is automated, it can be more cost-effective, less resolution time and the Service Desk team can focus on other productive tasks.

Objective:

- The main objective of this project is to – develop a Management System for such an agency to replace the manual works
- The goal is to build a classifier that can classify the tickets by analyzing text.
- While developing I will take a generalized approach so that the system can be implemented readily at any such agency

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CHAPTER 1 INTRODUCTION, SCOPE AND BACKGROUND

1. INTRODUCTION, SCOPE AND BACKGROUND

1.1 Overview of Project Case / Business case

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 initial diagnosis to see if they can resolve. Around ~54% of the incidents are resolved by L1 / L2 teams. Incase 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 diagnosis and resolve the incidents. Around ~56% of incidents are resolved by Functional / L3 teams. Incase 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 wrong functional groups. Around ~25% of Incidents are wrongly assigned to functional teams. Additional effort needed for Functional teams to re-assign to right functional groups. During this process, some of the incidents are in queue and not addressed timely resulting in poor customer service.

1.2 Problem definition

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1.3 Project Scope

Objective:

- The main objective of this project is to – develop a Management System for such an agency to replace the manual works
- The goal is to build a classifier that can classify the tickets by analyzing text.
- While developing I will take a generalized approach so that the system can be implemented readily at any such agency

Goal:

The goal here is to create an NLP based classifier that could automatically classify any ticket raised by analyzing ticket description to the suitable Assignment group, this could be integrated with any ticket management service like Service Now.

Based on the ticket description our model would assign a probability of it to being assigned to one of the 74 Groups.

This project intends to reduce the manual effort of IT support teams by automating the process of ticket allocation.

CHAPTER 2:
REVIEW OF LITERATURE

2. REVIEW OF LITERATURE

2.1 Literature Review

Automatic text classification can be seen as a specific field of application of text classification. The processing of support tickets is made challenging by the nature of the bodies of text involved: many of these help requests are very brief, and almost always contain technical jargon that should be taken into careful consideration.

In this section, we provide an overview of Ticket Automation, describing its most prominent subtasks as well as listing notable and recent work in this field. We will put particular emphasis on text classification, as our research reveals it to be the most common automation procedure in practice. At the end of this section, we also provide a list of datasets often used in this domain's literature.

Background of the Selected Topic:

Currently the incidents are created by various stakeholders (Business Users, IT Users and Monitoring Tools) within 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 initial diagnosis to see if they can resolve. Around ~54% of the incidents are resolved by L1 / L2 teams.

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Review of Relevant Literature:

As per the current project scenario based review given above. Let's go through the data understanding:

The given dataset consists of the following four attributes:

3 Short Description (a summary of the issue faced by the user)
4 Description (detailed description of the issue)
5 Caller (ID of the caller)
6 Assignment group (GRP_0 ~ GRP_73 i.e., total 74 classes of Assignment group) – Target class

Sample Data:

	Short description	Description	Caller	Assignment group
0	login issue	-verified user details.(employee# & manager na...	spxjnwir pjlcoqds	GRP_0
1	outlook	\r\n\r\nreceived from: hmjdrvpb.komuaywn@gmail...	hmjdrvpb komuaywn	GRP_0
2	cant log in to vpn	\r\n\r\nreceived from: eylqgodm.ybqkwiam@gmail...	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

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6.1 Feasibility Analysis

A feasibility study is a critical phase in project planning that assesses the viability of undertaking a proposed project. Automatic Ticket Allocation project is quite feasible which would reduce time, human error/tracking and cost. Automatic Ticket Allocation is quite beneficial for business because it will allocate the incident or ticket to the relevant team instead of laying the ticket from one team to another. Technically, we would implement the NLP models even though we need to convert languages. It's quite feasible will reduce lots of manual efforts efficiently. Below are the data findings been analyzed:

- Caller ID are present in a random manner (may not be useful for training data)
- Languages other than English for example- German, etc. are also present in the dataset
- Non-English languages are also found in the data
- Email/chat format with symbols in description
- Hyperlinks and URLS are found in the description
- Blank records are present in either short description or description
- Few descriptions are replica of the short description
- Few words were combined together
- Spelling mistakes and typo errors are found

CHAPTER 3
PROJECT PLANNING AND METHODOLOGY

3. PROJECT PLANNING AND METHODOLOGY

3.1 Project Planning

A well-structured project plan is essential for the successful execution of the Automatic Ticket Allocation developed using Machine Learning. This plan encompasses various Exploratory Data Analysis that provide comprehensive guidance throughout the project lifecycle. The plan includes a Gantt chart outlining project activities, an acceptance plan, ensuring quality standards, a resource plan for efficient allocation, and a risk management plan for proactive risk mitigation.

Gantt Chart:

The Gantt chart below depicts the project's activities, their timing, and dependencies from June 18, 2023, to August 18, 2023:

Task	Start Date	End Date	Dependencies
Examine Literature	06/18/2023	06/24/2023	***None***
Data Gathering & Understanding	06/25/2023	07/08/2023	***Examine Literature***
Exploratory Data Analysis	06/25/2023	07/08/2023	***Data Gathering & Understanding***
Language Conversion	07/09/2023	07/15/2023	***Exploratory Data Analysis***
Charts, Cluster & EDA	07/16/2023	07/22/2023	***Language Conversion***
Training Model	07/16/2023	07/22/2023	***Charts, Cluster & EDA***
Testing & Accuracy	07/23/2023	08/04/2023	***Training Model***
Documentation and Reporting	08/05/2023	08/11/2023	***Testing & Accuracy***
Finalize Documentation	08/12/2023	08/18/2023	***Documentation and Reporting***

Acceptance Plan:

The acceptance plan ensures that the project meets quality standards before deployment.

- Criteria: Functional requirements, Better Accuracy, testing and training Dataset been trained well, security measures.
- Testing: Unit testing, integration testing, security testing, usability testing.
- Responsible Parties: Quality assurance team, development team, project manager.

- Approval Process: Testing results will be documented and reviewed by the quality assurance team and project manager before approval.

Resource Plan:

Efficient resource allocation is critical for project success. The resource plan outlines the allocation of human resources, tools, and equipment.

- Human Resources: Frontend and backend developers, quality assurance specialists, project manager.
- Tools: Anaconda, development environment, Jupiter, Python.
- Equipment: Laptop.

Risk Management Plan:

The risk management plan identifies potential risks, assesses their impact, and outlines strategies for mitigation.

- Risks: Technical glitches, scope changes, resource constraints, security vulnerabilities.
- Mitigation Strategies: Regular communication, iterative development, proactive testing, security protocols.

3.2 Methodology

Chosen Methodology: Agile
Development Comparative Study of
Methodologies:
Before settling on the Agile methodology, a comparative analysis of various methodologies was conducted. Waterfall, Iterative, and Agile methodologies were considered.

- Waterfall Methodology: The Waterfall methodology follows a sequential approach, where each phase (requirement, design, implementation, testing, deployment) is completed before moving to the next. This approach is rigid and lacks flexibility, making it less suitable for projects with evolving requirements and rapid changes.
- Iterative Methodology: The Iterative methodology involves repeating cycles of development, with each cycle adding new features or improvements. While it offers some flexibility, it may lead to incomplete features and the final product might not align perfectly with user needs.
- Agile Methodology: Agile is a flexible and iterative approach that emphasizes collaboration, continuous improvement, and delivering increments of the product at regular intervals. It accommodates changes in requirements and allows for regular user feedback, making it suitable for projects with evolving features.

Rationale for Choosing Agile Methodology:

The Agile methodology aligns well with the complex nature of the "Automatic Ticket Allocation” project. The project's requirements are subject to change as user preferences evolve, and rapid iterations are necessary to ensure the application's relevance. The following justifications support the choice of Agile:

- Adaptability:Agile allows for incremental development, meaning features can be added, modified, or removed as needed. This is crucial for an application where market trends and customer demands change frequently.
- Frequent User Feedback: The Agile approach promotes regular user feedback through iterations. This ensures that the application meets user expectations, providing an optimal shopping experience.
- Collaboration: Agile encourages collaboration among team members, stakeholders, and clients. This ensures that the application aligns with business goals and customer needs.
- Risk Mitigation:The Agile methodology's iterative nature allows for early identification and mitigation of risks. Any issues can be addressed in subsequent iterations, reducing the chances of major setbacks.
- Quality Assurance: Agile emphasizes continuous testing and quality assurance, leading to a more robust and bug-free application.

Application of Agile Methodology:

The Agile methodology will be applied as follows:

- Sprint Planning: Each development cycle (sprint) will last 2 weeks. In each sprint, tasks will be selected from the project backlog based on priority and feasibility.

- Iterative Development: The application will be developed iteratively, with each sprint adding new features or improving existing ones based on feedback and changing requirements.

- Frequent Testing: Testing will occur in every sprint, ensuring that the application functions as expected and meets quality standards.

- User Feedback: Regular demos and feedback sessions will be held with stakeholders and potential users to ensure alignment with expectations.

CHAPTER 4

DATA ANALYSIS, DESIGN AND IMPLEMENTATION

4. DATA ANALYSIS, DESIGN AND IMPLEMENTATION

- **Requirement Analysis**
  - **Data Collection:**

Data Source

- Details about the data and dataset files. The data set contains 4 string columns

Column	Description	Data type
Short description	Short description for problem for which the incident is being raised	8492 non-null object
Description	Detailed description of the problem for which the incident is being raised	8499 non-null object
Caller	Masked user name	8500 non-null object
Assignment Group	IT Support Group to which the incident has to be assigned	8500 non-null object

- The dataset is divided into two parts, features and the target classes.
- For a given dataset, features are Short description, Description and Caller .
- For a given dataset, the class variable name is Assignment group
- There are totally 8500 row
- Caller columns mainly contain the details of the user who raised the incident and is of not much use in our analysis and can be dropped.
- "Short Description" and "Description" could be concatenated into a single column, so that we don't miss information about the tickets.
- There seems to be missing values in Short description and Description columns, which needs to be looked into and handled.
  - There are 8 null/missing values present in the Short description and 1 null/missing values present in the description column

■ **Data Analysis and tools of data analysis**

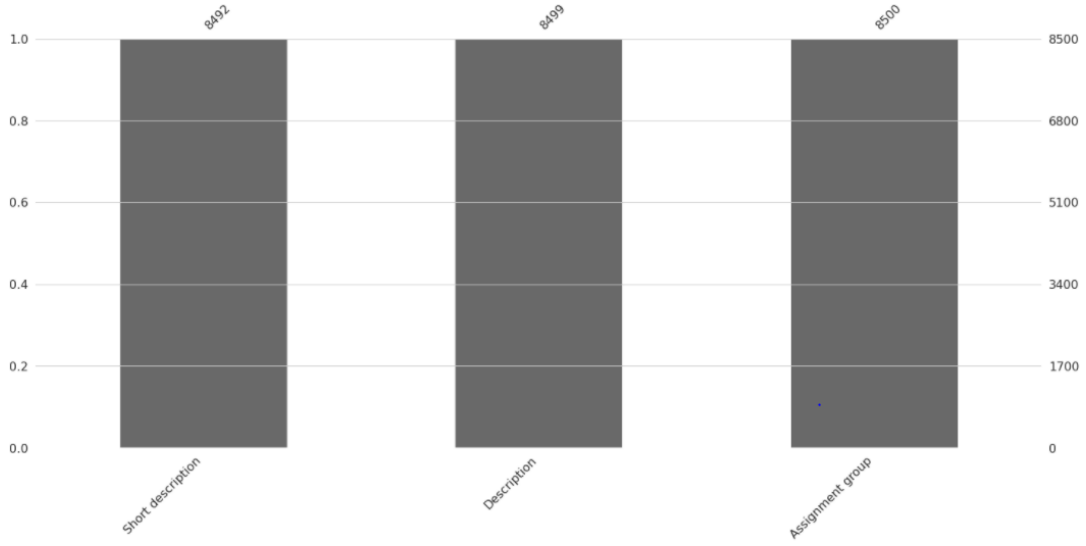
Summary of Approach to EDA and Pre-processing

Step-by-step walk through the solution with the observations

- Loaded the input csv file into pandas' data frame.
- EDA has been performed on the dataset and following are the observations from that:
  - All columns are of type object containing textual information.
  - Assignment group is our predictor / target column with multiple classes. So, this is a Multiclass Classification problem.
  - There are **8 null/missing values** present in the Short description and **1 null/missing values** present in the description column.

	Short description	Description	Assignment group
2604	NaN	\r\n\r\nreceived from: ohdrnswl.rezuibdt@gmail...	GRP_34
3383	NaN	\r\n-connected to the user system using teamvi...	GRP_0
3906	NaN	-user unable tologin to vpn.\r\n-connected to...	GRP_0
3910	NaN	-user unable tologin to vpn.\r\n-connected to...	GRP_0
3915	NaN	-user unable tologin to vpn.\r\n-connected to...	GRP_0
3921	NaN	-user unable tologin to vpn.\r\n-connected to...	GRP_0
3924	NaN	name:wvqgbdhm fwchqjor\nlanguage:\nbrowser:mic...	GRP_0
4341	NaN	\r\n\r\nreceived from: eqmuniov.ehxkcbgj@gmail...	GRP_0
4395	i am locked out of skype	NaN	GRP_0

Visually the number of missing values are as shown below:

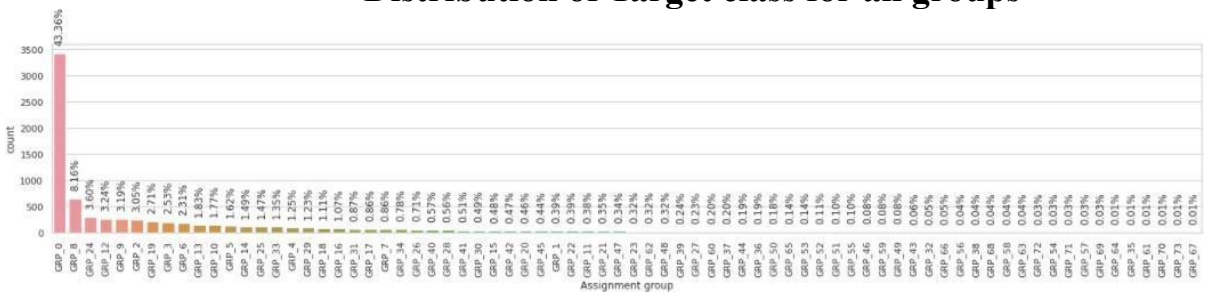


- Dropped the duplicate entries of the incidents. Thus, the size of the dataset gets reduced to (7909,4)
- Dropped the caller attribute as the data was not found to be useful for analysis
- Replaced Null values in Short description & description with space.
- Merged Short Description & Description fields for analysis

OBSERVATIONS REGARDING TARGET CLASS

- A large number of entries belonged to GRP_0 (mounting to 3429 which account for ~ more than 40% of the data)

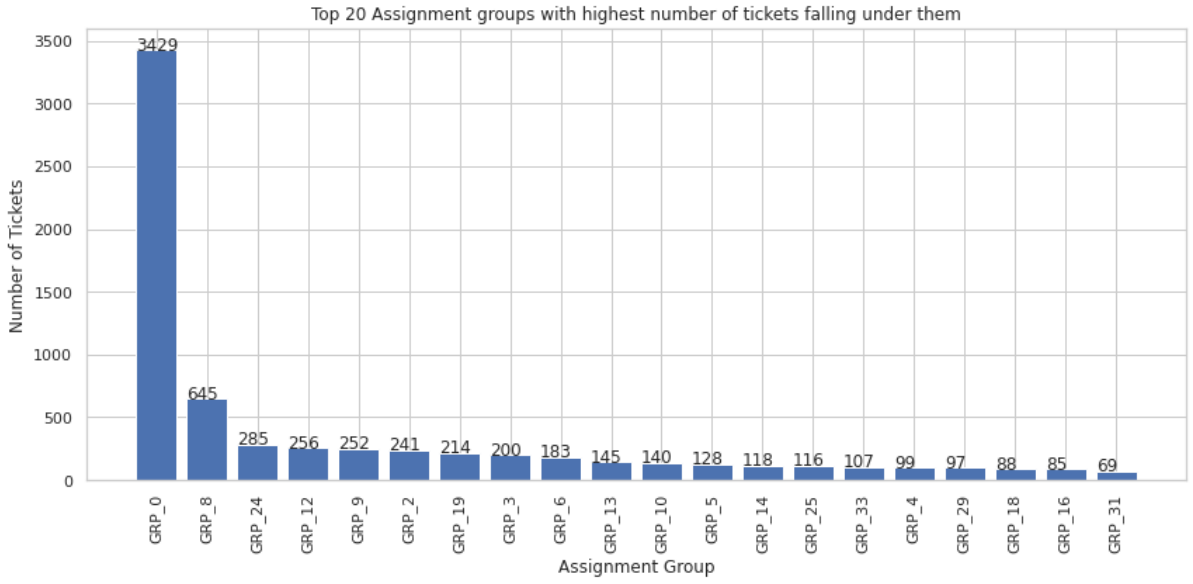
Distribution of Target class for all groups



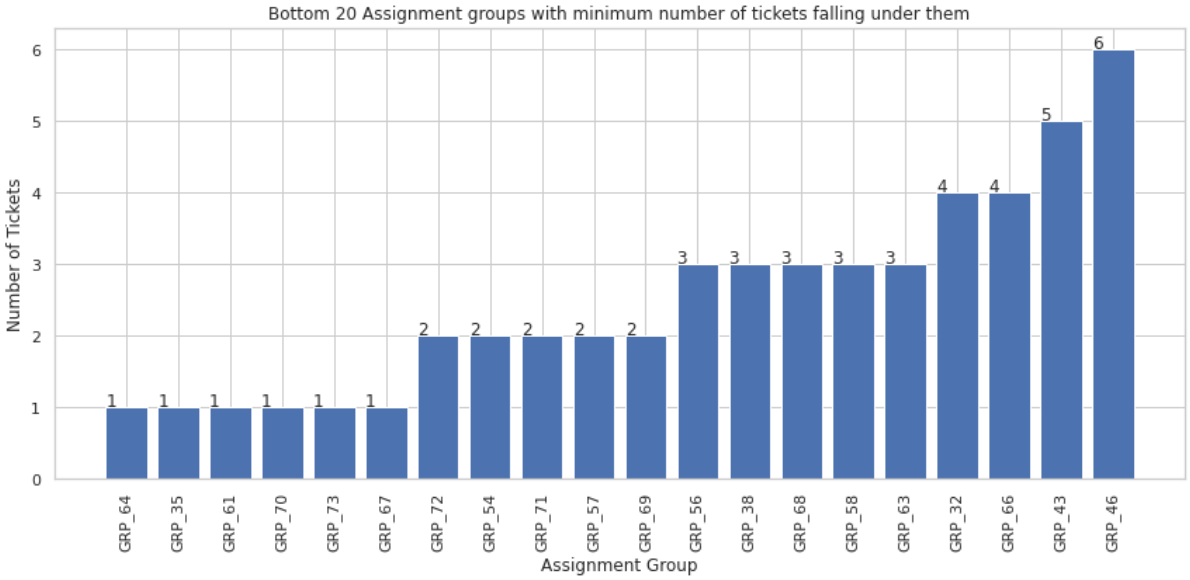
- The Target class distribution is extremely skewed
- The data is too much biased towards a single group and seems to be highly imbalanced, with majority of incidents are from Group 0 followed by Group 8 , 24 , 12 , 9 , 2 and so on
- There are few classes which just have less than 10 incidents per class and even classes with just 1 or 2 incidents (samples), need to see if we can drop those rows due to the lack of samples representing those classes. They might not be of

much help as a predictor

- Top 20 Assignment groups having the highest number of tickets for training the data.



- Following are the Tickets with less number of tickets per Assignment groups.

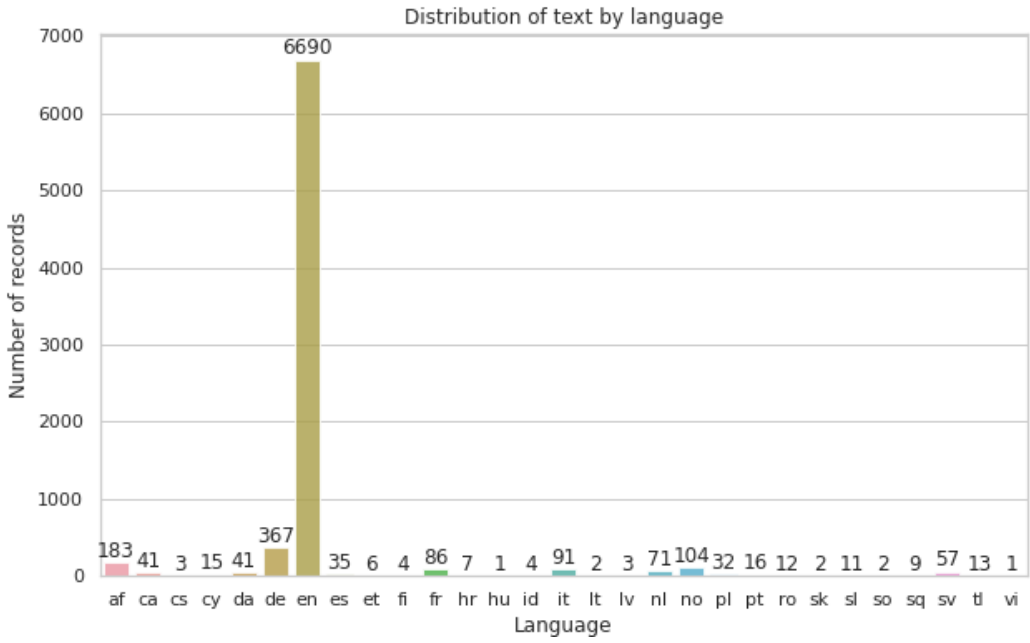


- **Design**

DATA PRE-PROCESSING

Below steps have been performed for initial pre-processing and clean-up of data:

- Replaced the gibberish text using **FTFY**
- Contraction words found in the merged Description are removed for ease of word modeling.
- Changed the case sensitivity of words to the common one
- Removed Hashtags and kept the words, Hyperlinks, URLs, HTML tags & non-ASCII symbols from merged fields.
- There were quite a few entries with languages different from English.



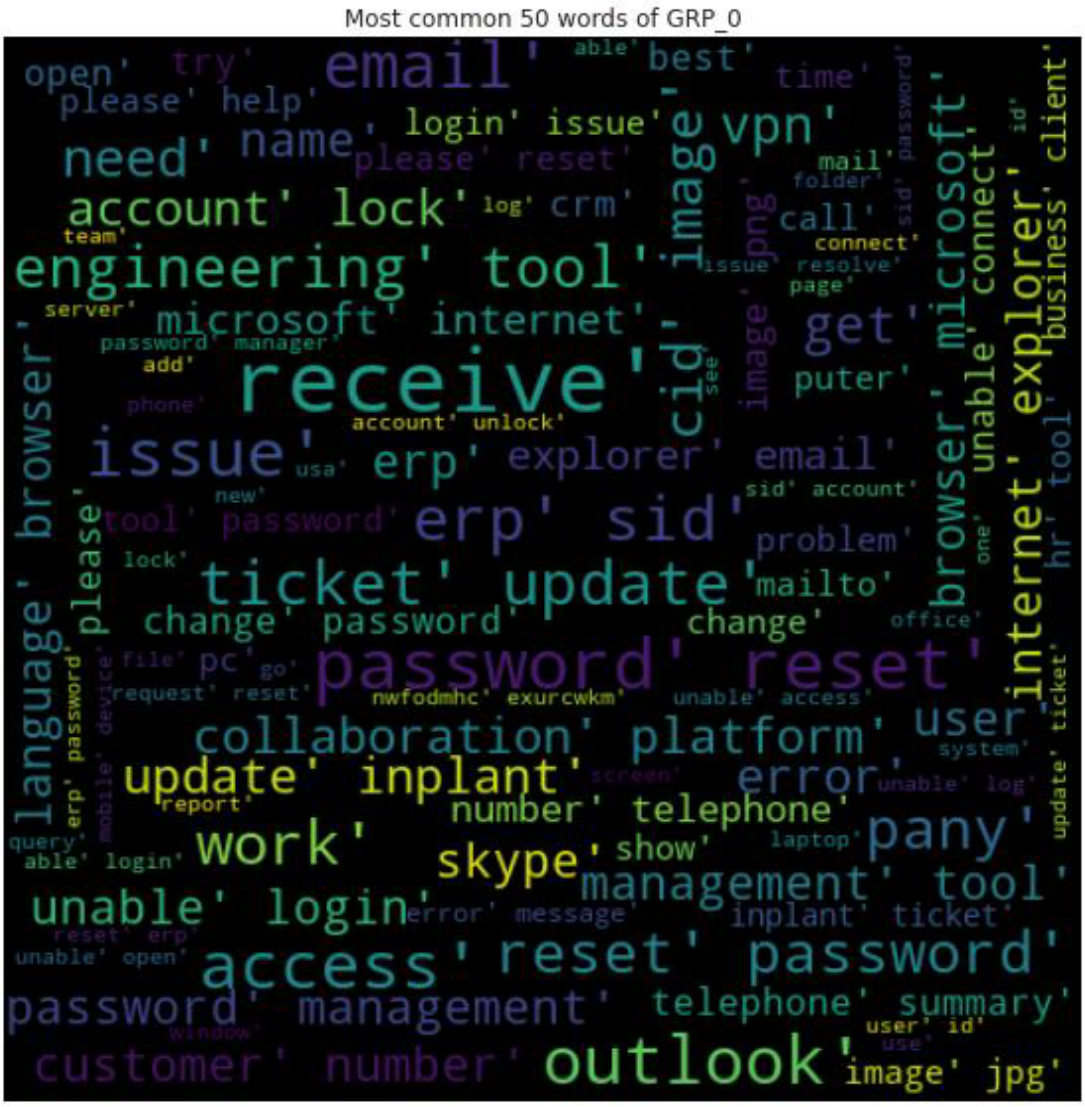
We can see that most of the tickets are in English, followed by tickets in German language.

- Tokenization of merged data
- Stop words have been removed using nltk corpus modules.
- Lemmatization is the process of grouping together the different inflected forms of a word so they can be analyzed as a single item. Lemmatization is similar to Stemming but it brings context to the words. So, it links words with similar meanings to one word.

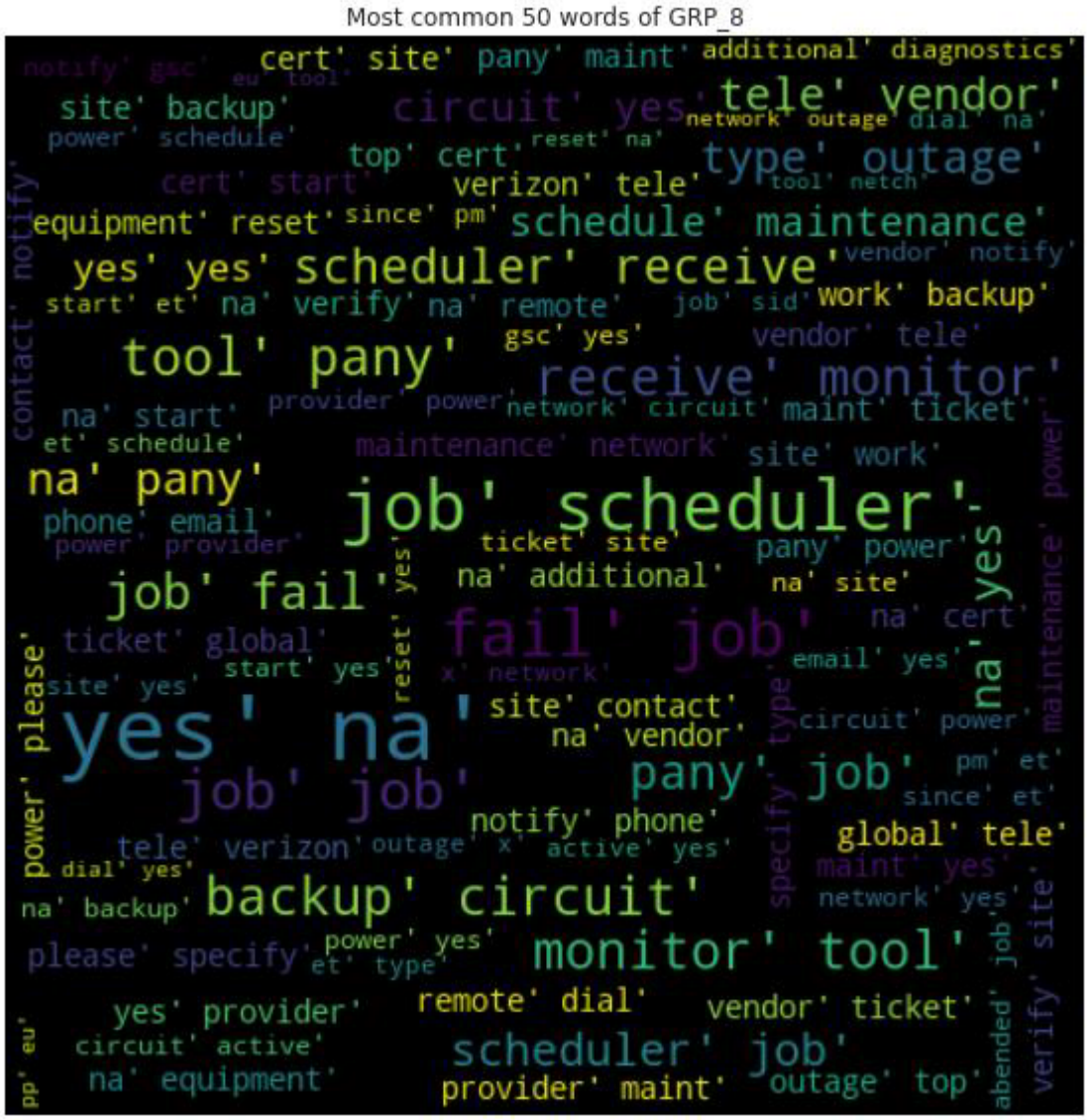
Here we have preferred Lemmatization over Stemming because lemmatization does morphological analysis of the words.

	Short description	Description	Assignment group	New Description	Language	Lemmatized clean
0	login issue	-verified user details.(employee# & manager na...	GRP_0	login issue verified user details employee man...	en	[login, issue, verify, user, detail, employee,...
1	outlook	\r\n\r\nreceived from: hmjdrvpb.komuaywn@gmail...	GRP_0	outlook received from hmjdrvpb komuaywn team m...	en	[outlook, receive, hmjdrvpb, komuaywn, team, m...
2	cant log in to vpn	\r\n\r\nreceived from: eylqgodm.ybqkwiam@gmail...	GRP_0	cannot log in to vpn received from eylqgodm yb...	en	[log, vpn, receive, eylqgodm, ybqkwiam, log, v...
3	unable to access hr_tool page	unable to access hr_tool page	GRP_0	unable to access hr tool page unable to access...	en	[unable, access, hr, tool, page, unable, acces...
4	skype error	skype error	GRP_0	skype error skype error	no	[skype, error, skype, error]

- WordCloud created for all available 50 groups to have more information specific to Assignment groups



Analysis on GRP_0 which is the most frequent group to assign a ticket reveals that this group deals with mostly the maintenance problems such as password, receive, reset ,outlook, account lock , login issue , ticket update etc.

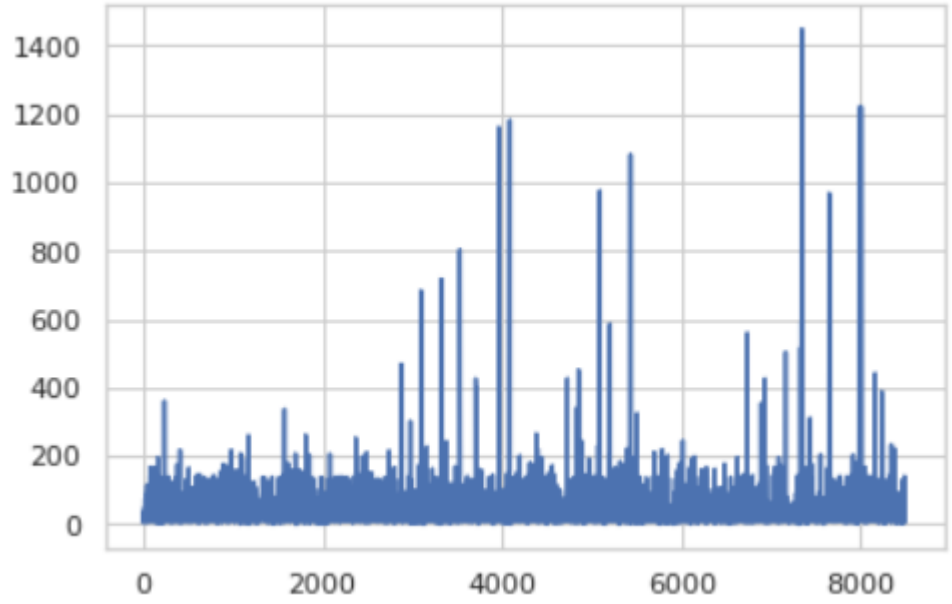


GRP_8 seems to have tickets related to scheduler, job failures, monitoring tool etc.

GRP_24 - Tickets are mainly in German.

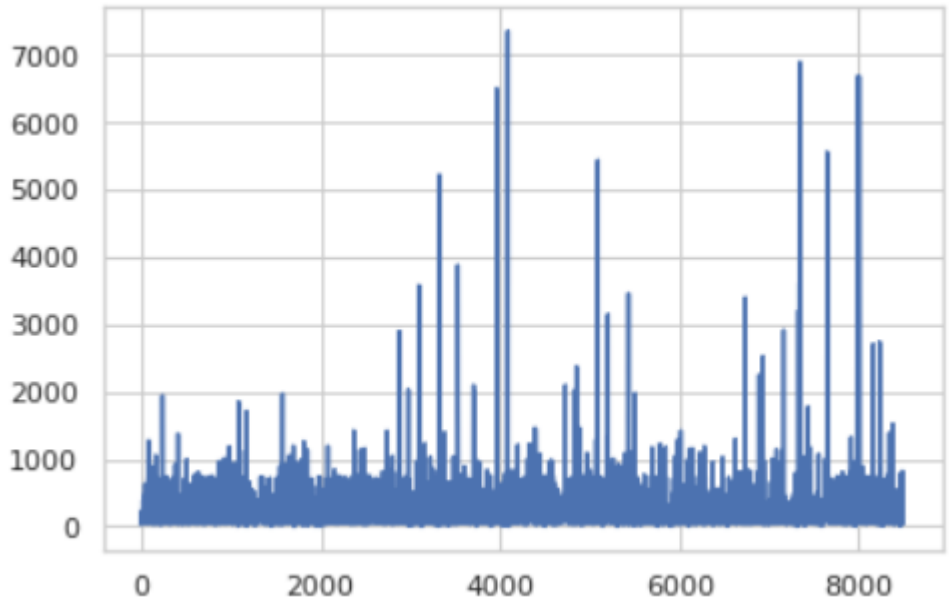
- **Word Count Distribution**

The distribution of the words in the concatenated description attribute is as shown below:



- **Distribution Of The Length**

The distribution of the length of the concatenated description attribute has been shown below:



- The distribution of top unigrams before removing stop words for Concatenated Description is as shown below:

```
to 8248
the 6856
in 5155
job 4952
from 3545
is 3526
no 2991
not 2948
on 2935
pany 2755
and 2687
for 2626
tool 2611
at 2466
received 2363
please 2181
yes 2027
na 2022
password 1950
scheduler 1888
```

- The distribution of top unigrams after removing stop words for concatenated Description is as shown below:

```
job 4952
pany 2755
tool 2611
received 2363
yes 2027
na 2022
password 1950
scheduler 1888
erp 1852
failed 1695
sid 1440
access 1413
user 1382
unable 1281
issue 1242
reset 1209
ticket 1196
error 983
hostname 981
monitoring 976
```

- The distribution of top bigrams after removing stop words for Concatenated Description is as shown below:

```
job scheduler 1888
failed job 1574
yes na 1570
job job 1240
monitoring tool 967
tool pany 953
received monitoring 939
job failed 920
scheduler received 783
pany job 765
password reset 488
cid image 478
backup circuit 441
engineering tool 409
erp sid 357
collaboration platform 338
tele vendor 325
abended job 300
ticket update 294
na pany 290
```

- The distribution of top trigrams after removing stop words for Concatenated Description is as shown below:

```
failed job scheduler 1574
received monitoring tool 939
monitoring tool pany 939
job job failed 918
job failed job 918
job scheduler received 783
scheduler received monitoring 783
tool pany job 765
pany job job 454
job job scheduler 300
abended job job 298
yes na pany 285
na yes na 285
cid image png 270
password management tool 255
backup circuit yes 242
yes yes na 231
cid image jpg 208
src inside dst 185
access group acl 185
```

Model Selection

Modeling:

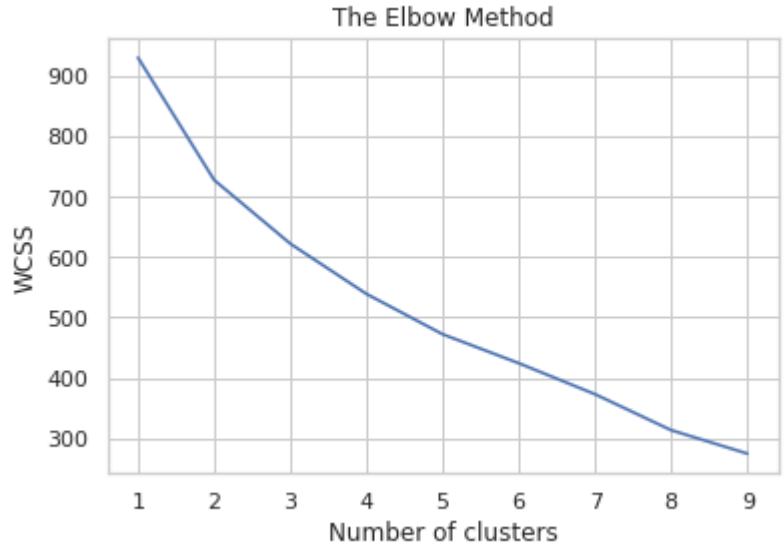
As the target class is completely skewed, various models have been tried with the below set of datasets to compare each performance. Datasets used for each model are:

- Raw data with the target class without any sampling
- Resampled data where all the Grp_0 has been subdivided on the basis of cluster analysis and clubbed with the rest of the dataset.
- Resampled data where all the groups(except Grp_0) has been are sampled with a count of 645 and clubbed with the subdivided dataset for Grp_0.

K-Means Clustering:

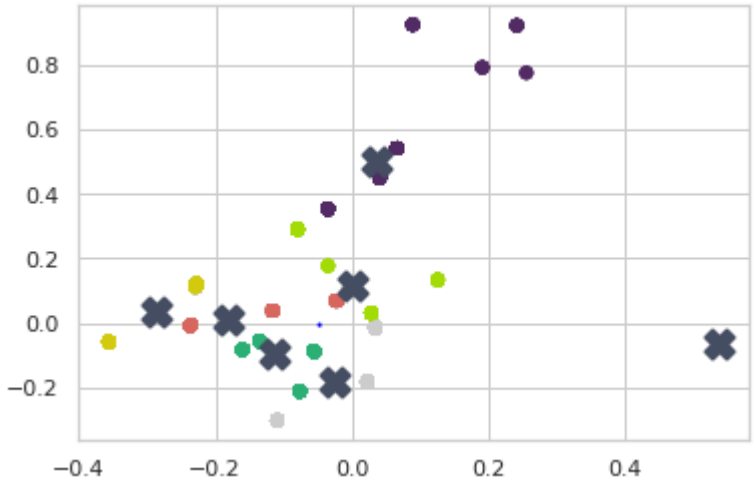
K-means clustering is one of the simplest and popular unsupervised machine learning algorithms. In this method, the K-means algorithm identifies the k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. In cluster analysis, the elbow method is a heuristic used in determining the number of clusters in a data set. The method consists of plotting the explained variation as a function of the number of clusters, and picking the elbow of the curve as the number of clusters to use. The same method can be used to choose the number of parameters in other data-driven models, such as the number of principal components to describe a data set.

The elbow plot for the unsampled data is as shown below:

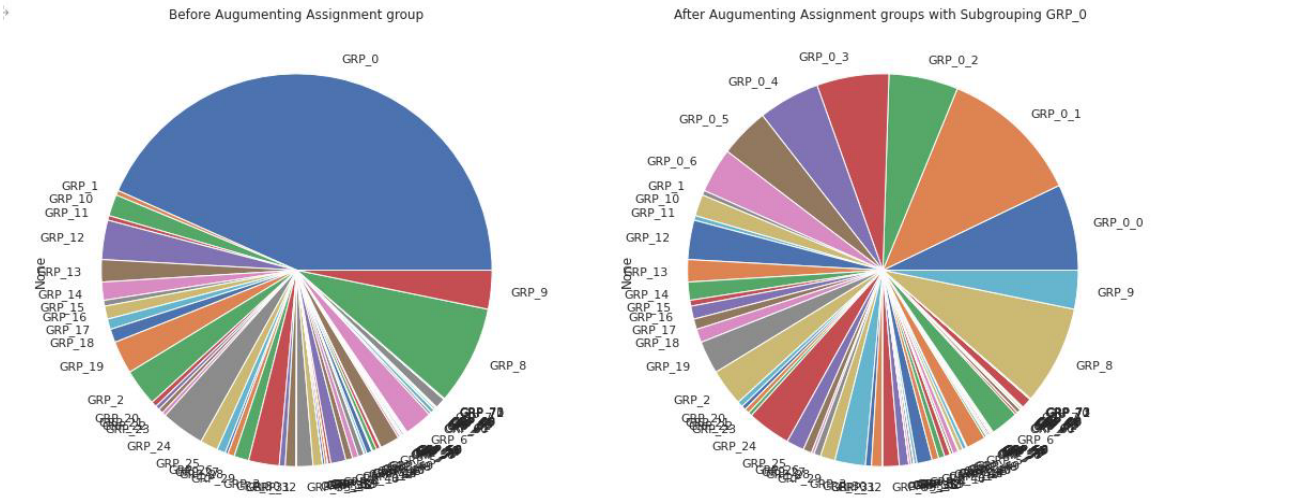


From this plot, we have taken the number of clusters to be 7.

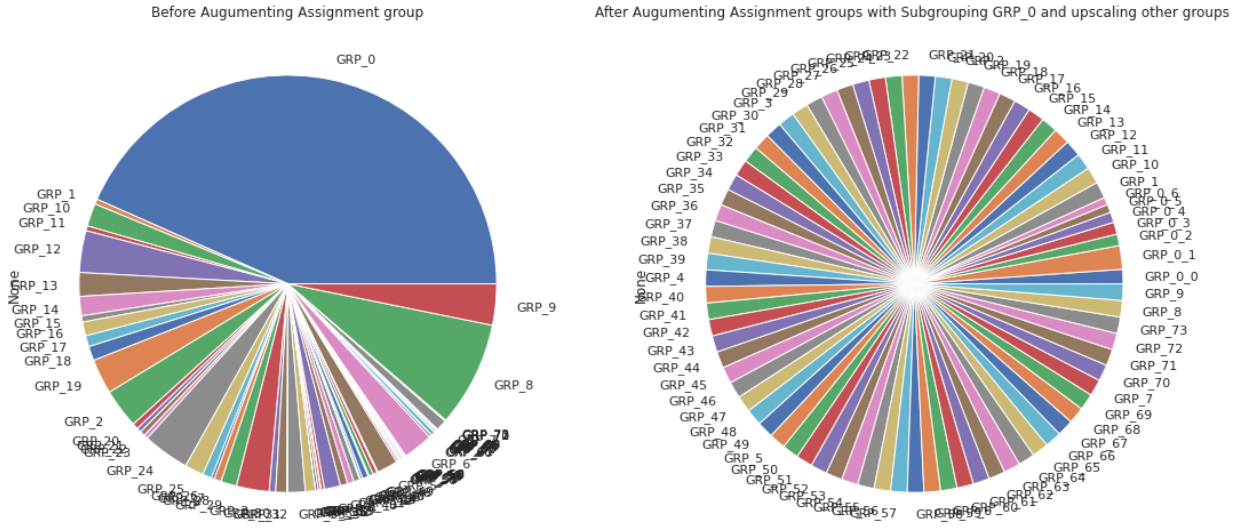
The centroids of the clusters has been visualized as shown below:



On the basis of cluster analysis, Grp_0 has been subdivided into 7 sub-groups and then clubbed with the rest of the dataset. This has been visualized as shown below:



Now, another dataset was prepared in which the rest groups(except Grp_0) has been up-sampled and then clubbed with the subdivided Grp_0 dataset. It has been visualized as shown below:



Defining independent and dependent features

We are concatenating the Short description and Description as “New_Description”.

“New_Description” is considered as an **Independent attribute** and Target – “Assignment group” is a **Dependent attribute**.

Splitting Datasets

We have used the train_test_split function for splitting a single dataset into training and testing in 70:30 ratios.

The testing subset is for building the model. The testing subset is for using the model on unknown data to evaluate the performance of the model.

Machine Learning Models

We will be using classification algorithms, to start with we have used below basic Machine Learning algorithm:

RANDOM FOREST CLASSIFIER

Random forest, like its name implies, consists of a large number of individual decision trees that operate as an ensemble. Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction. The fundamental concept behind random forest is a simple but powerful one — the wisdom of crowds. In data science speak, the reason that the random forest model works so well is:

A large number of relatively uncorrelated models (trees) operating as a committee will outperform any of the individual constituent models.

Below steps have been performed with the initial model:

- Split the data into training and test sets.
- Feed the data to the Random Classifier Model.
- Find the accuracy.

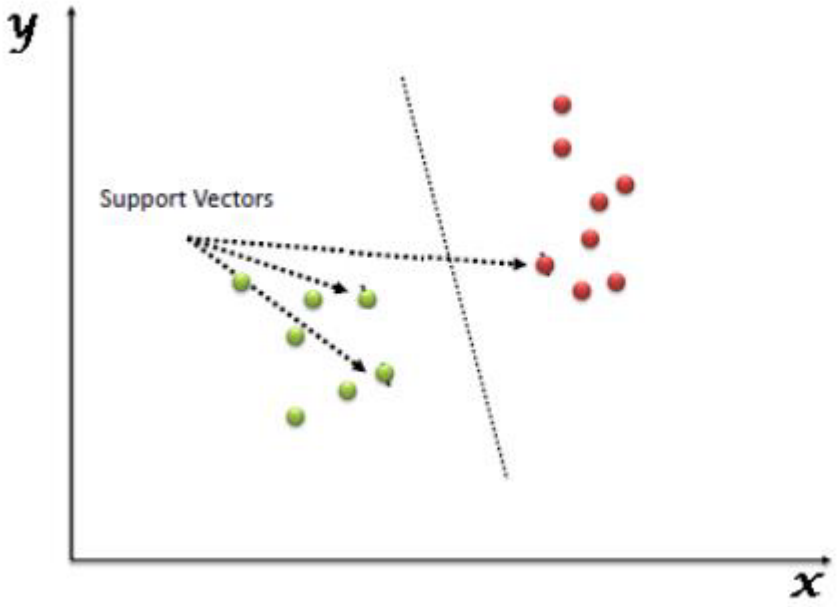
```
Random forest classifier accuracy: 0.5739570164348925
```

Bag of Words

The bag-of-words model is a simplifying representation used in natural language processing and information retrieval. In this model, a text is represented as the bag of its words, disregarding grammar and even word order but keeping multiplicity.

SUPPORT VECTOR MACHINE

"Support Vector Machine" (SVM) is a supervised machine learning algorithm which can be used for both classification or regression challenges. However, it is mostly used in classification problems. In the SVM algorithm, we plot each data item as a point in n-dimensional space (where n is the number of features you have) with the value of each feature being the value of a particular coordinate. Then, we perform classification by finding the hyper-plane that differentiates the two classes very well (as shown in the below snapshot).



Below steps have been performed with the initial model:

- Split the data into training and test set using Bag of words.
- Feed the data to the Support vector Classifier Model.
- Find the accuracy.

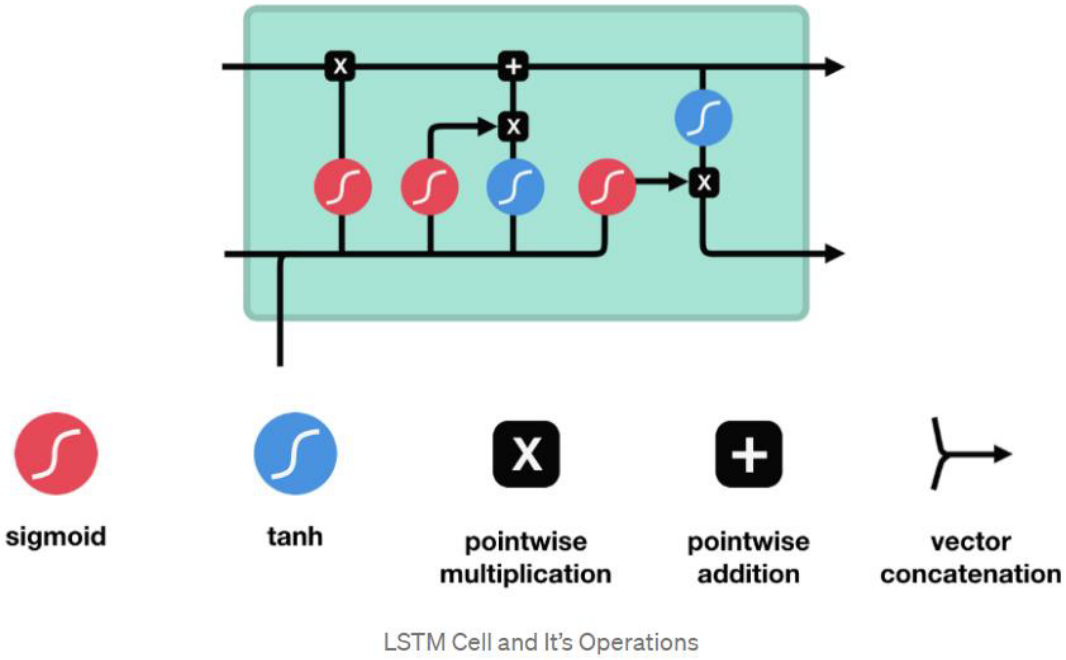
```
SVM-Linear Score for BoW Model is  0.627897176569743
SVM F1 Score for BoW Model is  0.6124185889559783
```

Accuracy result for the sampled data(when only Grp_0 has been resampled)

```
SVM-Linear Score for sampled Model is  0.22187104930467763
SVM F1 Score for sampled Model is  0.23639178929623778
```

LSTM

Long Short-Term Memory (LSTM) networks are a type of recurrent neural network capable of learning order dependence in sequence prediction problems. An LSTM has a similar control flow as a recurrent neural network. It processes data passing on information as it propagates forward. The differences are the operations within the LSTM's cells.



LSTM Cell and It's Operations

These operations are used to allow the LSTM to keep or forget information.

Observation :

LSTM with unsampled data:

Model:

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 300)]             0
_________________________________________________________________
embedding (Embedding)        (None, 300, 128)          1969792
_________________________________________________________________
lstm (LSTM)                  (None, 64)                49408
_________________________________________________________________
dense (Dense)                (None, 32)                2080
_________________________________________________________________
dense_1 (Dense)              (None, 74)                2442
=================================================================
Total params: 2,023,722
Trainable params: 2,023,722
Non-trainable params: 0
```

Model Accuracy:

```
0.5663716814159292
```

LSTM with sampled data(when only Grp_0 has been resampled):

Model:

```
Model: "functional_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_4 (InputLayer)         [(None, 300)]             0
_________________________________________________________________
embedding_3 (Embedding)      (None, 300, 128)          1969792
_________________________________________________________________
lstm_3 (LSTM)                (None, 64)                49408
_________________________________________________________________
dense_6 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_7 (Dense)              (None, 80)                2640
=================================================================
Total params: 2,023,920
Trainable params: 2,023,920
Non-trainable params: 0
```

Model Accuracy:

```
0.3282764433206911
```

LSTM with sampled data(when only rest groups (except Grp_0) has been resampled and clubbed with the subdivided groups of Grp_0)

Model:

```
Model: "functional_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_5 (InputLayer)         [(None, 300)]             0
_________________________________________________________________
embedding_4 (Embedding)      (None, 300, 128)          1969792
_________________________________________________________________
lstm_4 (LSTM)                (None, 64)                49408
_________________________________________________________________
dense_8 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_9 (Dense)              (None, 80)                2640
=================================================================
Total params: 2,023,920
Trainable params: 2,023,920
Non-trainable params: 0
```

Model Accuracy:

```
0.8918508742989113
```

Word Embedding

As all our Machine Learning and Deep learning algorithms are incapable of processing strings or plain text in their raw form, word embeddings are used to convert the texts into numbers. There may be different numerical representations of the same text. It tries to map a word using a dictionary to a vector.
We have experimented below 2 types of embedding in our models with the dimension as 100.

1. **Word2Vector Embedding:**

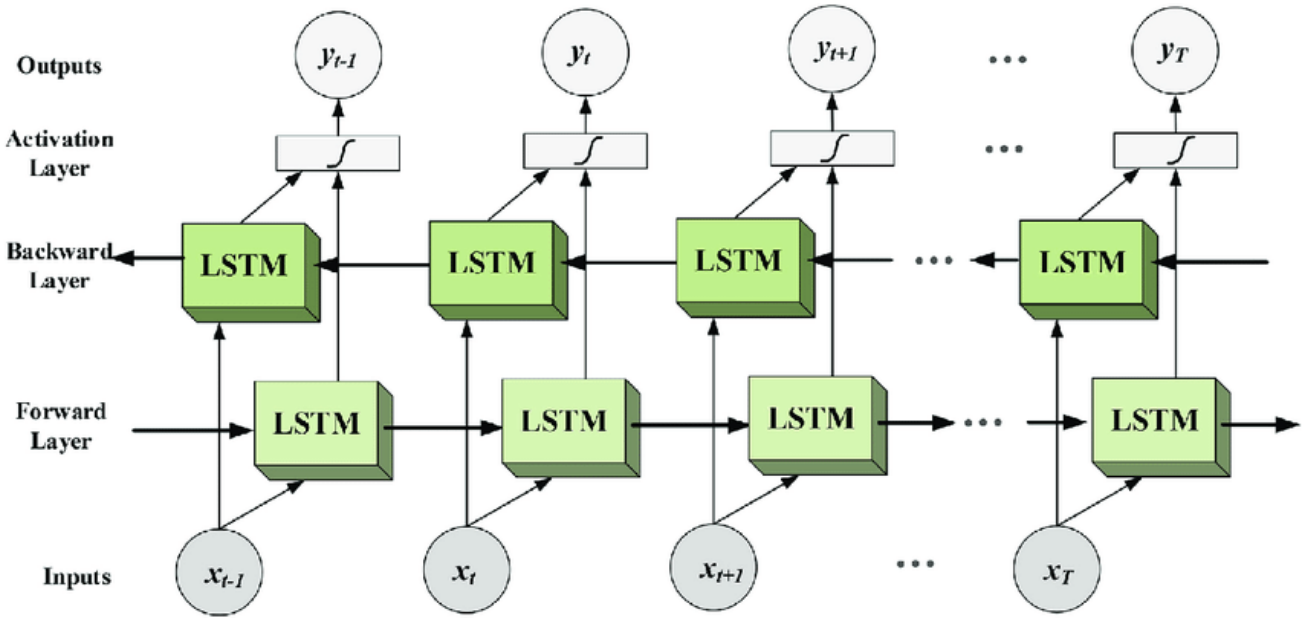
Word2Vec models are shallow, two-layer neural networks that are trained to reconstruct linguistic contexts of words. Word2vec takes as its input a large corpus of text and produces a vector space, typically of several hundred dimensions, with each unique word in the corpus being assigned a corresponding vector in the space.

2. **GloVe (Global Vectors) Embedding:**

GloVe is an unsupervised learning algorithm for obtaining vector representations for words. Training is performed on aggregated global word-word co-occurrence statistics from a corpus, and the resulting representations showcase interesting linear substructures of the word vector space.

Bi-directional LSTM Model

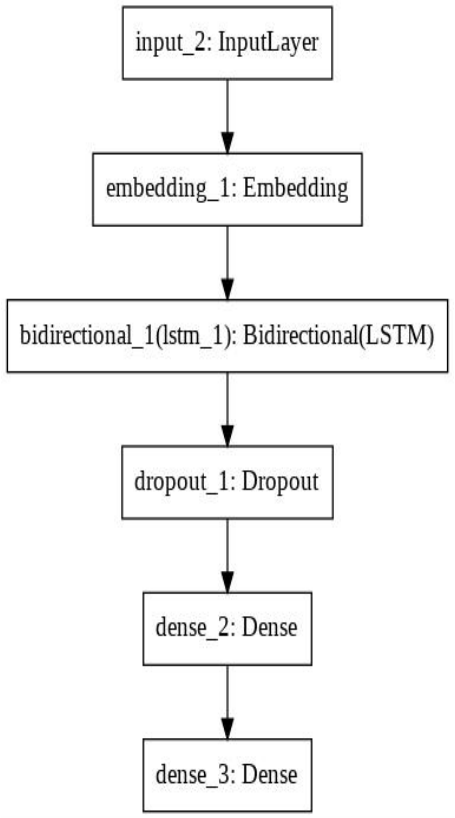
Bidirectional LSTMs are an extension of traditional LSTMs that can improve model performance on classification problems. In problems where all timesteps of the input sequence are available, Bidirectional LSTMs train two instead of one LSTMs on the input sequence. The first on the input sequence as-is and the second on a reversed copy of the input sequence. This can provide additional context to the network and result in faster and even fuller learning on the problem.



Observations:

Bi-LSTM with unsampled data:

Network flow:

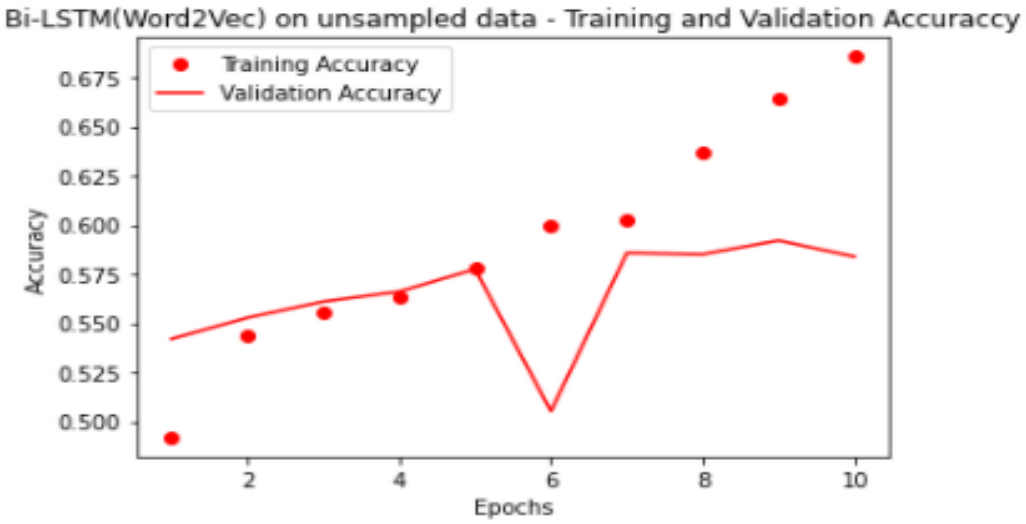


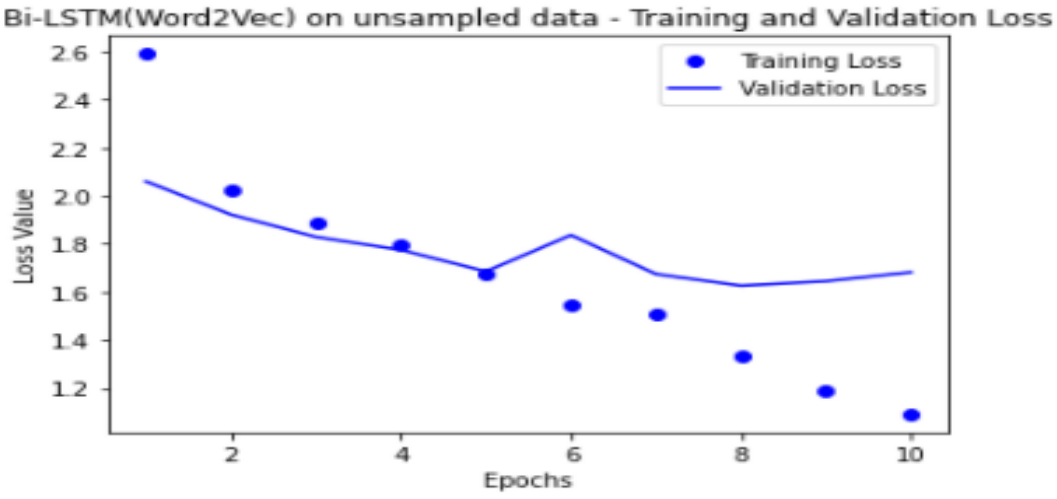
Model:

```
Model: "functional_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 300)]             0
_________________________________________________________________
embedding_1 (Embedding)      (None, 300, 100)          1539000
_________________________________________________________________
bidirectional_1 (Bidirection (None, 256)               234496
_________________________________________________________________
dropout_1 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_2 (Dense)              (None, 100)               25700
_________________________________________________________________
dense_3 (Dense)              (None, 74)                7474
=================================================================
Total params: 1,806,670
Trainable params: 1,806,670
Non-trainable params: 0
_________________________________________________________________
```

Model History:

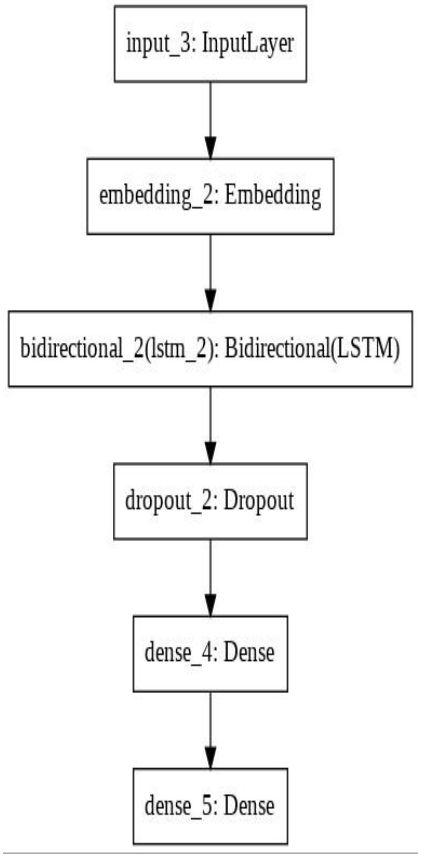
	loss	accuracy	val_loss	val_accuracy	lr
0	2.590919	0.491746	2.059931	0.541878	0.001
1	2.026844	0.543651	1.921705	0.552665	0.001
2	1.884818	0.555238	1.828696	0.560914	0.001
3	1.793860	0.563175	1.774456	0.565990	0.001
4	1.677173	0.578413	1.684860	0.577411	0.001
5	1.546688	0.599841	1.836435	0.505076	0.001
6	1.505949	0.602063	1.673810	0.585660	0.001
7	1.329751	0.637143	1.625634	0.585025	0.001
8	1.186250	0.664127	1.644304	0.592005	0.001
9	1.090733	0.685714	1.681478	0.583756	0.001





Bi-LSTM(Word2Vec) on sampled data:

Network flow:



Model:

```
Model: "functional_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_3 (InputLayer)         [(None, 300)]             0
_________________________________________________________________
embedding_2 (Embedding)      (None, 300, 100)          1234400
_________________________________________________________________
bidirectional_2 (Bidirection (None, 256)               234496
_________________________________________________________________
dropout_2 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_4 (Dense)              (None, 100)               25700
_________________________________________________________________
dense_5 (Dense)              (None, 75)                7575
=================================================================
Total params: 1,502,171
Trainable params: 1,502,171
Non-trainable params: 0
_________________________________________________________________
```

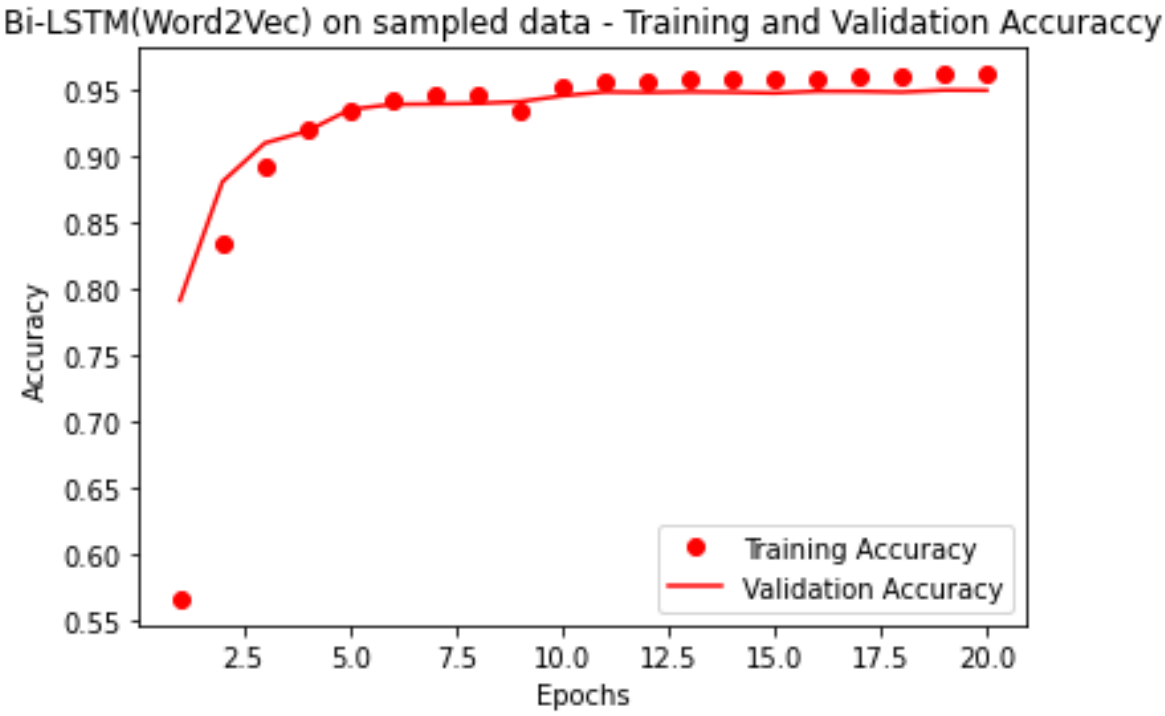
Sample Class Level accuracies:

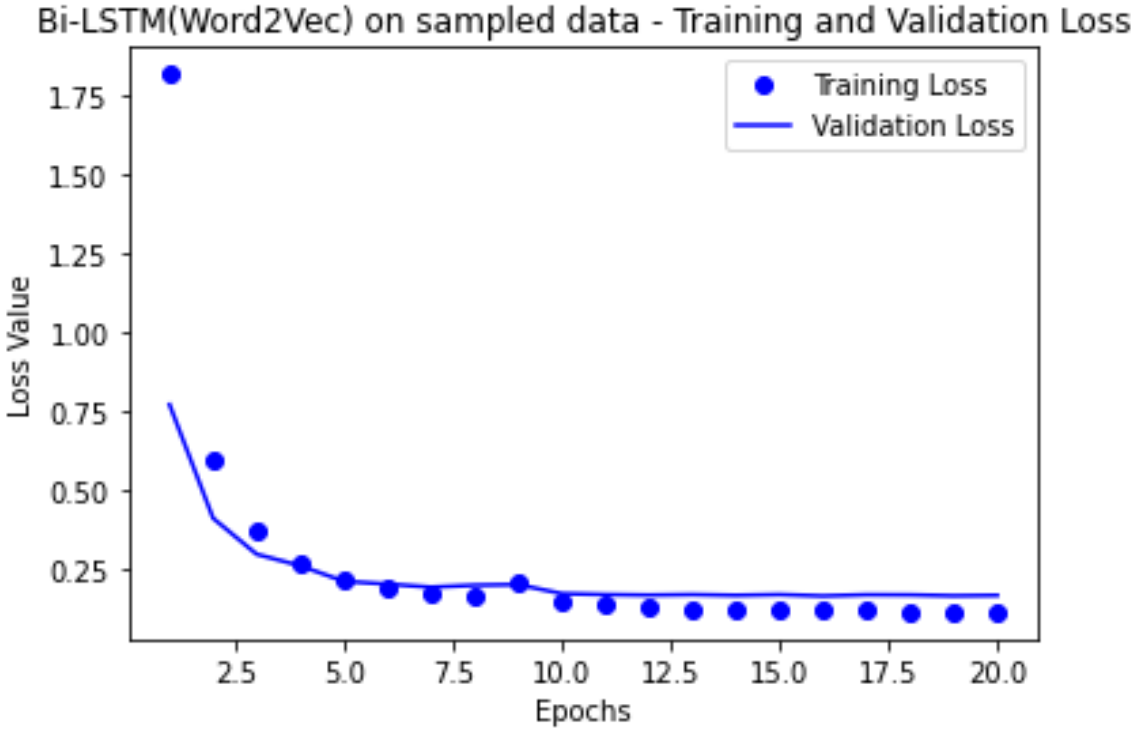
Classification Report

	precision	recall	f1-score	support
GRP_0	0.86	0.62	0.72	208
GRP_1	0.88	1.00	0.94	196
GRP_3	0.99	0.91	0.95	206
GRP_4	0.98	1.00	0.99	179
GRP_5	0.93	0.85	0.89	207
GRP_6	0.99	0.93	0.96	203
GRP_7	0.96	0.99	0.97	196
GRP_8	1.00	1.00	1.00	191
GRP_9	0.97	1.00	0.98	200
GRP_10	0.99	1.00	1.00	180
GRP_11	0.99	0.97	0.98	182
GRP_12	0.94	0.92	0.93	200
GRP_13	0.87	0.90	0.88	179
GRP_14	1.00	1.00	1.00	194
GRP_15	1.00	1.00	1.00	187
GRP_16	0.98	1.00	0.99	191
GRP_17	0.99	1.00	0.99	210
GRP_18	1.00	0.97	0.99	180
GRP_19	0.98	0.99	0.99	175
GRP_2	0.98	1.00	0.99	208
GRP_20	0.99	1.00	1.00	194
GRP_21	0.95	1.00	0.97	195
GRP_22	0.99	0.96	0.97	190
GRP_23	0.91	0.96	0.93	164
GRP_24	0.97	0.90	0.93	200
GRP_25	0.99	0.96	0.98	221
GRP_26	1.00	1.00	1.00	192
GRP_27	0.96	0.98	0.97	219
GRP_28	0.97	0.98	0.97	182
GRP_29	1.00	1.00	1.00	172
GRP_30	1.00	1.00	1.00	183
GRP_31	1.00	1.00	1.00	198
GRP_33	1.00	1.00	1.00	179
GRP_34	0.98	1.00	0.99	213
GRP_35	0.97	0.95	0.96	197
GRP_36	0.99	1.00	0.99	191

Model Summary:

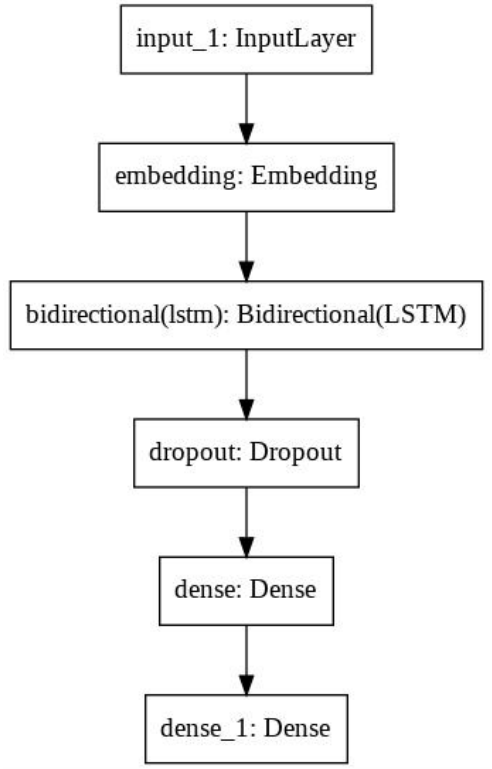
	loss	accuracy	val_loss	val_accuracy	lr
0	1.820108	0.566999	0.771188	0.791885	0.0010
1	0.599273	0.833947	0.410437	0.881277	0.0010
2	0.371160	0.891952	0.296099	0.910399	0.0010
3	0.270763	0.919817	0.259521	0.919478	0.0010
4	0.216182	0.934812	0.210211	0.935680	0.0010
5	0.187062	0.941905	0.201337	0.939591	0.0010
6	0.171066	0.946604	0.191683	0.939870	0.0010
7	0.167370	0.947442	0.197675	0.940289	0.0010
8	0.207073	0.934872	0.199867	0.941616	0.0010
9	0.146212	0.952890	0.171111	0.945946	0.0002
10	0.133810	0.956092	0.168065	0.948949	0.0002
11	0.130367	0.957439	0.166273	0.948600	0.0002
12	0.124093	0.958936	0.167935	0.949019	0.0002
13	0.122936	0.958816	0.165489	0.948739	0.0002
14	0.121579	0.959624	0.168001	0.948111	0.0002
15	0.120823	0.959474	0.163602	0.949438	0.0002
16	0.117007	0.960791	0.167374	0.949368	0.0002
17	0.115380	0.960193	0.166939	0.948809	0.0002
18	0.112731	0.961779	0.164172	0.950276	0.0001
19	0.112321	0.962288	0.165474	0.950136	0.0001


Bi-LSTM(Word2Vec) on sampled data - Training and Validation Accuraccy
Accuracy
Epochs
Training Accuracy
Validation Accuracy
0.55
0.60
0.65
0.70
0.75
0.80
0.85
0.90
0.95
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0


Bi-LSTM(Word2Vec) on sampled data - Training and Validation Loss
Loss Value
Epochs
Training Loss
Validation Loss
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

Bi-LSTM(Glove) on sampled data:

Network flow:



Model:

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 300)]             0
_________________________________________________________________
embedding (Embedding)        (None, 300, 100)          1234400
_________________________________________________________________
bidirectional (Bidirectional (None, 256)               234496
_________________________________________________________________
dropout (Dropout)            (None, 256)               0
_________________________________________________________________
dense (Dense)                (None, 100)               25700
_________________________________________________________________
dense_1 (Dense)              (None, 75)                7575
=================================================================
Total params: 1,502,171
Trainable params: 1,502,171
Non-trainable params: 0
_________________________________________________________________
```

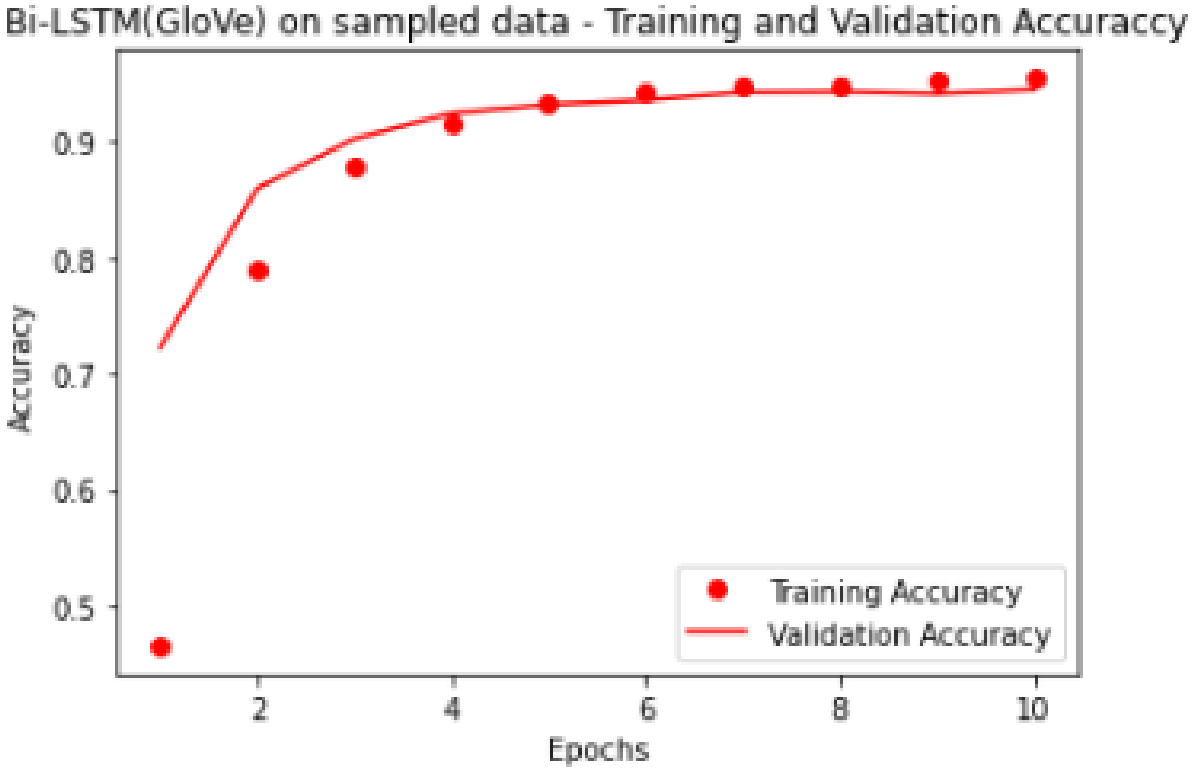
Sample Class Level accuracies:

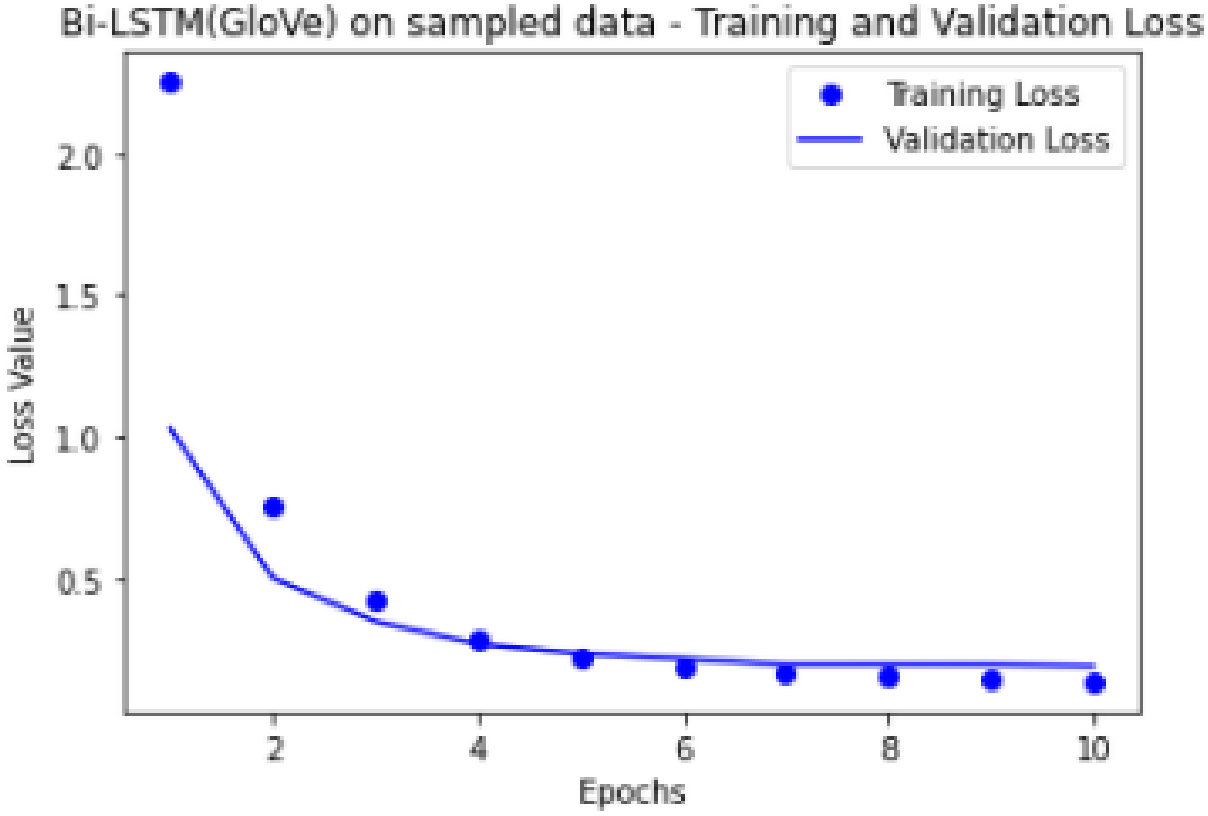
Classification Report

	precision	recall	f1-score	support
GRP_0	0.77	0.51	0.61	207
GRP_1	0.89	1.00	0.94	192
GRP_3	0.98	0.85	0.91	196
GRP_4	0.98	1.00	0.99	195
GRP_5	0.97	0.84	0.90	199
GRP_6	1.00	0.98	0.99	188
GRP_7	0.99	0.96	0.97	186
GRP_8	1.00	1.00	1.00	173
GRP_9	0.97	1.00	0.98	198
GRP_10	0.99	1.00	1.00	191
GRP_11	0.98	0.95	0.97	175
GRP_12	0.97	0.84	0.90	180
GRP_13	0.83	0.89	0.86	197
GRP_14	0.99	1.00	1.00	189
GRP_15	1.00	1.00	1.00	202
GRP_16	0.98	1.00	0.99	197
GRP_17	0.98	1.00	0.99	188
GRP_18	0.97	0.95	0.96	194
GRP_19	0.99	1.00	0.99	205
GRP_2	0.99	1.00	0.99	198
GRP_20	0.98	1.00	0.99	200
GRP_21	0.94	1.00	0.97	202
GRP_22	0.98	0.97	0.97	193
GRP_23	0.87	0.94	0.90	186
GRP_24	0.99	0.91	0.95	192
GRP_25	0.97	0.93	0.95	182
GRP_26	0.99	1.00	1.00	198
GRP_27	0.95	0.94	0.95	202
GRP_28	0.97	0.98	0.98	202
GRP_29	1.00	1.00	1.00	181
GRP_30	0.99	1.00	0.99	193
GRP_31	1.00	1.00	1.00	187
GRP_33	1.00	1.00	1.00	203
GRP_34	0.99	0.97	0.98	202
GRP_35	0.98	0.96	0.97	192
GRP_36	0.98	1.00	0.99	205
GRP_37	1.00	1.00	1.00	207
GRP_38	0.98	1.00	0.99	193

Model Summary:

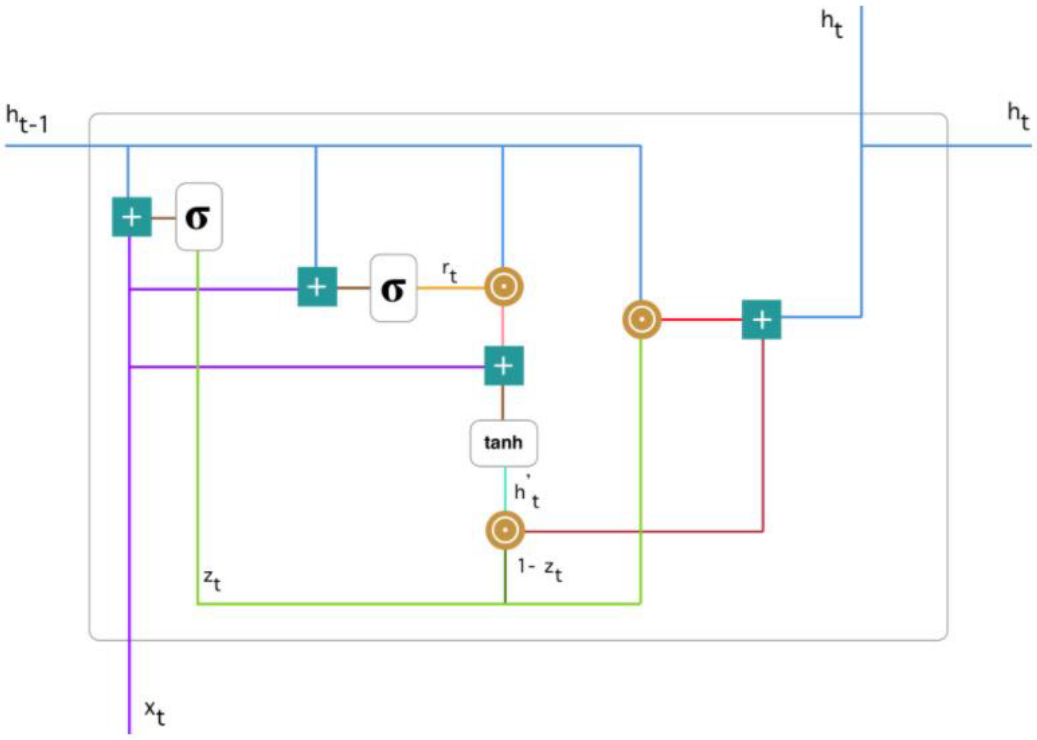
	loss	accuracy	val_loss	val_accuracy	lr
0	2.251849	0.465386	1.028216	0.722257	0.001
1	0.754033	0.790249	0.501520	0.859557	0.001
2	0.419844	0.878334	0.349133	0.902437	0.001
3	0.281623	0.916285	0.268246	0.924227	0.001
4	0.222347	0.932537	0.236002	0.931909	0.001
5	0.187849	0.942684	0.217934	0.935680	0.001
6	0.167533	0.947652	0.197007	0.942384	0.001
7	0.160648	0.948610	0.197122	0.943152	0.001
8	0.145717	0.952770	0.196685	0.941057	0.001
9	0.136313	0.954656	0.191815	0.944898	0.001


Bi-LSTM(GloVe) on sampled data - Training and Validation Accuraccy
Accuracy
0.9
0.8
0.7
0.6
0.5
2
4
6
8
10
Epochs
Training Accuracy
Validation Accuracy


Bi-LSTM(GloVe) on sampled data - Training and Validation Loss
Loss Value
2.0
1.5
1.0
0.5
2
4
6
8
10
Epochs
Training Loss
Validation Loss

GRU

GRU (Gated Recurrent Unit) aims to solve the **vanishing gradient problem** which comes with a standard recurrent neural network. GRU can also be considered as a variation on the LSTM because both are designed similarly and, in some cases, produce equally excellent results. To solve the vanishing gradient problem of a standard RNN, GRU uses, so-called, **update gate and reset gate**. Basically, these are two vectors which decide what information should be passed to the output. The special thing about them is that they can be trained to keep information from long ago, without washing it through time or remove information which is irrelevant to the prediction. Detailed version of a single GRU is as shown below:



Gated Recurrent Unit

where the notations are as follows:

Update Gate: The update gate acts similar to the forget and input gate of an LSTM. It decides what information to throw away and what new information to add.

Reset Gate: The reset gate is another gate used to decide how much past information to forget.

GRU's has fewer tensor operations; therefore, they are a little speedier to train than LSTM's.

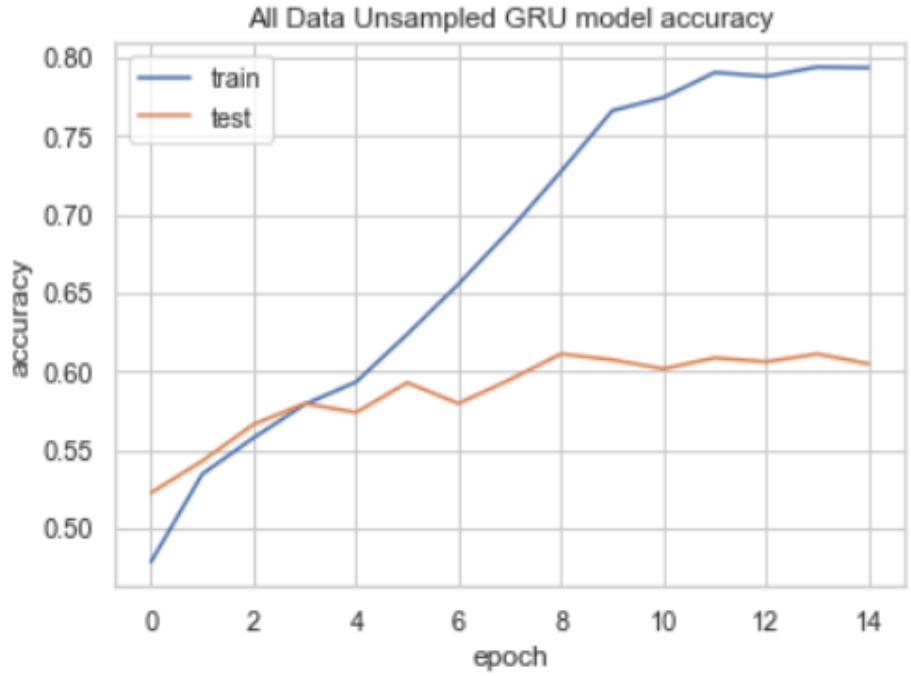
<u>GRU with unsampled data:</u>

Model:

```
Model: "functional_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 150)]             0
_________________________________________________________________
embedding (Embedding)        (None, 150, 100)          900100
_________________________________________________________________
gru (GRU)                    (None, 128)               88320
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense (Dense)                (None, 100)               12900
_________________________________________________________________
dense_1 (Dense)              (None, 74)                7474
=================================================================
Total params: 1,008,794
Trainable params: 1,008,794
Non-trainable params: 0
_________________________________________________________________
```

```
Accuracy of the model : 0.6049304677623262
```

Graphical representation of model accuracy and loss is as shown below:



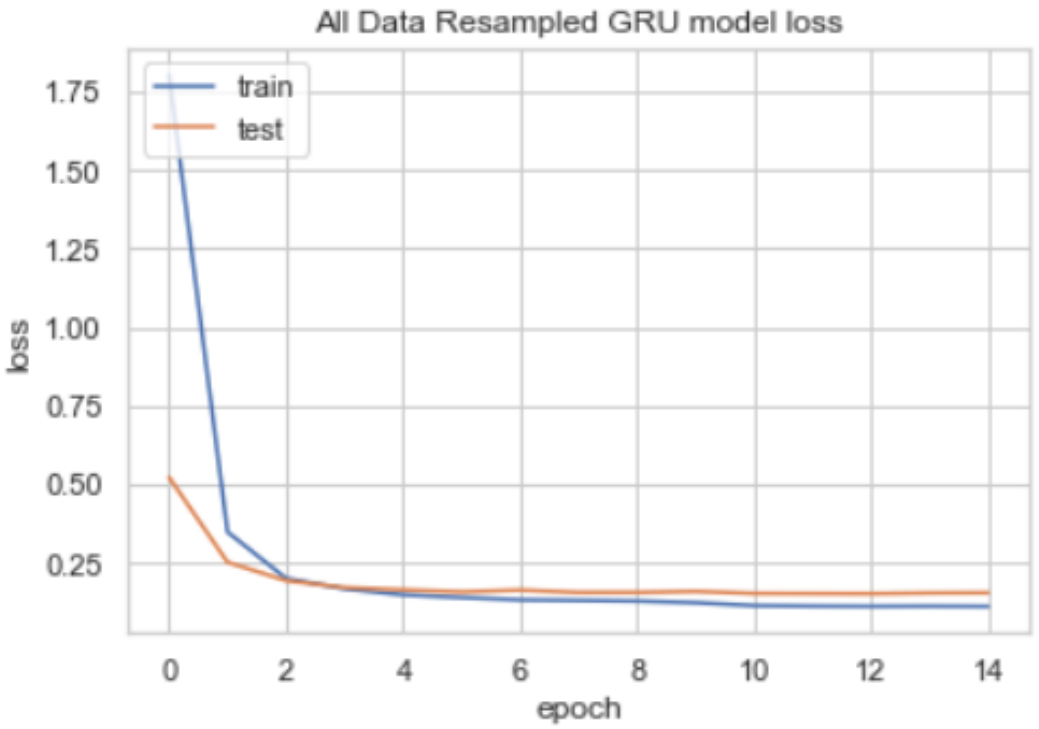
GRU with sampled data:

Model:

```
Model: "functional_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         [(None, 150)]             0
_________________________________________________________________
embedding_1 (Embedding)      (None, 150, 100)          900100
_________________________________________________________________
gru_1 (GRU)                  (None, 128)               88320
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_2 (Dense)              (None, 100)               12900
_________________________________________________________________
dense_3 (Dense)              (None, 75)                7575
=================================================================
Total params: 1,008,895
Trainable params: 1,008,895
Non-trainable params: 0
_________________________________________________________________
```

Accuracy of the model : 0.9492567567567568

Graphical representation of model accuracy and loss is as shown below:



BERT (language model)

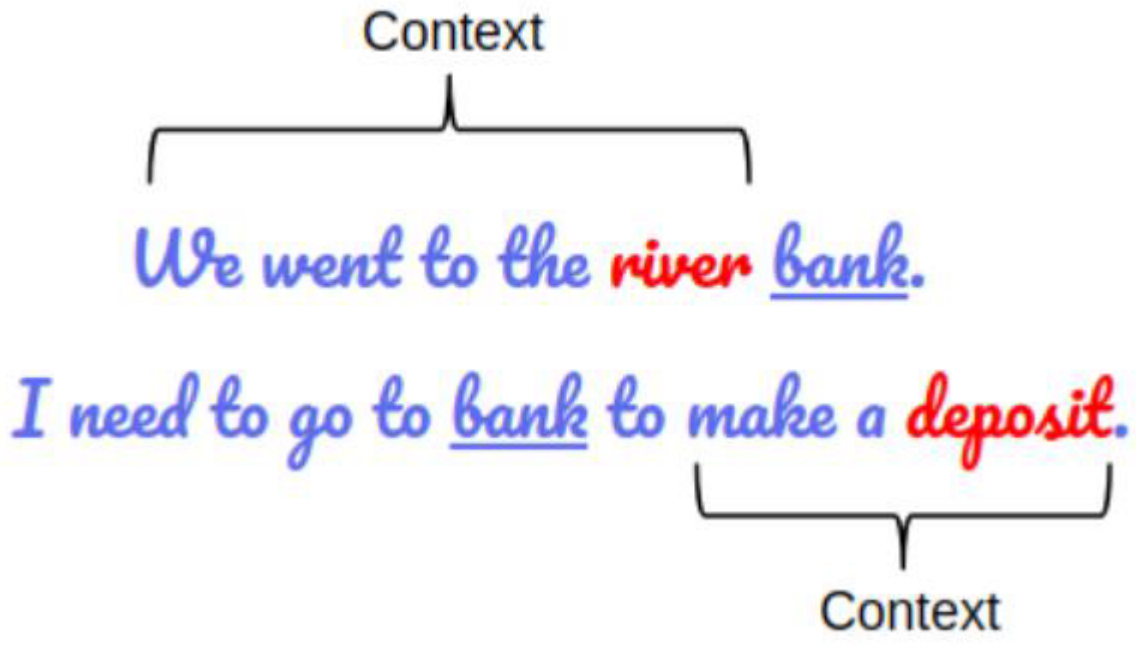
BERT is an open source machine learning framework for natural language processing (NLP). BERT is designed to help computers understand the meaning of ambiguous language in text by using surrounding text to establish context. The BERT framework was pre-trained using text from Wikipedia and can be fine-tuned with question and answer datasets.

BERT, which stands for Bidirectional Encoder Representations from Transformers, is based on Transformers, a deep learning model in which every output element is connected to every input element, and the weightings between them are dynamically calculated based upon their connection.

BERT is pre-trained on a large corpus of unlabelled text including the entire Wikipedia(that's 2,500 million words!) and Book Corpus (800 million words).

BERT is a **"deeply bidirectional"** model. Bidirectional means that BERT learns information from both the left and the right side of a token's context during the training phase.

The bidirectionality of a model is important for truly understanding the meaning of a language. Let's see an example to illustrate this. There are two sentences in this example and both of them involve the word "bank":

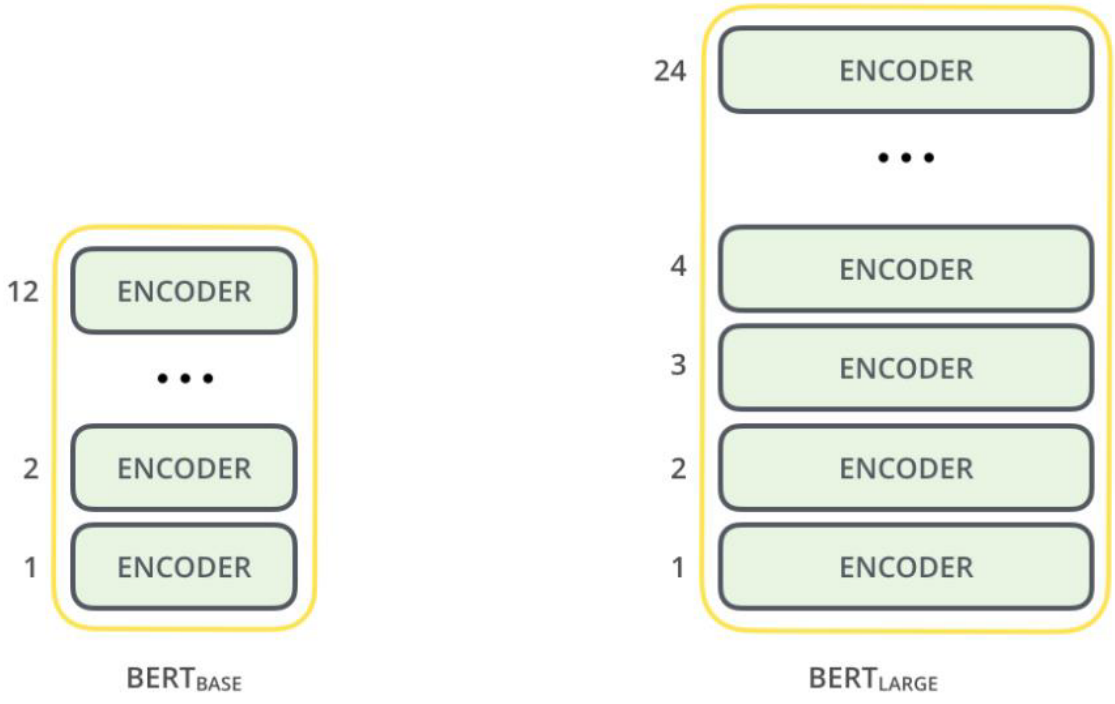


If we try to predict the nature of the word “bank” by only taking either the left or the right context, then we will be making an error in at least one of the two given examples.

One way to deal with this is to consider both the left and the right context before making a prediction. That’s exactly what BERT does!

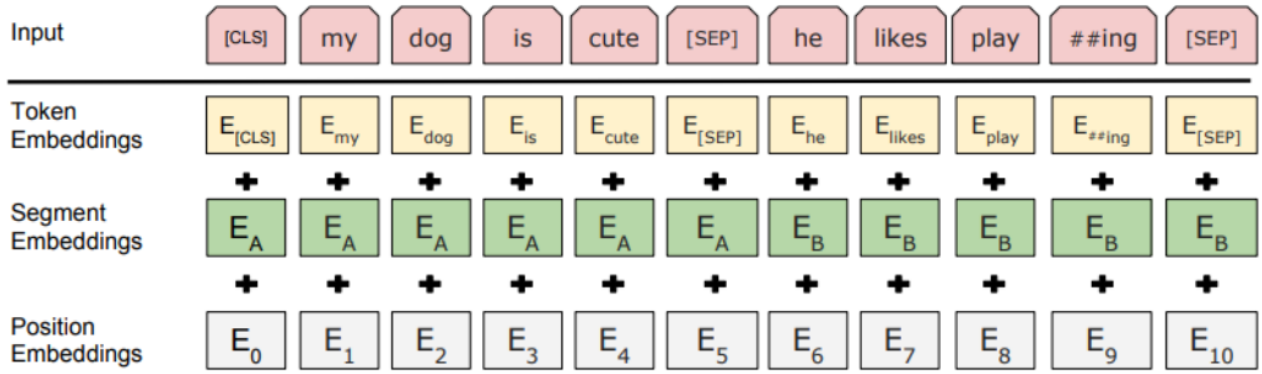
BERT’s Architecture:

The BERT architecture builds on top of Transformer. We currently have two variants available:
• BERT Base: 12 layers (transformer blocks), 12 attention heads, and 110 million parameters
• BERT Large: 24 layers (transformer blocks), 16 attention heads and, 340 million parameters



Both BERT model sizes have a large number of encoder layers (which the paper calls Transformer Blocks) – twelve for the Base version, and twenty-four for the Large version. These also have larger feedforward-networks (768 and 1024 hidden units respectively), and more attention heads (12 and 16 respectively) than the default configuration in the reference implementation of the Transformer in the initial paper (6 encoder layers, 512 hidden units, and 8 attention heads).

Text Pre-processing:



The developers behind BERT have added a specific set of rules to represent the input text for the model. Many of these are creative design choices that make the model even better.

For starters, every input embedding is a combination of 3 embeddings:

1. **Position Embeddings:** BERT learns and uses positional embeddings to express the position of words in a sentence. These are added to overcome the limitation of Transformer which, unlike an RNN, is not able to capture "sequence" or "order" information
2. **Segment Embeddings:** BERT can also take sentence pairs as inputs for tasks (Question-Answering). That's why it learns a unique embedding for the first and the second sentences to help the model distinguish between them. In the above example, all the tokens marked as EA belong to sentence A (and similarly for EB)
3. **Token Embeddings:** These are the embeddings learned for the specific token from the Word Piece token vocabulary.

Such a comprehensive embedding scheme contains a lot of useful information for the model.

These combinations of pre-processing steps make BERT so versatile. This implies that without making any major change in the model's architecture, we can easily train it on multiple kinds of NLP tasks.

Pre-training Tasks

BERT is pre-trained on two NLP tasks:

- Masked Language Modeling
- Next Sentence Prediction

We have implemented BERT for multi class Text Classification using Python

```
def create_model(is_predicting, input_ids, input_mask, segment_ids, labels,
                 num_labels):

  bert_module = hub.Module(
      BERT_MODEL_HUB,
      trainable=True)
  bert_inputs = dict(
      input_ids=input_ids,
      input_mask=input_mask,
      segment_ids=segment_ids)
  bert_outputs = bert_module(
      inputs=bert_inputs,
      signature="tokens",
      as_dict=True)

  # Use "pooled_output" for classification tasks on an entire sentence.
  # Use "sequence_outputs" for token-level output.
  output_layer = bert_outputs["pooled_output"]

  hidden_size = output_layer.shape[-1].value

  # Create our own layer to tune for politeness data.
  output_weights = tf.get_variable(
      "output_weights", [num_labels, hidden_size],
      initializer=tf.truncated_normal_initializer(stddev=0.02))

  output_bias = tf.get_variable(
      "output_bias", [num_labels], initializer=tf.zeros_initializer())

  with tf.variable_scope("loss"):

    # Dropout helps prevent overfitting
    output_layer = tf.nn.dropout(output_layer, keep_prob=0.9)

    logits = tf.matmul(output_layer, output_weights, transpose_b=True)
    logits = tf.nn.bias_add(logits, output_bias)
    log_probs = tf.nn.log_softmax(logits, axis=-1)

    # Convert labels into one-hot encoding
    one_hot_labels = tf.one_hot(labels, depth=num_labels, dtype=tf.float32)

    predicted_labels = tf.squeeze(tf.argmax(log_probs, axis=-1, output_type=tf.int32))
    # If we're predicting, we want predicted labels and the probabiltiies.
    if is_predicting:
      return (predicted_labels, log_probs)

    # If we're train/eval, compute loss between predicted and actual label
    per_example_loss = -tf.reduce_sum(one_hot_labels * log_probs, axis=-1)
    loss = tf.reduce_mean(per_example_loss)
    return (loss, predicted_labels, log_probs)
```

1. With unsampled dataset

```
{'eval_accuracy': 0.6625,
 'false_negatives': 12.0,
 'false_positives': 2.0,
 'global_step': 733,
 'loss': 1.5365076,
 'true_negatives': 26.0,
 'true_positives': 40.0}
```

```
[ ]  out_pred
```

```
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         -2.6131139, -4.720424 , -5.354619 , -6.093379 , -4.389711 ,
         -5.661301 , -5.6110954, -5.3723   , -4.496852 , -5.6328683,
         -5.534894 , -5.3610606, -3.526041 , -4.6718736, -4.5846806,
         -5.6255   , -4.756266 , -4.7809014, -4.664539 , -5.5926285,
         -4.691828 , -5.031889 , -7.145944 , -6.223876 , -6.3596435,
         -5.0710807, -7.3286386, -5.2933726, -5.4655056, -5.5908575,
         -3.7838984, -2.961969 , -5.2152066, -1.9725279, -5.585659 ,
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         -5.4192715, -4.970331 , -5.378592 , -5.538104 , -5.9190135,
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         -5.5652304, -5.4079065, -6.1259947, -6.1167316, -5.700666 ,
         -5.4698257, -5.829477 , -6.0159287, -6.200753 , -5.618051 ,
         -5.891215 , -6.1349683, -5.965239 , -5.939263 ], dtype=float32),
  16,
  'GRP_12')]
```

```
out_pred=getPrediction(["skype issue","unable to login hotmail","data back up for germany"])
```

2. *With sampled dataset*

```
{'eval_accuracy': 0.95493245,
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 'false_positives': 95.0,
 'global_step': 5550,
 'loss': 0.12962137,
 'true_negatives': 104.0,
 'true_positives': 14600.0}
```

```
out_pred=getPrediction(["skype issue","unable to login hotmail","data back up for germany"])
```

```
out_pred
```

```
[('skype issue', array([ -8.29623   ,  -7.086216  ,  -5.152675  ,  -6.5905476 ,
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         -7.128983  ,  -2.3751988 ,  -8.504713  ,  -7.9747105 ,
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```

CHAPTER 5

RESULTS, FINDINGS, RECOMMENDATIONS, FUTURE SCOPE and CONCLUSION

5. RESULTS, FINDINGS, RECOMMENDATIONS, FUTURE SCOPE and CONCLUSION

5.1 Results of the project work

Model Evaluation

Following table represents the accuracy of the various model used:

Model Name	Accuracy
Random Forest Classifier (Unsampled dataset)	0.57396
SVM (for BoW on unsampled dataset)	0.62789
SVM (for BoW when only Grp_0 has been resampled)	0.22187
LSTM (Unsampled dataset)	0.56637
LSTM with sampled data(when only Grp_0 has been resampled)	0.32827
LSTM with sampled data(when only rest groups (except Grp_0) has been resampled and clubbed with the subdivided groups of Grp_0)	0.89185
Bi-LSTM (Word2Vec on unsampled dataset)	0.58375
Bi-LSTM(Word2Vec on sampled dataset)	0.95013
Bi-LSTM(Glove on sampled dataset)	0.94489
GRU (Unsampled dataset)	0.60493
GRU (Sampled dataset)	0.94925
BERT (Unsampled dataset)	0.66250
BERT (Sampled dataset)	0.95493

5.2 Findings based on analysis of data

Amongst all the models that we have run on the given dataset, BiLSTM with Word2Vec and Glove, GRU(on sampled dataset) and BERT(on sampled dataset) has given us the accuracies more than 90%. With this level of accuracy we can reduce the manual efforts and errors, thereby helping in assigning the tickets to the correct group. We can further improve the model

accuracy if we have more records of the groups having very less number of records since the given dataset is highly skewed..

5.3 Recommendation based on findings

In most of the project having incident or ticket or PROD Support could be assign automatically to the respective team and providing us better accuracy.

5.4 Suggestions for areas of improvement

We also found the data was present in multiple languages and in various formats such as emails, chat, etc bringing in a lot of variability in the data to be analysed. Also, the data distribution is highly skewed.

5.5 Scope for future work

The Business can improve the process of raising tickets via a common unified IT Ticket Service Portal which reduces the above mentioned variability. By doing this, the model can perform better which can help businesses to identify the problem area for relevant clusters of topics. Next time, we will try to do multilingual classification, so that if we have data from all around the world, then we will be able to assign the correct group across different global locations.

5.6 Conclusion

The goal achieved and beneficiary to most of the project via creating an NLP based classifier that could automatically classify any ticket raised by analyzing ticket description to the suitable Assignment group, this could be integrated with any ticket management service like Service Now.

Based on the ticket description our model would assign a probability of it to being assigned to one of the 74 Groups.

This project intends to reduce the manual effort of IT support teams by automating the process of ticket assignment.

BIBLIOGRAPHY

(APA style; below is only a sample)

- Atodaria, Z., & Sharma, R. (2019). Investment Pattern of Salaried Class of Somnath (Daman) –A Study of Various Investment Options Available. International Academic Journal of Social Sciences, 06(01), 49–61. https://doi.org/10.9756/iajss/v6i1/191000
- BERD_Model: https://towardsdatascience.com/bert-explained-state-of-the-art-language-model-for-nlp-f8b21a9b6270
- NLP: https://www.deeplearning.ai/resources/natural-language-processing/
- LSTM: https://intellipaat.com/blog/what-is-lstm/#:~:text='%20LSTM%20stands%20for%20long%20short,especially%20in%20sequence%20prediction%20problems
- GRU: https://www.geeksforgeeks.org/gated-recurrent-unit-networks/

ANNEXURE

Created a Git Repository with public access and shared the code and the html file with dry run to address the concerns quickly. The repository name is "MCA-AI-ML-PROJECT" and its path been mentioned below:

https://github.com/Nishant703/MCA-AI-ML-PROJECT