

SUBMITTED BY :-

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```

In [2]: # Importing Required Libraries

import pandas as pd
import numpy as np
from nltk.tokenize import sent_tokenize
from nltk.tokenize import word_tokenize
from pprint import pprint
import nltk
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.pipeline import Pipeline
from sklearn.naive_bayes import MultinomialNB
from sklearn import svm
import re
from nltk.corpus import stopwords
from nltk.tag import pos_tag
import xml.etree.ElementTree as et
import os
from nltk.stem.snowball import SnowballStemmer
from sklearn.model_selection import KFold, cross_val_score
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import cross_validate
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.tree import DecisionTreeClassifier
from sklearn import linear_model
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
from sklearn.preprocessing import OneHotEncoder
from keras.models import Sequential
from sklearn import metrics
from sklearn.decomposition import TruncatedSVD
from tensorflow.keras import backend
from tensorflow.keras.models import Sequential
from tensorflow.keras import layers
%matplotlib inline
import warnings
from sklearn.exceptions import DataConversionWarning
warnings.filterwarnings(action='ignore', category=DataConversionWarning)
warnings.filterwarnings(action='ignore', category=FutureWarning)
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.models import Model

```

Using TensorFlow backend.

1) Loading the data using assignment one dataset.

In [3]: *# Function to extract the xml data to a dataframe*

```
def create_dataframe():
    df_cols = ["headline", "text", "bip_topics", "date_published", "itemid", "filename"]
    rows = []
    for root, dirs, files in os.walk('.\\Data'):
        for file in files:
            if(file.endswith('.xml')):
                xtree = et.parse(os.path.join(root,file))
                xroot = xtree.getroot()
                text = ""
                dc_date = ""
                bip_topics = []
                itemid= ""
                xmlFileName = ""
                txt = ""

                headline = xroot.find('headline').text

                for texts in xroot.find('text'):
                    text = et.tostring(texts)
                    txt = txt + text.decode("utf-8")

                for metadata in xroot.iter('metadata'):
                    for dc in metadata.iter('dc'):
                        if dc.attrib.get('element') == 'dc.date.published':
                            dc_date = dc.attrib.get('value')

                for metadata in xroot.iter('metadata'):
                    for bip in metadata.iter('codes'):
                        if bip.attrib.get('class') == 'bip:topics:1.0':
                            for cd in bip.iter('code'):
                                bip_topics.append(cd.attrib.get('code'))

                itemid = xroot.attrib.get("itemid")
                xmlFileName = file

                rows.append({"headline": headline, "text": txt, "bip_topics": bip_topics, "date_published": dc_date, "itemid": itemid, "filename": xmlFileName})

    my_df = pd.DataFrame(rows, columns = df_cols)

    return my_df

# Calling the function create_dataframe and showing the head of dataframe.
df = create_dataframe()
df.head()
```

Out[3]:

	headline	text	bip_topics	date_published	itemid	filename
0	OFFICIAL JOURNAL CONTENTS - OJ L 66 OF MARCH 6...	<p> Council Regulation (EC) No 390/97 of 20 D...	[G15, GCAT]	1997-03-10	429411	429411newsML.xml

	headline	text	bip_topics	date_published	itemid	filename
1	OFFICIAL JOURNAL CONTENTS - OJ C 74 OF MARCH 8...	<p>*(Note - contents are displayed in reverse...	[G15, GCAT]	1997-03-10	429412	429412newsML.xml
2	OFFICIAL JOURNAL CONTENTS - OJ C 73 OF MARCH 8...	<p>*(Note - contents are displayed in reverse...	[G15, GCAT]	1997-03-10	429413	429413newsML.xml
3	OFFICIAL JOURNAL CONTENTS - OJ L 68 OF MARCH 8...	<p>*(Note - contents are displayed in reverse...	[G15, GCAT]	1997-03-10	429414	429414newsML.xml
4	Canada provincial T- bill auction results - Man...	<p>DATE PROV MAT C\$AMT AVG CHG PRIC...	[M13, M131, MCAT]	1997-03-10	429415	429415newsML.xml

In [4]: *# Unstacking the multilabel target*

```
Topic = 'bip_topics'
df_unstack = pd.DataFrame({col:np.repeat(df[col].values, df[Topic].str.len())
                           for col in df.columns.difference([Topic])}).assign
```

In [5]: *# Preprocessing the data*

```
def data_preparing(df_unstack):
    # I am considering only the first topic as the label of an article for simpl
    newsgroup_df = df_unstack.drop_duplicates(subset=['itemid', 'filename', 'date_

    # Replacing the <p> tags in text column of dataframe
    newsgroup_df['text'] = newsgroup_df['text'].str.replace(r'<p>', r' ', regex=True)
    newsgroup_df['text'] = newsgroup_df['text'].str.replace(r'</p>', r' ', regex=True)

    # Stripping the whitespaces
    newsgroup_df['text'] = newsgroup_df['text'].str.strip()
    newsgroup_df['bip_topics'] = newsgroup_df['bip_topics'].str.strip()

    # To remove the white
    newsgroup_df['text'].replace('', np.nan, inplace=True)
    newsgroup_df['bip_topics'].replace('', np.nan, inplace=True)

    # Removing the null rows
    newsgroup_df = newsgroup_df.dropna(axis=0, subset=['text'])
    newsgroup_df = newsgroup_df.dropna(axis=0, subset=['bip_topics'])

    # Converting the text column to lower case so that we can remove stop words
    newsgroup_df['text'] = newsgroup_df['text'].apply(lambda x: str(x))
    newsgroup_df['text'] = newsgroup_df['text'].str.lower()

    # Removing all numbers and non-letter characters
    newsgroup_df['text'] = newsgroup_df['text'].str.replace(r'[^a-zA-Z ]\s?', r'

    # Word tokenization
    newsgroup_df['text'] = newsgroup_df.apply(lambda row: nltk.word_tokenize(row

    # r Removing the stop words and stemming the words
    stop_words=set(stopwords.words("english"))
    newsgroup_df['text'] = newsgroup_df['text'].apply(lambda x: [item for item in

    stemmer = SnowballStemmer("english")
    newsgroup_df['text'] = newsgroup_df['text'].apply(lambda x: [stemmer.stem(y)

    return newsgroup_df

newsgroup_df = data_preparing(df_unstack)
newsgroup_df.head()
```

Out[5]:

	headline	text	bip_topics	date_published	itemid	filename
0	OFFICIAL JOURNAL CONTENTS - OJ L 66 OF MARCH 6...	[council, regul, ec, decemb, fix, certain, fis...	G15	1997-03-10	429411	429411newsML.xml

	headline	text	bip_topics	date_published	itemid	filename
1	OFFICIAL JOURNAL CONTENTS - OJ C 74 OF MARCH 8...	[note, content, display, revers, order, print,...	G15	1997-03-10	429412	429412newsML.xml
2	OFFICIAL JOURNAL CONTENTS - OJ C 73 OF MARCH 8...	[note, content, display, revers, order, print,...	G15	1997-03-10	429413	429413newsML.xml
3	OFFICIAL JOURNAL CONTENTS - OJ L 68 OF MARCH 8...	[note, content, display, revers, order, print,...	G15	1997-03-10	429414	429414newsML.xml
4	Canada provincial T-bill auction results - Man...	[date, prov, mat, c, amt, avg, chg, price, hi,...	M13	1997-03-10	429415	429415newsML.xml

In [6]: *# tfidf and count vector*

```
def extract_features(newsgroup_df):
    data_count_vec = CountVectorizer(tokenizer=lambda doc: doc, lowercase=False,
    tfidf_transformer = TfidfTransformer()
    data_tfidf = tfidf_transformer.fit_transform(data_count_vec)
    return data_tfidf

# Label encoding the target column i.e, "bip_topics"

def label_encoder(newsgroup_df):
    target = pd.DataFrame(newsgroup_df['bip_topics'])
    target = target.to_numpy()
    labelencoder = LabelEncoder()
    newsgroup_target = labelencoder.fit_transform(target)
    return newsgroup_target

# One hot encoding the target column i.e, "bip_topcs"
def one_hot_encoder(newsgroup_df):
    target = pd.DataFrame(newsgroup_df['bip_topics'])
    target = target.to_numpy()
    labelencoder = LabelEncoder()
    newsgroup_target = labelencoder.fit_transform(target)
    onehot_encoder = OneHotEncoder(sparse=False)
    newsgroup_target = newsgroup_target.reshape(len(newsgroup_target), 1)
    onehot_encoded = onehot_encoder.fit_transform(newsgroup_target)
    return onehot_encoded

data_tfidf = extract_features(newsgroup_df)
newsgroup_target = label_encoder(newsgroup_df)
print("TFIDF shape :- ", data_tfidf.shape)
print('Label encoded target data shape:- ', newsgroup_target.shape)
```

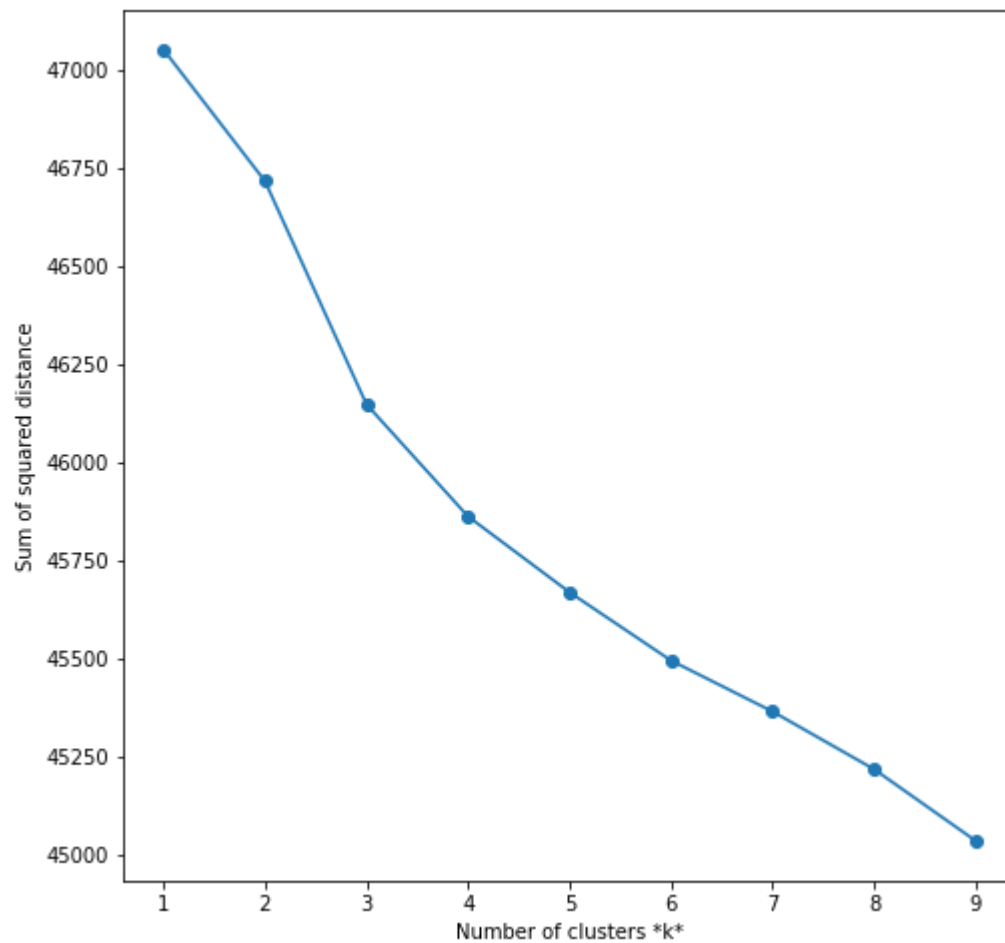
TFIDF shape :- (48258, 20000)

Label encoded target data shape:- (48258,)

```
In [12]: # Demonstrating the ELBOW for selecting the correct "K" value in k-means algorithm
sse = []
list_k = list(range(1, 10))

for k in list_k:
    km = KMeans(n_clusters=k, n_init=5)
    km.fit(data_tfidf)
    sse.append(km.inertia_)

# Plot sse against k
plt.figure(figsize=(8, 8))
plt.plot(list_k, sse, '-o')
plt.xlabel(r'Number of clusters *k*')
plt.ylabel('Sum of squared distance');
plt.show()
```



In [7]: *# Function for Dimensional reduction using PCA, TruncatedSVD()*

```
def reduce_dimensions(data):  
    pca = TruncatedSVD(n_components=100)  
    vec_matrix_pca = pca.fit_transform(data)  
    return vec_matrix_pca  
  
data_idf_matrix = reduce_dimensions(data_tfidf)
```

2) Function to cluster all documents and assign a cluster id to each document.

- First we have loaded the data and pre processed the text data using various nlp preprocessing techniques used in step 1
- We are feeding the data to Data TF-IDF to create a sparse matrix
- Then we have done the **ELBOW** method to find the best **K** value for k means clustering.
- We have selected value of K as 6 because we can deduce from the elbow that the curve starts to bend less where number of clusters is 6.
- **Reasons for using k-means** - As we will see in step 3, k-means generalizes our clusters to different shapes and sizes i.e, elliptical clusters. It is easy to implement and guarantees convergences. As our dataset is relatively large k-means scales to large datasets.

In [21]: *# Function to cluster all the documents and assign the cluster id*

```
def create_clusters(data, newsgroup):
    clusters = KMeans(n_clusters=6, n_init=10)
    clusters.fit(data)
    newsgroup['cluster_id'] = clusters.labels_
    labels = clusters.labels_
    return newsgroup, labels

# Newsgroup_df with cluster_ids
newsgroup_df, labels = create_clusters(data_idf_matrix, newsgroup_df)
newsgroup_df.head()
```

Out[21]:

	headline	text	bip_topics	date_published	itemid	filename	clus
0	OFFICIAL JOURNAL CONTENTS - OJ L 66 OF MARCH 6...	[council, regul, ec, decemb, fix, certain, fis...	G15	1997-03-10	429411	429411newsML.xml	
1	OFFICIAL JOURNAL CONTENTS - OJ C 74 OF MARCH 8...	[note, content, display, revers, order, print,...	G15	1997-03-10	429412	429412newsML.xml	
2	OFFICIAL JOURNAL CONTENTS - OJ C 73 OF MARCH 8...	[note, content, display, revers, order, print,...	G15	1997-03-10	429413	429413newsML.xml	
3	OFFICIAL JOURNAL CONTENTS - OJ L 68 OF MARCH 8...	[note, content, display, revers, order, print,...	G15	1997-03-10	429414	429414newsML.xml	
4	Canada provincial T- bill auction results - Man...	[date, prov, mat, c, amt, avg, chg, price, hi,...	M13	1997-03-10	429415	429415newsML.xml	

```
In [24]: # creating different dataframes for different cluster so that we can classify each cluster

cluster0 = newsgroup_df.loc[newsgroup_df['cluster_id'] == 0].reset_index(drop=True)
cluster1 = newsgroup_df.loc[newsgroup_df['cluster_id'] == 1].reset_index(drop=True)
cluster2 = newsgroup_df.loc[newsgroup_df['cluster_id'] == 2].reset_index(drop=True)
cluster3 = newsgroup_df.loc[newsgroup_df['cluster_id'] == 3].reset_index(drop=True)
cluster4 = newsgroup_df.loc[newsgroup_df['cluster_id'] == 4].reset_index(drop=True)
cluster5 = newsgroup_df.loc[newsgroup_df['cluster_id'] == 5].reset_index(drop=True)
```

```
In [25]: def hold_out_set(data_tfidf, newsgroup_taget):
    X_train, X_test, y_train, y_test = train_test_split(data_tfidf, newsgroup_taget,
    return X_train, X_test, y_train, y_test
```

Generating classifier for each identified cluster

I have used two classifications models for classifying each clusters namely:-

- SVM
- Random Forest

Reason for Using SVM

For text classification of single class, svm classifier offers **good accuracy** and **faster predictions** than any other text classifiers such as naives bayes. They are generally faster because they **use less memory** as they only uses subset of training point in decision phase. Another reason why I have choosed SVM is they offers **clear margin of separation** and with high dimensional space.

```
In [40]: # svm.SVC() classifier
# Calling the functions to classify documents in each cluster

def classifier_svm(X_train, X_test, y_train, y_test):
    svm_clf = svm.SVC(kernel='linear')
    svm_clf.fit(X_train, y_train)
    predicted_svm_linear = svm_clf.predict(X_test)
    accuracy = accuracy_score(y_test, predicted_svm_linear)
    f1_scores = f1_score(y_test, predicted_svm_linear, average='micro')
    print("Accuracy of SVM :- ", accuracy)
    print("F1 Score of SVM :- ", f1_scores)
    return accuracy
```

Reason for Using Random Forest

I have used Random forest for **higher dimensional clusters** below. This is because the random forest is a bagging technique based on weak learners and thus they are **faster to train**. They are also highly **resistant to instability** i.e, if the data changes a bit it can affect a single tree but the overall outcome of forest remain same. The second reason for using random forest is it **generates an internal unbiased estimate of generalization error** as the forest building progresses. It also provides methods for **balancing error in class population and unbalanced set**. It is also **fully parallizable** although I have not used GPU.

```
In [41]: # Random Forest Clasifier
def classifier_random_forest(X_train, X_test, y_train, y_test):
    clf=RandomForestClassifier(n_estimators = 10)
    clf.fit(X_train,y_train)
    y_predicted=clf.predict(X_test)
    accuracy = accuracy_score(y_true = y_test, y_pred = y_predicted)
    f1_scores = f1_score(y_test, y_predicted,average='micro')
    print("Accuracy of random forest :- ", accuracy)
    print("F1 Score random forest :- ", f1_score(y_test, y_predicted,average='micro'))
    return accuracy
```

Classifying each clusters with SVM and RandomForest

```
In [42]: data_tfidf0 = extract_features(cluster0)
newsgroup_taget0 = label_encoder(cluster0)

print("TFIDF shape :- ", data_tfidf0.shape)
print('Label encoded target data shape:- ', newsgroup_taget0.shape)
X_train, X_test, y_train, y_test = hold_out_set(data_tfidf0,newsgroup_taget0)
accuracy_cluster0 = classifier_svm(X_train, X_test, y_train, y_test)
```

```
TFIDF shape :- (524, 1357)
Label encoded target data shape:- (524,)
Accuracy of SVM :- 0.9936708860759493
F1 Score of SVM :- 0.9936708860759493
```

```
In [43]: data_tfidf1 = extract_features(cluster1)
newsgroup_taget1 = label_encoder(cluster1)
print("TFIDF shape :- ", data_tfidf1.shape)
print('Label encoded target data shape:- ', newsgroup_taget1.shape)
X_train, X_test, y_train, y_test = hold_out_set(data_tfidf1,newsgroup_taget1)
accuracy_cluster1 = classifier_svm(X_train, X_test, y_train, y_test)
```

```
TFIDF shape :- (3244, 10578)
Label encoded target data shape:- (3244,)
Accuracy of SVM :- 0.8357289527720739
F1 Score of SVM :- 0.8357289527720738
```

```
In [44]: data_tfidf2 = extract_features(cluster2)
newsgroup_taget2 = label_encoder(cluster2)
print("TFIDF shape :- ", data_tfidf2.shape)
print('Label encoded target data shape:- ', newsgroup_taget2.shape)
X_train, X_test, y_train, y_test = hold_out_set(data_tfidf2,newsgroup_taget2)
accuracy_cluster2 = classifier_svm(X_train, X_test, y_train, y_test)
```

```
TFIDF shape :- (1354, 3970)
Label encoded target data shape:- (1354,)
Accuracy of SVM :- 0.972972972972973
F1 Score of SVM :- 0.972972972972973
```

```
In [45]: data_tfidf3 = extract_features(cluster3)
newsgroup_taget3 = label_encoder(cluster3)
print("TFIDF shape :- ", data_tfidf3.shape)
print('Label encoded target data shape:- ', newsgroup_taget3.shape)
X_train, X_test, y_train, y_test = hold_out_set(data_tfidf3,newsgroup_taget3)
accuracy_cluster3 = classifier_svm(X_train, X_test, y_train, y_test)
```

```
TFIDF shape :- (1097, 2361)
Label encoded target data shape:- (1097,)
Accuracy of SVM :- 0.996969696969697
F1 Score of SVM :- 0.996969696969697
```

```
In [46]: data_tfidf4 = extract_features(cluster4)
newsgroup_taget4 = label_encoder(cluster4)
print("TFIDF shape :- ", data_tfidf4.shape)
print('Label encoded target data shape:- ', newsgroup_taget4.shape)
X_train, X_test, y_train, y_test = hold_out_set(data_tfidf4,newsgroup_taget4)
accuracy_cluster4 = classifier_random_forest(X_train, X_test, y_train, y_test)
```

```
TFIDF shape :- (30497, 20000)
Label encoded target data shape:- (30497,)
Accuracy of random forest :- 0.653551912568306
F1 Score random forest :- 0.653551912568306
```

```
In [47]: data_tfidf5 = extract_features(cluster5)
newsgroup_taget5 = label_encoder(cluster5)
print("TFIDF shape :- ", data_tfidf5.shape)
print('Label encoded target data shape:- ', newsgroup_taget5.shape)
X_train, X_test, y_train, y_test = hold_out_set(data_tfidf5,newsgroup_taget5)
accuracy_cluster5 = classifier_random_forest(X_train, X_test, y_train , y_test)
```

```
TFIDF shape :- (11542, 20000)
Label encoded target data shape:- (11542,)
Accuracy of random forest :- 0.6459717008374242
F1 Score random forest :- 0.6459717008374242
```

(3) Function to evaluate the quality of clusters using shilloutte

I have two kind of evaluation strategies i.e,

Internal Evaluation - Clustering data is evaluated based on data that was cluster itself.

External Evaluation - Clustering data is evaluated based on data that was not used for clustering such as class labels and external benchmarks.

- In this step I have tried to plot all the silhouette diagram and k means sampling from the range (2,6). This is direct implementation given in scikit library.

```

In [8]: from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score

import matplotlib.pyplot as plt
import matplotlib.cm as cm
import numpy as np

range_n_clusters = [2, 3, 4, 5, 6]

for n_clusters in range_n_clusters:
    # Create a subplot with 1 row and 2 columns
    fig, (ax1, ax2) = plt.subplots(1, 2)
    fig.set_size_inches(18, 7)

    ax1.set_xlim([-0.1, 1])

    ax1.set_ylim([0, len(data_idf_matrix) + (n_clusters + 1) * 10])

    clusterer = KMeans(n_clusters=n_clusters, random_state=10)
    cluster_labels = clusterer.fit_predict(data_idf_matrix)

    silhouette_avg = silhouette_score(data_idf_matrix, cluster_labels)
    print("For n_clusters =", n_clusters,
          "The average silhouette_score is :", silhouette_avg)

    sample_silhouette_values = silhouette_samples(data_idf_matrix, cluster_labels)

    y_lower = 10
    for i in range(n_clusters):
        ith_cluster_silhouette_values = \
            sample_silhouette_values[cluster_labels == i]

        ith_cluster_silhouette_values.sort()

        size_cluster_i = ith_cluster_silhouette_values.shape[0]
        y_upper = y_lower + size_cluster_i

        color = cm.nipy_spectral(float(i) / n_clusters)
        ax1.fill_betweenx(np.arange(y_lower, y_upper),
                          0, ith_cluster_silhouette_values,
                          facecolor=color, edgecolor=color, alpha=0.7)

        ax1.text(-0.05, y_lower + 0.5 * size_cluster_i, str(i))

        y_lower = y_upper + 10

    ax1.set_title("The silhouette plot for the various clusters.")
    ax1.set_xlabel("The silhouette coefficient values")
    ax1.set_ylabel("Cluster label")

    ax1.axvline(x=silhouette_avg, color="red", linestyle="--")

```

```

ax1.set_yticks([])
ax1.set_xticks([-0.1, 0, 0.2, 0.4, 0.6, 0.8, 1])

colors = cm.nipy_spectral(cluster_labels.astype(float) / n_clusters)
ax2.scatter(data_idf_matrix[:, 0], data_idf_matrix[:, 1], marker='.', s=30,
            c=colors, edgecolor='k')

centers = clusterer.cluster_centers_
ax2.scatter(centers[:, 0], centers[:, 1], marker='o',
            c="white", alpha=1, s=200, edgecolor='k')

for i, c in enumerate(centers):
    ax2.scatter(c[0], c[1], marker='$_d$' % i, alpha=1,
                s=50, edgecolor='k')

ax2.set_title("The visualization of the clustered data.")
ax2.set_xlabel("Feature space for the 1st feature")
ax2.set_ylabel("Feature space for the 2nd feature")

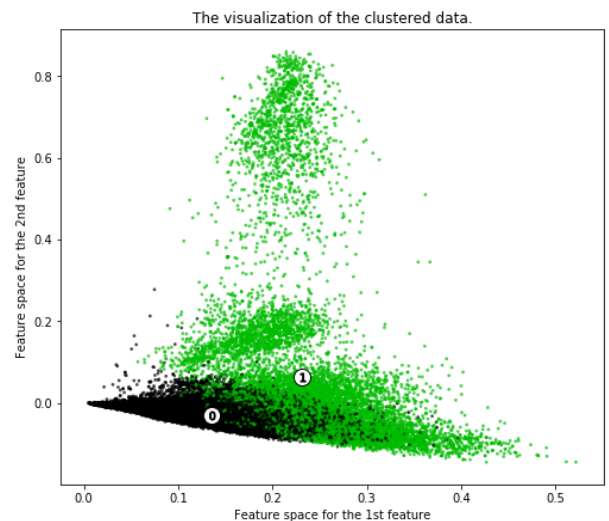
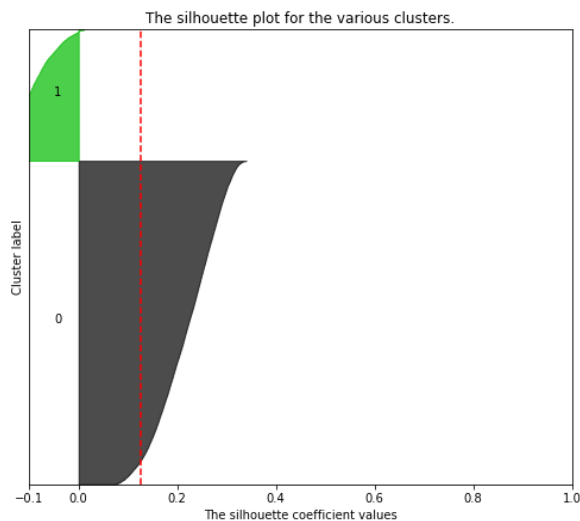
plt.suptitle(("Silhouette analysis for KMeans clustering on sample data "
              "with n_clusters = %d" % n_clusters),
              fontsize=14, fontweight='bold')

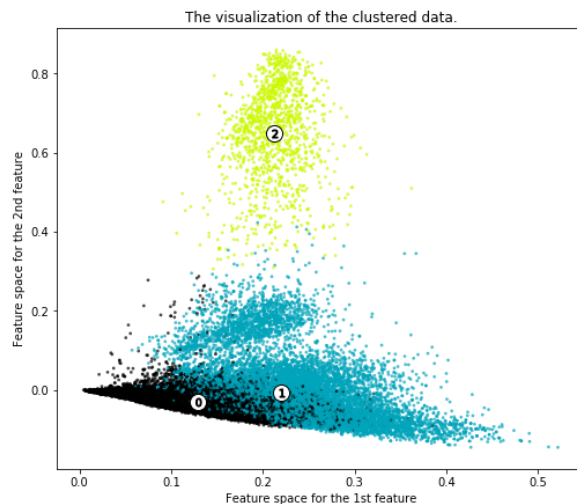
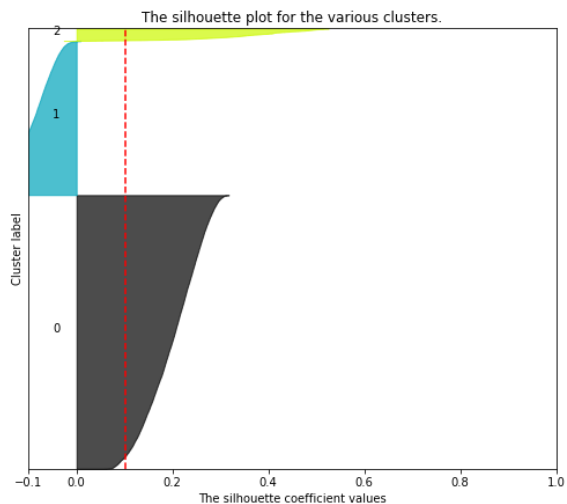
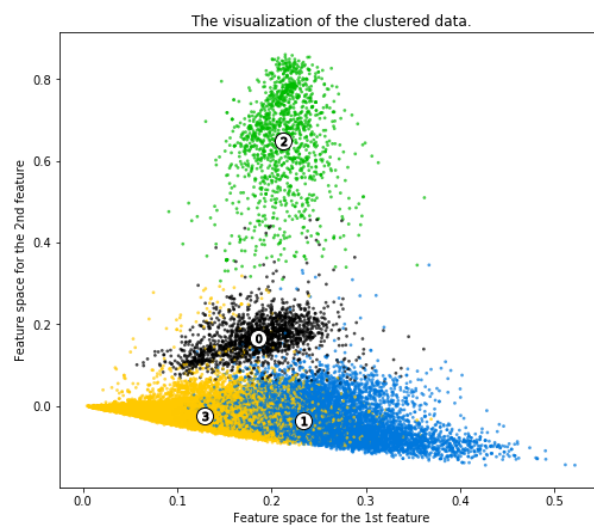
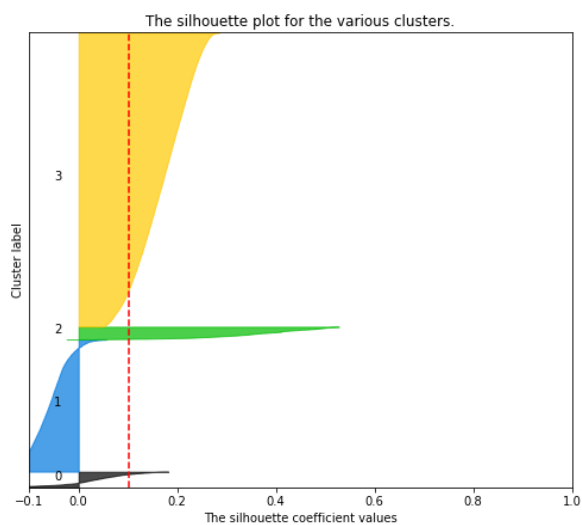
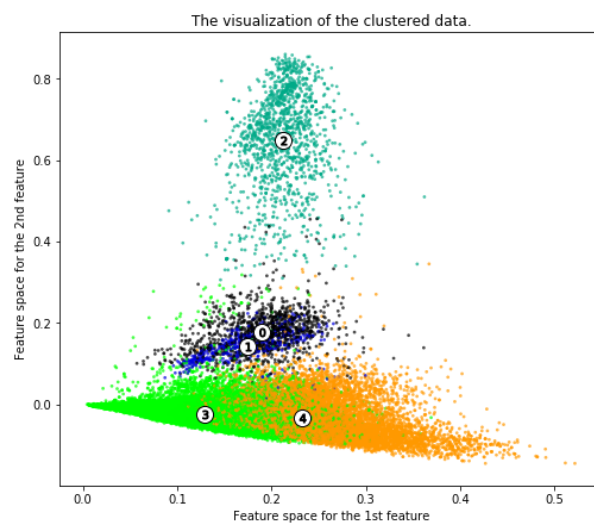
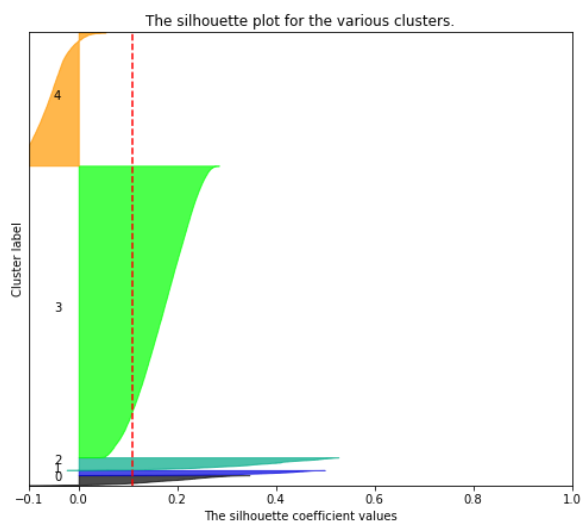
plt.show()

```

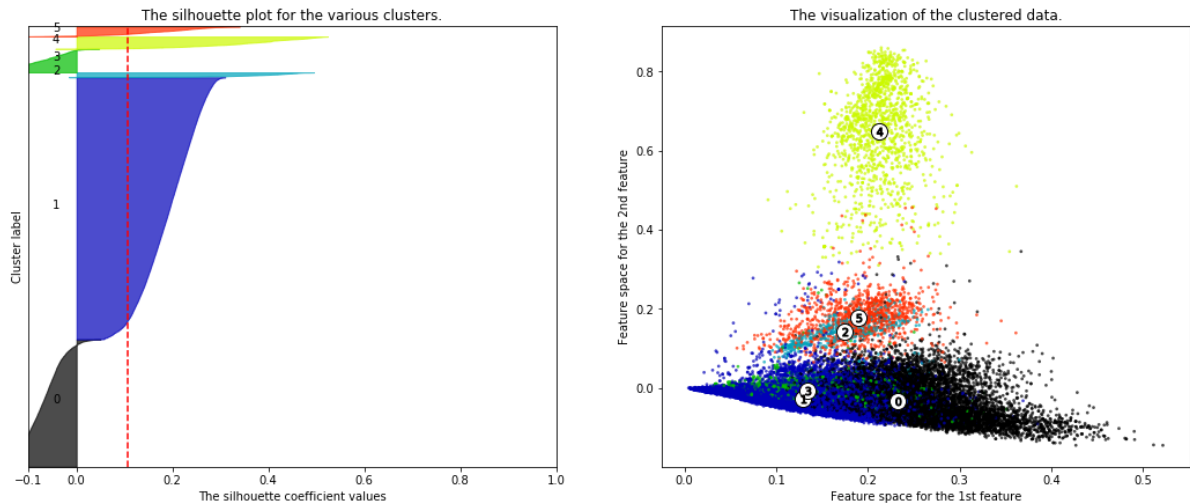
For n_clusters = 2 The average silhouette_score is : 0.12700562796376524
 For n_clusters = 3 The average silhouette_score is : 0.1020879156394196
 For n_clusters = 4 The average silhouette_score is : 0.1025733915143742
 For n_clusters = 5 The average silhouette_score is : 0.10835659034756641
 For n_clusters = 6 The average silhouette_score is : 0.10564568109859142

Silhouette analysis for KMeans clustering on sample data with n_clusters = 2



Silhouette analysis for KMeans clustering on sample data with $n_clusters = 3$ **Silhouette analysis for KMeans clustering on sample data with $n_clusters = 4$** **Silhouette analysis for KMeans clustering on sample data with $n_clusters = 5$** 

Silhouette analysis for KMeans clustering on sample data with n_clusters = 6



Intrinsic Evaluation

- **Silhouette_score** - I have directly calculated the silhouette on our data which was converted in tf-idf matrix and the labels assigned after clustering. Silhouette score can range from (-1,1) where scores are higher towards 1 when cluster are dense and separated. In our case we got an **silhouette of 0.113** which signifies the few clusters are dense and well separated and few are overlapping with other clusters.
- **Daves Bouldin Score** - I have computed daves bouldin index as the it is faster to implement than silhouette and it computes the index of only quantities and features, inherent to our dataset. The best possible value is close to zero. In our case we got an value of **2.72** which says that there are few overlapping clusters.

```
In [48]: # Assigning the labels first and then finding the silhouette score
metrics.silhouette_score(data_idf_matrix, labels, metric='euclidean')
```

```
Out[48]: 0.11319510355398887
```

```
In [49]: # Davies-Bouldin Index

from sklearn.metrics import davies_bouldin_score
davies_bouldin_score(data_idf_matrix, labels)
```

```
Out[49]: 2.7207061370996435
```

Extrinsic Evaluation

I have used calinski harabasz score to calculate the external evaluation of cluster. Our score is higher which suggests few clusters are dense and well separated.

In [50]: *# Calinski-Harabasz Index*

```
metrics.calinski_harabasz_score(data_idf_matrix, labels)
```

Out[50]: 1832.5628248845637

(4) Extracting features for each cluster with Auto-Encoders

I have built an autoencoder as suggested in paper 1 for feature extraction. I have used relu as the activation function for the encoder and decoder. The optimizer I have used is adam and the loss function is binary crossentropy. My `get_cluster_features_autoencoders()` accepts two parameters i.e, each cluster data and then the target label for that cluster. Then I am training the autoencoder to minimize the loss with epochs as 3. Finally I have taken enhancing the feature selection by taking the result of last encoded layer i.e, `encoder3` as our extracted features.

```

In [122]: # Auto encoder function to extract/select features for each cluster as suggested

def get_cluster_features_autoencoders(data_tfidf,newsgroup_taget):
    ncol = data_tfidf.shape[1] # gives us the total number of features to train
    input_dim = Input(shape = (ncol, ))
    encoding_dim = 1000 # Gives us the number of features in each clustetr to ex

    # Encoder Layers
    encoded1 = Dense(5000, activation = 'relu')(input_dim)
    encoded2 = Dense(3500, activation = 'relu')(encoded1)
    encoded3 = Dense(encoding_dim, activation = 'relu')(encoded2)

    # Decoder Layers
    decoded1 = Dense(3500, activation = 'relu')(encoded3)
    decoded2 = Dense(5000, activation = 'relu')(decoded1)
    decoded3 = Dense(ncol, activation = 'sigmoid')(decoded2)

    # Combine Encoder and Deocder Layers
    autoencoder = Model(inputs = input_dim, outputs = decoded3)

    # Compile the Model
    autoencoder.compile(optimizer = 'adam', loss = 'binary_crossentropy')

    #Model Summary
    autoencoder.summary()

    #dividing into training and testing set by calling our previously defined fun
    X_train, X_test, y_train, y_test = hold_out_set(data_tfidf,newsgroup_taget)

    # to find the total information loss in autoencoder
    autoencoder.fit(X_train, X_train, epochs = 3, batch_size = 128, shuffle = Fa

    # FOR EXTRACTING FEATURES WE NEED THE LAST ENCODER LAYER i.e, ENCODER3 as asl
    encoder = Model(inputs = input_dim, outputs = encoded3)
    encoded_input = Input(shape = (encoding_dim, ))

    # Generating the set of features
    encoded_features = encoder.predict(data_tfidf)

    #returning the generated set of features
    return encoded_features

```

Calling get_cluster_features_autoencoders() on each clusters to select the best features in each cluster.

In [123]: *# SELECTING FEATURES FOR CLUSTER 0*

```
features_selected_cluster0 = get_cluster_features_autoencoders(data_tfidf0, newsg
```

Model: "model_7"

Layer (type)	Output Shape	Param #
input_8 (InputLayer)	[(None, 1357)]	0
dense_30 (Dense)	(None, 5000)	6790000
dense_31 (Dense)	(None, 3500)	17503500
dense_32 (Dense)	(None, 1000)	3501000
dense_33 (Dense)	(None, 3500)	3503500
dense_34 (Dense)	(None, 5000)	17505000
dense_35 (Dense)	(None, 1357)	6786357

Total params: 55,589,357

Trainable params: 55,589,357

Non-trainable params: 0

WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find data adapter that can handle input: <class 'scipy.sparse.csr.csr_matrix'>, <class 'NoneType'>

Train on 366 samples, validate on 158 samples

Epoch 1/3

366/366 [=====] - 2s 5ms/sample - loss: 0.6793 - val_loss: 0.3634

Epoch 2/3

366/366 [=====] - 2s 4ms/sample - loss: 0.1480 - val_loss: 0.0433

Epoch 3/3

366/366 [=====] - 2s 5ms/sample - loss: 0.0524 - val_loss: 0.0619

In [139]: *# SELECTING FEATURES FOR CLUSTER 1*

```
features_selected_cluster1 = get_cluster_features_autoencoders(data_tfidf1, newsg
```

Model: "model_9"

Layer (type)	Output Shape	Param #
input_10 (InputLayer)	[(None, 10578)]	0
dense_40 (Dense)	(None, 5000)	52895000
dense_41 (Dense)	(None, 3500)	17503500
dense_42 (Dense)	(None, 1000)	3501000
dense_43 (Dense)	(None, 3500)	3503500
dense_44 (Dense)	(None, 5000)	17505000
dense_45 (Dense)	(None, 10578)	52900578

Total params: 147,808,578

Trainable params: 147,808,578

Non-trainable params: 0

WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find data adapter that can handle input: <class 'scipy.sparse.csr.csr_matrix'>, <class 'NoneType'>

Train on 2270 samples, validate on 974 samples

Epoch 1/3

2270/2270 [=====] - 27s 12ms/sample - loss: 0.2403 - val_loss: 0.0107

Epoch 2/3

2270/2270 [=====] - 27s 12ms/sample - loss: 0.0117 - val_loss: 0.0120

Epoch 3/3

2270/2270 [=====] - 27s 12ms/sample - loss: 0.0118 - val_loss: 0.0120

In [140]: *# SELECTING FEATURES FOR CLUSTER 2*

```
features_selected_cluster2 = get_cluster_features_autoencoders(data_tfidf2, newsg
```

Model: "model_11"

Layer (type)	Output Shape	Param #
input_12 (InputLayer)	[(None, 3970)]	0
dense_46 (Dense)	(None, 5000)	19855000
dense_47 (Dense)	(None, 3500)	17503500
dense_48 (Dense)	(None, 1000)	3501000
dense_49 (Dense)	(None, 3500)	3503500
dense_50 (Dense)	(None, 5000)	17505000
dense_51 (Dense)	(None, 3970)	19853970

Total params: 81,721,970

Trainable params: 81,721,970

Non-trainable params: 0

WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find data adapter that can handle input: <class 'scipy.sparse.csr.csr_matrix'>, <class 'NoneType'>

Train on 947 samples, validate on 407 samples

Epoch 1/3

947/947 [=====] - 7s 8ms/sample - loss: 0.4224 - val_loss: 0.0204

Epoch 2/3

947/947 [=====] - 7s 7ms/sample - loss: 0.0194 - val_loss: 0.0191

Epoch 3/3

947/947 [=====] - 7s 7ms/sample - loss: 0.0192 - val_loss: 0.0191

In [141]: *# SELECTING FEATURES FOR CLUSTER 3*

```
features_selected_cluster3 = get_cluster_features_autoencoders(data_tfidf3, newsg
```

Model: "model_13"

Layer (type)	Output Shape	Param #
input_14 (InputLayer)	[(None, 2361)]	0
dense_52 (Dense)	(None, 5000)	11810000
dense_53 (Dense)	(None, 3500)	17503500
dense_54 (Dense)	(None, 1000)	3501000
dense_55 (Dense)	(None, 3500)	3503500
dense_56 (Dense)	(None, 5000)	17505000
dense_57 (Dense)	(None, 2361)	11807361

Total params: 65,630,361

Trainable params: 65,630,361

Non-trainable params: 0

WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find data adapter that can handle input: <class 'scipy.sparse.csr.csr_matrix'>, <class 'NoneType'>

Train on 767 samples, validate on 330 samples

Epoch 1/3

767/767 [=====] - 6s 8ms/sample - loss: 0.4553 - val_loss: 0.0307

Epoch 2/3

767/767 [=====] - 5s 6ms/sample - loss: 0.0370 - val_loss: 0.0453

Epoch 3/3

767/767 [=====] - 4s 6ms/sample - loss: 0.0454 - val_loss: 0.0453

In [142]: *# SELECTING FEATURES FOR CLUSTER 4*

```
features_selected_cluster4 = get_cluster_features_autoencoders(data_tfidf4,newsgt
```

Model: "model_15"

Layer (type)	Output Shape	Param #
input_16 (InputLayer)	[(None, 20000)]	0
dense_58 (Dense)	(None, 5000)	100005000
dense_59 (Dense)	(None, 3500)	17503500
dense_60 (Dense)	(None, 1000)	3501000
dense_61 (Dense)	(None, 3500)	3503500
dense_62 (Dense)	(None, 5000)	17505000
dense_63 (Dense)	(None, 20000)	100020000

=====
Total params: 242,038,000

Trainable params: 242,038,000

Non-trainable params: 0

WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find data adapter that can handle input: <class 'scipy.sparse.csr.csr_matrix'>, <class 'NoneType'>

Train on 21347 samples, validate on 9150 samples

Epoch 1/3

21347/21347 [=====] - 446s 21ms/sample - loss: 0.0368
- val_loss: 0.0054

Epoch 2/3

21347/21347 [=====] - 443s 21ms/sample - loss: 0.0053
- val_loss: 0.0054

Epoch 3/3

21347/21347 [=====] - 481s 23ms/sample - loss: 0.0053
- val_loss: 0.0054

In [143]: *# SELECTING FEATURES FOR CLUSTER 5*

```
features_selected_cluster5 = get_cluster_features_autoencoders(data_tfidf5, newsg
```

Model: "model_17"

Layer (type)	Output Shape	Param #
input_18 (InputLayer)	[(None, 20000)]	0
dense_64 (Dense)	(None, 5000)	100005000
dense_65 (Dense)	(None, 3500)	17503500
dense_66 (Dense)	(None, 1000)	3501000
dense_67 (Dense)	(None, 3500)	3503500
dense_68 (Dense)	(None, 5000)	17505000
dense_69 (Dense)	(None, 20000)	100020000

Total params: 242,038,000

Trainable params: 242,038,000

Non-trainable params: 0

WARNING:tensorflow:Falling back from v2 loop because of error: Failed to find data adapter that can handle input: <class 'scipy.sparse.csr.csr_matrix'>, <class 'NoneType'>

Train on 8079 samples, validate on 3463 samples

Epoch 1/3

8079/8079 [=====] - 167s 21ms/sample - loss: 0.0881 - val_loss: 0.0062

Epoch 2/3

8079/8079 [=====] - 173s 21ms/sample - loss: 0.0062 - val_loss: 0.0062

Epoch 3/3

8079/8079 [=====] - 178s 22ms/sample - loss: 0.0062 - val_loss: 0.0062

(5) Forming deep neural network with the extracted features in step 4

I am using a function called `get_deep_neural_network()` which accepts the selected features and target for every cluster. Here the target column is one hot encoded. I am building a deep neural network by forming a sequential model. The hyperparameters I have used in this are activation as `relu` and `sigmoid`, loss as `binary_crossentropy` (as it is a binary classification) and metrics as accuracy.

Changes from Assignment1 - I have preprocessed the data in a more better way compared to assignment 1. For neural network I have one hot encoded the target column when compared to label encoder in assignment 1. I have also made sure the feature selections gets the best features in the set in our project while in my last assignment I have selected features arbitrarily.

Because of these changes I am getting more than 95% accuracy in both training and testing set in all clusters. This shows the classification process has improved. We can verify the same by the accuracy diagram in the end.

```
In [161]: # Function for deep neural network
# This function gets the selected features and target

def get_deep_neural_network(selected_features, selected_target):
    X_train, X_test, y_train, y_test = hold_out_set(selected_features, selected_target)

    input_dim = X_train.shape[1] # Number of input features
    output_dim = y_train.shape[1] # Number of output features

    model = Sequential()
    model.add(layers.Dense(500, input_dim=input_dim, activation='relu'))
    model.add(layers.Dense(output_dim, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])
    model.summary()
    history = model.fit(X_train, y_train, epochs=5, verbose=True, validation_data=(X_test, y_test))
    loss, accuracy = model.evaluate(X_train, y_train, verbose=False)
    print("#####")
    print("Training Accuracy: {:.4f}".format(accuracy))
    loss, accuracy = model.evaluate(X_test, y_test, verbose=False)
    print("Testing Accuracy: {:.4f}".format(accuracy))
    return accuracy
```

Calling the `get_deep_neural_network()` on each cluster to classify the target correctly.

```
In [162]: # Cluster 0 prediction with deep neural network on extracted features in step 4
newsgroup_taget0 = one_hot_encoder(cluster0) # using one hot encoder for target
NN_accuracy_cluster0 = get_deep_neural_network(features_selected_cluster0, newsgroup_taget0)

Model: "sequential_15"
```

Layer (type)	Output Shape	Param #
dense_84 (Dense)	(None, 500)	500500
dense_85 (Dense)	(None, 4)	2004

```
=====
Total params: 502,504
Trainable params: 502,504
Non-trainable params: 0
```

```
Train on 366 samples, validate on 158 samples
Epoch 1/5
366/366 [=====] - 13s 35ms/sample - loss: 0.4176 - accuracy: 0.8607 - val_loss: 0.0331 - val_accuracy: 0.9968
Epoch 2/5
366/366 [=====] - 0s 203us/sample - loss: 0.0985 - accuracy: 0.9918 - val_loss: 0.0414 - val_accuracy: 0.9968
Epoch 3/5
366/366 [=====] - 0s 185us/sample - loss: 0.0968 - accuracy: 0.9918 - val_loss: 0.0489 - val_accuracy: 0.9968
Epoch 4/5
366/366 [=====] - 0s 180us/sample - loss: 0.0930 - accuracy: 0.9918 - val_loss: 0.0519 - val_accuracy: 0.9968
Epoch 5/5
366/366 [=====] - 0s 168us/sample - loss: 0.0839 - accuracy: 0.9918 - val_loss: 0.0586 - val_accuracy: 0.9968
#####
Training Accuracy: 0.9918
Testing Accuracy: 0.9968
```

```
In [163]: # Cluster 1 prediction with deep neural network on extracted features in step 4
newsgroup_taget1 = one_hot_encoder(cluster1) # using one hot encoder for target
NN_accuracy_cluster1 = get_deep_neural_network(features_selected_cluster1, newsgroup_taget1)
Model: "sequential_16"
```

Layer (type)	Output Shape	Param #
dense_86 (Dense)	(None, 500)	500500

dense_87 (Dense)	(None, 24)	12024
------------------	------------	-------

=====
Total params: 512,524

Trainable params: 512,524

Non-trainable params: 0

Train on 2270 samples, validate on 974 samples

Epoch 1/5

2270/2270 [=====] - 1s 340us/sample - loss: 0.9708 - accuracy: 0.9504 - val_loss: 0.3006 - val_accuracy: 0.9756

Epoch 2/5

2270/2270 [=====] - 0s 118us/sample - loss: 0.3832 - accuracy: 0.9646 - val_loss: 0.3444 - val_accuracy: 0.9756

Epoch 3/5

2270/2270 [=====] - 0s 112us/sample - loss: 0.2989 - accuracy: 0.9651 - val_loss: 0.3037 - val_accuracy: 0.9583

Epoch 4/5

2270/2270 [=====] - 0s 112us/sample - loss: 0.2193 - accuracy: 0.9653 - val_loss: 0.2160 - val_accuracy: 0.9756

Epoch 5/5

2270/2270 [=====] - 0s 128us/sample - loss: 0.1976 - accuracy: 0.9659 - val_loss: 0.1850 - val_accuracy: 0.9756

#####

Training Accuracy: 0.9757

Testing Accuracy: 0.9756

```
In [164]: # Cluster 2 prediction with deep neural network on extracted features in step 4
newsgroup_taget2 = one_hot_encoder(cluster2) # using one hot encoder for target
NN_accuracy_cluster2 = get_deep_neural_network(features_selected_cluster2, newsgroup_taget2)
Model: "sequential_17"
```

Layer (type)	Output Shape	Param #
dense_88 (Dense)	(None, 500)	500500

dense_89 (Dense)	(None, 11)	5511
------------------	------------	------

=====
Total params: 506,011

Trainable params: 506,011

Non-trainable params: 0

Train on 947 samples, validate on 407 samples

Epoch 1/5

947/947 [=====] - 1s 557us/sample - loss: 0.3145 - accuracy: 0.9683 - val_loss: 0.1053 - val_accuracy: 0.9920

Epoch 2/5

947/947 [=====] - 0s 120us/sample - loss: 0.1477 - accuracy: 0.9929 - val_loss: 0.1385 - val_accuracy: 0.9920

Epoch 3/5

947/947 [=====] - 0s 116us/sample - loss: 0.1558 - accuracy: 0.9845 - val_loss: 0.1708 - val_accuracy: 0.9920

Epoch 4/5

947/947 [=====] - 0s 117us/sample - loss: 0.1951 - accuracy: 0.9929 - val_loss: 0.2430 - val_accuracy: 0.9091

Epoch 5/5

947/947 [=====] - 0s 119us/sample - loss: 0.2186 - accuracy: 0.9869 - val_loss: 0.1637 - val_accuracy: 0.9920

#####

Training Accuracy: 0.9929

Testing Accuracy: 0.9920

```
In [165]: # Cluster 3 prediction with deep neural network on extracted features in step 4
newsgroup_target3 = one_hot_encoder(cluster3) # using one hot encoder for target
NN_accuracy_cluster3 = get_deep_neural_network(features_selected_cluster3, newsgroup_target3)
Model: "sequential_18"
```

Layer (type)	Output Shape	Param #
dense_90 (Dense)	(None, 500)	500500

dense_91 (Dense)	(None, 4)	2004
------------------	-----------	------

=====
Total params: 502,504

Trainable params: 502,504

Non-trainable params: 0

Train on 767 samples, validate on 330 samples

Epoch 1/5

767/767 [=====] - 1s 678us/sample - loss: 0.5844 - accuracy: 0.9355 - val_loss: 0.0949 - val_accuracy: 0.9985

Epoch 2/5

767/767 [=====] - 0s 131us/sample - loss: 0.1132 - accuracy: 0.9980 - val_loss: 0.1150 - val_accuracy: 0.9985

Epoch 3/5

767/767 [=====] - 0s 117us/sample - loss: 0.1234 - accuracy: 0.9980 - val_loss: 0.1241 - val_accuracy: 0.9985

Epoch 4/5

767/767 [=====] - 0s 120us/sample - loss: 0.1066 - accuracy: 0.9980 - val_loss: 0.1355 - val_accuracy: 0.9985

Epoch 5/5

767/767 [=====] - 0s 120us/sample - loss: 0.0995 - accuracy: 0.9980 - val_loss: 0.1343 - val_accuracy: 0.9985

#####

Training Accuracy: 0.9980

Testing Accuracy: 0.9985

```
In [166]: # Cluster 4 prediction with deep neural network on extracted features in step 4
newsgroup_taget4 = one_hot_encoder(cluster4) # using one hot encoder for target
NN_accuracy_cluster4 = get_deep_neural_network(features_selected_cluster4, newsgroup_taget4)
Model: "sequential_19"
```

Layer (type)	Output Shape	Param #
dense_92 (Dense)	(None, 500)	500500
dense_93 (Dense)	(None, 66)	33066

```
=====
Total params: 533,566
Trainable params: 533,566
Non-trainable params: 0
```

```
Train on 21347 samples, validate on 9150 samples
```

```
Epoch 1/5
```

```
21347/21347 [=====] - 3s 126us/sample - loss: 0.1650 - accuracy: 0.9793 - val_loss: 0.1138 - val_accuracy: 0.9797
```

```
Epoch 2/5
```

```
21347/21347 [=====] - 2s 107us/sample - loss: 0.0824 - accuracy: 0.9827 - val_loss: 0.0790 - val_accuracy: 0.9848
```

```
Epoch 3/5
```

```
21347/21347 [=====] - 2s 106us/sample - loss: 0.0681 - accuracy: 0.9834 - val_loss: 0.0618 - val_accuracy: 0.9848
```

```
Epoch 4/5
```

```
21347/21347 [=====] - 2s 96us/sample - loss: 0.0662 - accuracy: 0.9836 - val_loss: 0.0652 - val_accuracy: 0.9798
```

```
Epoch 5/5
```

```
21347/21347 [=====] - 2s 103us/sample - loss: 0.0643 - accuracy: 0.9836 - val_loss: 0.0627 - val_accuracy: 0.9848
```

```
#####
```

```
Training Accuracy: 0.9849
```

```
Testing Accuracy: 0.9848
```



```
In [167]: # Cluster 5 prediction with deep neural network on extracted features in step 4
newsgroup_target5 = one_hot_encoder(cluster5) # using one hot encoder for target
NN_accuracy_cluster5 = get_deep_neural_network(features_selected_cluster5, newsgroup_target5)

Model: "sequential_20"
```

Layer (type)	Output Shape	Param #
dense_94 (Dense)	(None, 500)	500500
dense_95 (Dense)	(None, 56)	28056
Total params: 528,556		
Trainable params: 528,556		
Non-trainable params: 0		

Train on 8079 samples, validate on 3463 samples

Epoch 1/5

8079/8079 [=====] - 1s 150us/sample - loss: 0.2894 - accuracy: 0.9716 - val_loss: 0.1591 - val_accuracy: 0.9706

Epoch 2/5

8079/8079 [=====] - 1s 108us/sample - loss: 0.1506 - accuracy: 0.9744 - val_loss: 0.1244 - val_accuracy: 0.9583

Epoch 3/5

8079/8079 [=====] - 1s 106us/sample - loss: 0.1162 - accuracy: 0.9765 - val_loss: 0.0996 - val_accuracy: 0.9821

Epoch 4/5

8079/8079 [=====] - 1s 107us/sample - loss: 0.0963 - accuracy: 0.9782 - val_loss: 0.0863 - val_accuracy: 0.9821

Epoch 5/5

8079/8079 [=====] - 1s 102us/sample - loss: 0.0939 - accuracy: 0.9783 - val_loss: 0.0888 - val_accuracy: 0.9699

#####

Training Accuracy: 0.9698

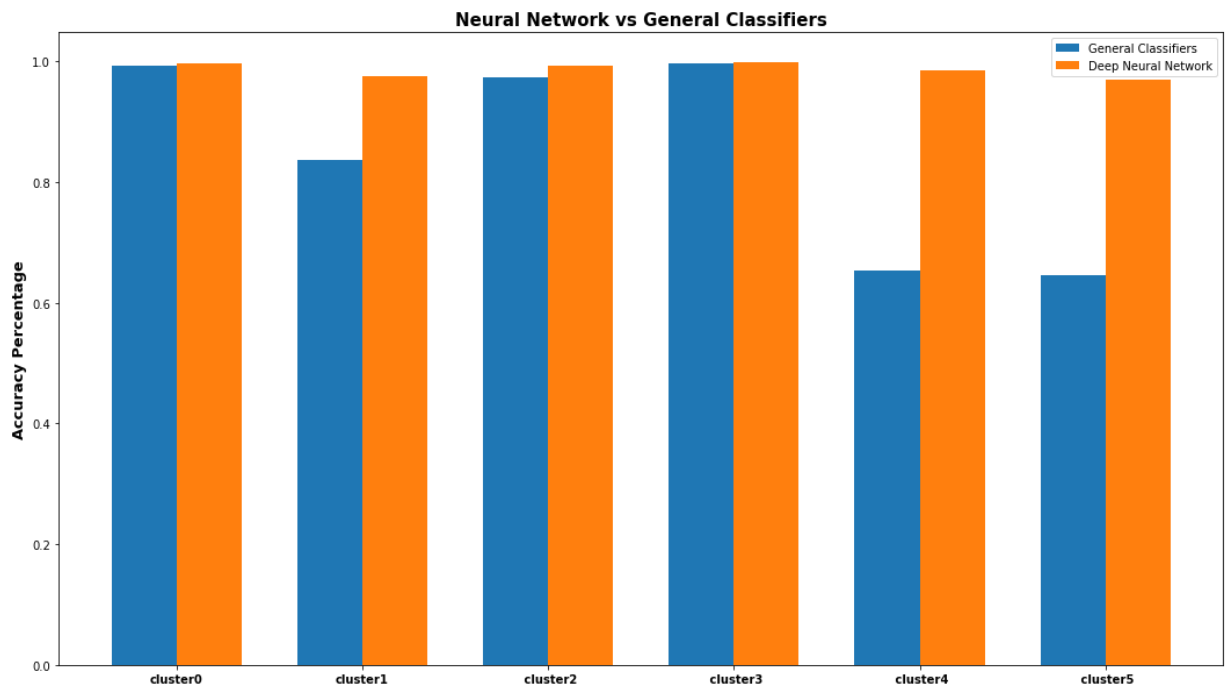
Testing Accuracy: 0.9699

By Visualization proving that our deep neural networks improves the classification approach

In [176]: *#compare the accuracy and average_class accuracy for each algorithm*

```
no_of_clusters = 6
normal_classifier_accuracy = [accuracy_cluster0, accuracy_cluster1, accuracy_cluster2, accuracy_cluster3, accuracy_cluster4, accuracy_cluster5]
deep_nural_network_accuracy = [NN_accuracy_cluster0, NN_accuracy_cluster1, NN_accuracy_cluster2, NN_accuracy_cluster3, NN_accuracy_cluster4, NN_accuracy_cluster5]

no = np.arange(no_of_clusters)
width = 0.35
plt.figure(figsize=(18,10))
plt.bar(no, normal_classifier_accuracy, width, label='General Classifiers')
plt.bar(no + width, deep_nural_network_accuracy, width, label='Deep Neural Network')
plt.title('Neural Network vs General Classifiers',fontsize=15,fontweight='bold')
plt.xticks(no + width / 2, ('cluster0','cluster1',' cluster2',' cluster3',' cluster4',' cluster5'))
plt.ylabel("Accuracy Percentage",fontweight='bold',fontsize=13)
plt.legend(loc='best')
plt.show()
```



REFERENCES :-

- [1] I have recieved TA's help (Mohammad Etemad) for better understanding and clarity of problem statements in the project.
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