SPAM COMMENTS CLASSIFICATION

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ACKNOWLEDGMENT

I want to acknowledge the Flip Robo Technologies team for giving me the chance to work with this dataset during my internship. It enabled me to develop my analytical abilities. I want to thank Khushboo Garg (SME, Flip Robo) for her assistance.

Reference used in this project:

1. Different projects on Github and Kaggle.
2. Hands on Machine learning with scikit learn and tensor flow by Aurelien Geron.
3. “A Review of Machine Learning Approaches to Spam Filtering”, Thiago S. Guzella et al. in 2009.
4. Different conference papers on Recharchgate.

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1. Introduction

The SMS Spam Collection is a set of SMS tagged messages that have been collected for SMS Spam research. It contains one set of SMS messages in English of 5,574 messages, tagged according being ham (legitimate) or Spam.

Spam Detector is used to detect unwanted, malicious and virus infected texts and helps to separate them from the nonspam texts. It uses a binary type of classification containing the labels such as 'ham' (nonspam) and spam. Application of this can be seen in Google Mail (GMAIL) where it segregates the spam emails in order to prevent them from getting into the user's inbox. The files contain one message per line. Each line is composed by two columns: v1 contains the label (ham or spam) and v2 contains the raw text.

2. Analytical Problem Framing

2.1 Mathematical/ Analytical Modelling of the Problem

The goal of this project is to predict spam massage from SMS in social media. We would use a classification method, which is a sort of supervised learning. We will only do classification in this case. Filtering the words is necessary to avoid overfitting because the dataset only contains one feature.

This project have one big set of data one for both training and testing. Throughout the project's classification phase, we would first eliminate all numbers, words, spaces and other terms with stops, in order to calculate the regularisation parameter. We also used Count Vectorizer to transform the tokens into vectors so that the machine could carry out additional processing in order to further enhance our models.

Here 4 different algorithm are used and final model is chosen by best AUC-ROC score and accuracy score.

2.2 Data Sources and their formats

There are one set of data. The dataset has 5572 rows and 2 columns. Primarily it has 5 columns wher e 3 columns are unnecessary. After deleting those 3 columns, finally this dataset has 2 columns name d v1 and v2. Later rename the columns as type and massage_body.
Later the dataset is divided into two parts, training and testing. After determine the proper model, the model is applied to predict the target variable for the test dataset.

```
data = data.drop(["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"], axis=1)
data = data.rename(columns={"v1":"type", "v2":"massage_body"})
```

```
print('No. of Rows of test dataset :',data.shape[0])
print('No. of Columns of test dataset :',data.shape[1])
```

```
No. of Rows of test dataset : 5572
No. of Columns of test dataset : 2
```

2.3 Data Pre-processing Done:

2.3.1 Feature Engineering:

' --', 'null', 'NA', ' ' are not present in the dataset.

```
data.isin([' --','null','NA',' ']).sum().any()
```

```
False
```

```
data.isnull().sum()
```

```
type            0
massage_body    0
dtype: int64
```

2.3.2 Drop unnecessary columns:

Drop the unnecessary column Unnamed: 2, Unnamed: 3, Unnamed: 4 from the dataset.

```
data = data.drop(["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"], axis=1)
data = data.rename(columns={"v1":"type", "v2":"massage_body"})
```

2.3.3 Calculate length before cleaning of 'massage_body' column:

Let's calculate the comment length before cleaning.

```
data['length_before_cleaning'] = data['massage_body'].str.len()
data.head()
```

	type	massage_body	length_before_cleaning
0	0	Go until jurong point, crazy.. Available only ...	111
1	0	Ok lar... Joking wif u oni...	29
2	1	Free entry in 2 a wkly comp to win FA Cup fina...	155
3	0	U dun say so early hor... U c already then say...	49
4	0	Nah I don't think he goes to usf, he lives aro...	61

2.3.4 Encoding type dataset:

Here 'type' dataset is object datatype. Let's encoded the type columns as ham=0 and spam =1 for further progress.

```
data.loc[:,'type'] = data.type.map({'ham':0, 'spam':1})
data.head()
```

	type	massage_body
0	0	Go until jurong point, crazy.. Available only ...
1	0	Ok lar... Joking wif u oni...
2	1	Free entry in 2 a wkly comp to win FA Cup fina...
3	0	U dun say so early hor... U c already then say...
4	0	Nah I don't think he goes to usf, he lives aro...

2.3.5 Length of massage_body:

Here the maximum length of the massage is 910 where minimum length is 2. The median of the comment length is 61.

```
data['length_before_cleaning'].min()
```

```
2
```

```
data['length_before_cleaning'].max()
```

```
910
```

```
data['length_before_cleaning'].median()
```

```
61.0
```

2.3.6 Natural Language Processing:

Import all necessary libraries for NLP. Now let's remove all alphabates, numbers from the text body. Then apply Stemmer, Stop words and such necessary NLP steps on massage body for cleaning the dataset.

```
allmassage=[] # initialize empty list for adding all text messages
for i in range(0, 5572):
    ps=PorterStemmer()
    message=data['massage_body'][i]
    message=re.sub('[^a-zA-Z]',' ', message)
    message=re.sub(r'\d+', '', message)
    message=message.lower()
    message=message.split()
    message=[ps.stem(word) for word in message if not word in set(stopwords.words('english')+ ['u','ur','4','2','im',
                                                'dont','doin','I','numbr','YOU','You','A','If'])]
    message=' '.join(message)
    allmassage.append(message)
```

We also use Count Vectorizer method on the features and label encoding on target variable.

2.4 State the set of assumptions (if any) related to the problem under consideration

No such assumptions are taken for this case.

2.5 Hardware and Software Requirements and Tools Used

Processor: Intel(R) Core(TM) i3-5005U CPU @ 2.00GHz 2.00 GHz
RAM: 4.00 GB
System Type: 64-bit operating system, x64-based processor
Window: Windows 10 Pro
Anaconda – Jupyter Notebook
Libraries Used –

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')

from sklearn.model_selection import train_test_split
```

For Word-Cloud the following libraries are used.

```
#Importing Required libraries
import nltk
import re
import string
from nltk.corpus import stopwords
from wordcloud import WordCloud
from nltk.tokenize import word_tokenize
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer
```

Except this, different libraries are used for machine learning model building from sklearn.

3. Model/s Development and Evaluation

3.1 Identification of possible problem-solving approaches (methods):

In this problem Classification-based machine learning algorithm like logistic regression can be used. Removed any excess spaces, changed the email addresses subject line to a phone number that is probably wise, etc. For building an appropriate ML model before implementing classification algorithms, data is split in training & test data using train_test_split. Then different statistical parameter like accuracy score, confusion matrix, classification report, precision, recall etc. are determined for every algorithm. Hyper parameter tuning is performed to get the accuracy score much higher and accurate than earlier.

Then the best model is chosen from 4 different algorithm.

3.2 Testing of Identified Approaches (Algorithms)

Total 7 algorithms used for the training and testing are:

1. Logistic Regression
2. Decision Tree Classifier
3. Gradient Boosting Classifier
4. Multinomial Naive Bayes

3.3 Key Metrics for success in solving problem under consideration:

From metrics module of sklearn library import classification_report, accuracy_score, confusion_matrix, classification_report and f1_score. From model_selection also, we use cross_val_score. Those are the matrices use to validate the model's quality. Let's discuss every metrics shortly.

- Classification report: It is a performance evaluation metric in machine learning which is used to show the precision, recall, F1 Score, and support score of your trained classification model
- Accuracy score: It is used when the True Positives and True negatives are more important. Accuracy can be used when the class distribution is similar.
- Confusion Matrix: It is a table that is used in classification problems to assess where errors in the model were made. The rows represent the actual classes the outcomes should have been. While the columns represent the predictions we have made. Using this table it is easy to see which predictions are wrong.
- Precision: It can be seen as a measure of quality. If the precision is high, an algorithm returns more relevant results than irrelevant ones.
- Recall: The recall is calculated as the ratio between the numbers of Positive samples correctly classified as Positive to the total number of Positive samples.
- F1 Score: F1 = 2 * (precision * recall) / (precision + recall)

3.4 Run and Evaluate selected models

First find the best random state of train_test_split to get best accuracy. Here the random state is 8. Then after splitting the data into 4 different part and check the shape of the data.

```
print('Training feature shape:',x_train.shape)
print('Training target shape:',y_train.shape)
print('Test feature shape:',x_test.shape)
print('Test target shape:',y_test.shape)
```

```
Training feature shape: (3900, 6221)
Training target shape: (3900,)
Test feature shape: (1672, 6221)
Test target shape: (1672,)
```

A Logistic Regression:

```
from sklearn.linear_model import LogisticRegression
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.3, random_state= 8)
log = LogisticRegression()
log.fit(x_train, y_train)
y_pred = log.predict(x_test)

print('accu score : ', accuracy_score(y_test, y_pred))
print ('cof_mat:\n ', confusion_matrix(y_test, y_pred))
print('classification report:\n ', classification_report(y_test, y_pred))
print("-----------")
print("-----------")
print('training score : ', log.score(x_train, y_train))
print('testing score : ', log.score(x_test, y_test))
```

```
accu score :  0.9856459330143541
cof_mat:
  [[1447    3]
 [  21  201]]
classification report:
                precision    recall  f1-score   support

           0       0.99      1.00      0.99      1450
           1       0.99      0.91      0.94       222

    accuracy                           0.99      1672
   macro avg       0.99      0.95      0.97      1672
weighted avg       0.99      0.99      0.99      1672

-----------
-----------
training score :  0.9953846153846154
testing score :  0.9856459330143541
```

In this way accuracy score is determined for each 4 different classification model.

B Decision Tree Classifier*:*

The accuracy score, confusion matrix and classification report after using Decision tree Classifier is as follows.

```
accu score :  0.9700956937799043
cof_mat:  [[1425   25]
 [  25  197]]
classification report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1450
           1       0.89      0.89      0.89       222

    accuracy                           0.97      1672
   macro avg       0.94      0.94      0.94      1672
weighted avg       0.97      0.97      0.97      1672

-----------
-----------
training score :  1.0
testing score :  0.9700956937799043
```

C *Gradient Boosting Classifier:*

The accuracy score, confusion matrix and classification report after using Gradient Boosting Classifier is as follows.

```
accu score :  0.9688995215311005
cof_mat:  [[1447    3]
 [  49  173]]
classification report:
              precision    recall  f1-score   support

           0       0.97      1.00      0.98      1450
           1       0.98      0.78      0.87       222

    accuracy                           0.97      1672
   macro avg       0.98      0.89      0.93      1672
weighted avg       0.97      0.97      0.97      1672

-----------
-----------
training score :  0.9784615384615385
testing score :  0.9688995215311005
```

D *Multinomial Naïve Bayes Classifier:*

The accuracy score, confusion matrix and classification report after using Multinomial Naïve Bayes Classifier is as follows.

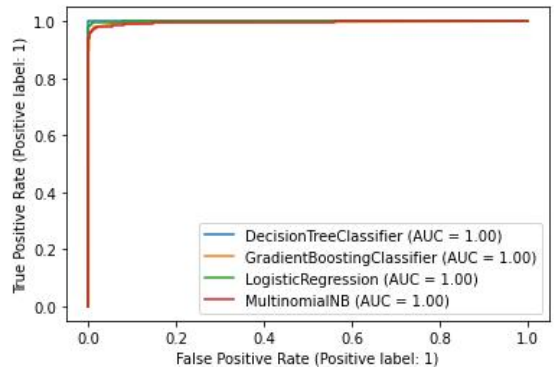
```
accu score :  0.9850478468899522
cof_mat:  [[1433   17]
           [   8  214]]

classification report:
              precision    recall  f1-score   support

           0       0.99      0.99      0.99      1450
           1       0.93      0.96      0.94       222

    accuracy                           0.99      1672
   macro avg       0.96      0.98      0.97      1672
weighted avg       0.99      0.99      0.99      1672

-----------
-----------
training score :  0.9915384615384616
testing score :  0.9850478468899522
```

As per 4 different model, Naïve Bayes is the best model.

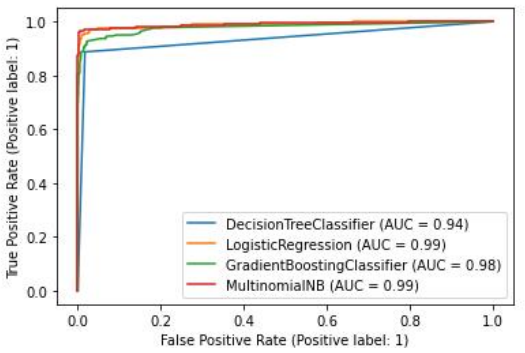
But for Logistic Regression the difference between training and testing is very small as well as it also gives good accuracy.

3.5 AUC- ROC Curve:

```
from sklearn.metrics import plot_roc_curve

disp = plot_roc_curve(clf, x_train, y_train)
plot_roc_curve(gbdt, x_train, y_train, ax=disp.ax_)
plot_roc_curve(log, x_train, y_train, ax=disp.ax_)
plot_roc_curve(naive, x_train, y_train, ax=disp.ax_)
plt.show()
```




```
from sklearn.metrics import plot_roc_curve

disp = plot_roc_curve(clf, x_test, y_test)

plot_roc_curve(log, x_test, y_test, ax=disp.ax_)
plot_roc_curve(gbdt, x_test, y_test, ax=disp.ax_)
plot_roc_curve(naive, x_test, y_test, ax=disp.ax_)
plt.show()
```



3.6 Hyper Parameter Tuning:

Here for Naive bayes, Logistic Regression the AUC score is same. Here we take Naive bayes for final model. So it is the final model for this dataset.

```
from sklearn.model_selection import GridSearchCV
grid = dict(alpha=[1, 0.5,0.0001,0.001],fit_prior=[True, False])

grid_naive = GridSearchCV(estimator=naive, param_grid= grid,refit = True)

grid_naive.fit(x_train, y_train)
print('best params : ', grid_naive.best_params_)
```

```
best params :  {'alpha': 1, 'fit_prior': True}
```

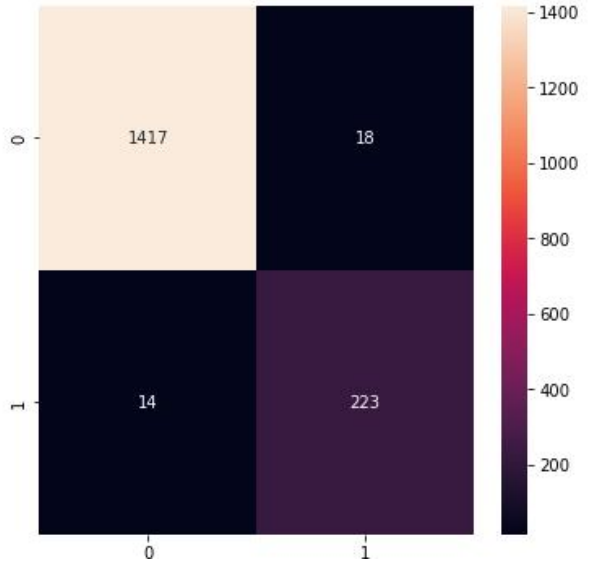
Best params: {'alpha': 1, 'fit_prior': 'True'}
Here accuracy score is not improved after using hyper parameter tuning.

3.7 Final Model:

For final model the target variable is as follows after using Naïve Bayes.

3.8 Confusion Matrix:

```
conf = confusion_matrix (y_test, y_pred)
fig , ax = plt.subplots(figsize=(6,6))
sns.heatmap(conf, annot = True, fmt = ".0f")
plt.show()
```



3.9 Load the model:

Let's save the model using pickle for future use. Then see the actual and predicted value of 6 random sample.

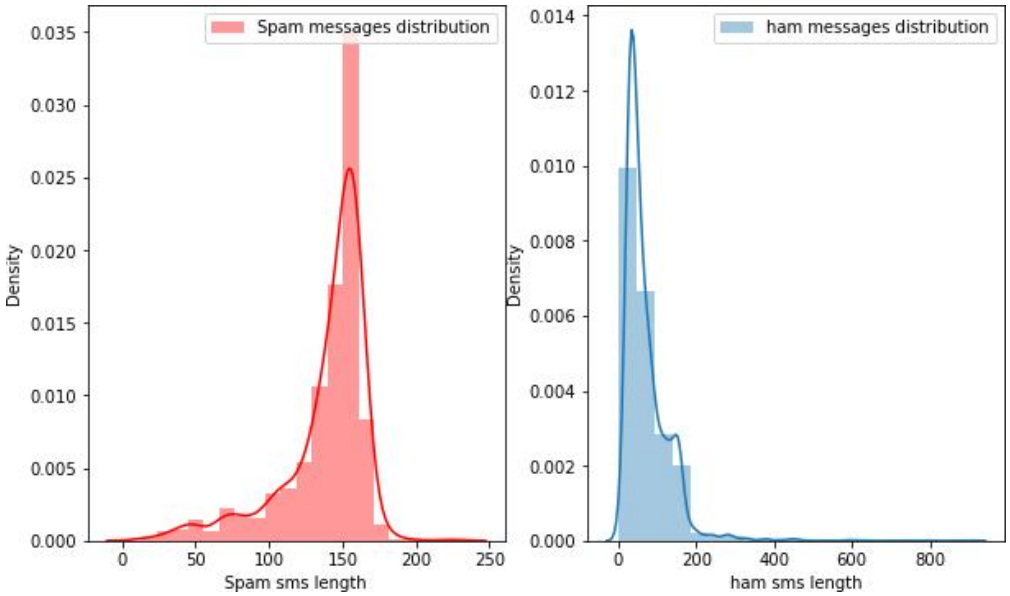
```
import pickle
pickle.dump(grid_naive_best, open("Spam_SMS_Classification_model", "wb"))
load_Spam_SMS_Classification_model= pickle.load(open("Spam_SMS_Classification_model", "rb"))
```

```
y_pred = load_Spam_SMS_Classification_model.predict(x_test)

y_test = np.array(y_test)
data_prediction_by_model = pd.DataFrame()
data_prediction_by_model["Predicted Values"] = y_pred
data_prediction_by_model["Actual Values"] = y_test
data_prediction_by_model.sample(n=6)
```

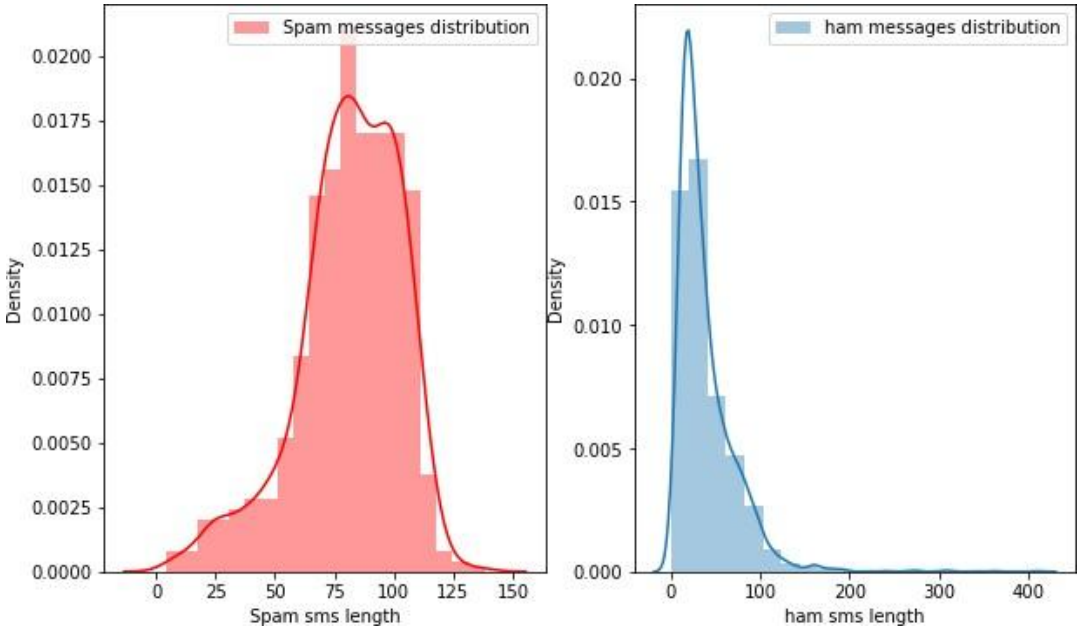
	Predicted Values	Actual Values
1070	0	1
27	0	0
522	1	1
193	0	0
1621	0	0
474	1	1

3.10 Visualizations:

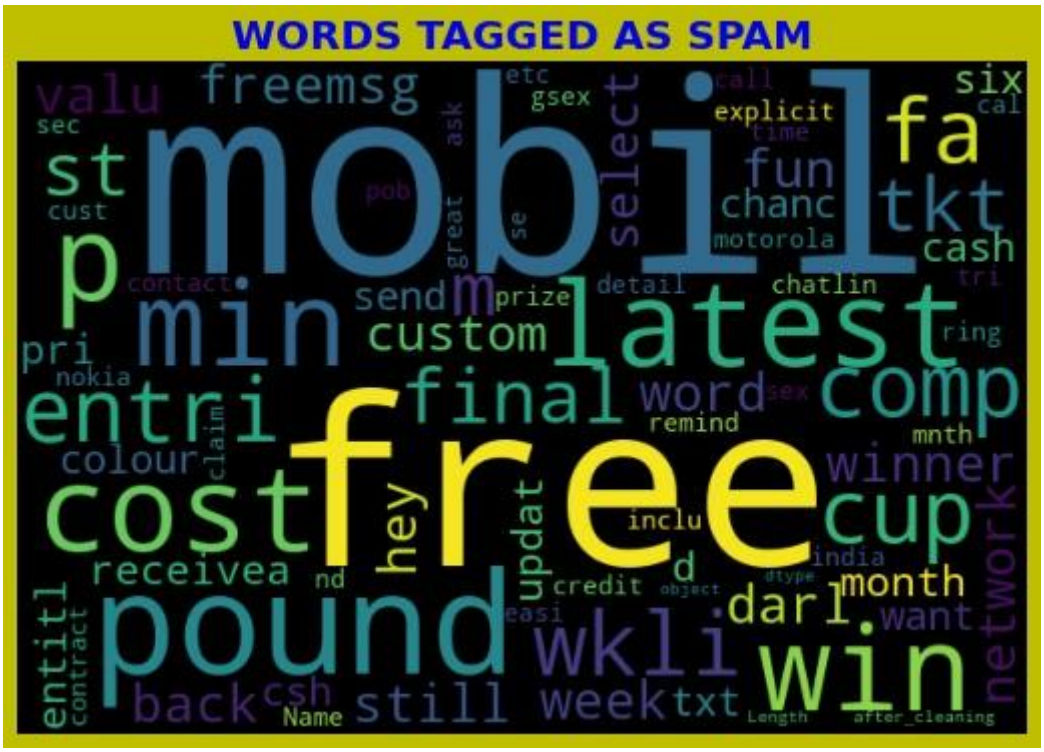
Let's start the observation exploration of feature analysis. Visualize the dataset before cleaning for span and not spam massages.



Let's visualize it after cleaning the dataset.



3.11 Word Cloud for Spam sms:



3.12 Interpretation of the Results

After all the pre-processing steps, the dataset is ready to train machine learning models. All unnecessary words from comment text are deleted as they might give overfitting problem as well as it also could increase the time complexity. Now apply this dataset on different ML Classification Model (as discussed on part 3.4 - 'Run and Evaluate selected models') and check the best model for this particular dataset.

4. CONCLUSION

- **Key Findings and Study Conclusions**

Here, we noticed the different spam SMSs. We have also seen how simple algorithms can be applied in this way to deal with this challenge. In this particular experiment, it was demonstrated that a logistic regression solution provides a notable improvement in classification compared to any alternative strategy.

- **Learning Objectives for the Data Science Study**

One of the most important steps is data purification, thus I made an effort to keep my remarks brief while yet including all the necessary keywords. The ability to visualise data is useful for turning it into a graphical representation since it makes it easier for me to understand what the data is trying to say.

I used a variety of techniques on this dataset to identify the best outcome and keep that model. The usage of NLP methodology to identify the spam massage is highly beneficial.