VERZEO MAJOR PROJECT

PROBLEM STATEMENT: Problem Statement: For a given dataset (problem) which is the best classification algorithm (as per accuracy)

Pick up a dataset of your choice or the one attached with mail (Preferable)

Ask any two questions on the dataset of your choice and provide answers for the same.

Take up three classification algorithms of your own choice and build three respective Machine learning models. Compare the Accuracy of all three and suggest which ML algorithms suits best for the given problem.

ANALYSIS

In [3]:

The Dataset given titled 'Information.csv' shows the tweet written by different twitter users and analysis is done in order to classify the tweeting habits of male and female users respectively. All the user data whose gender has not been specified will not be considered for analysis.

Also note that 'Gender' is the target variable here.

_unit_i	d _golden	_unit_state	_trusted_judgments	_last_judgment_at	gender	gender:confidence	profile_yn	profile_yn:confidence	create	d profileimage	retweet_count	sidebar_color	text	tweet_coord twee
0 81571922	6 False	finalized	3	10/26/15 23:24	male	1.0000	yes	1.0	12/5/1 1:4	3 https://pbs.twimg.com/profile_images/414342229	0	FFFFFF	Robbie E Responds To Critics After Win Against	NaN
1 81571922	7 False	finalized	3	10/26/15 23:30	male	1.0000	yes	1.0	10/1/1 13:5	2 https://pbs.twimg.com/profile_images/539604221	0	CODEED	ÛÏIt felt like they were my friends and I was	NaN
2 81571922	8 False	finalized	3	10/26/15 23:33	male	0.6625	yes	1.0	11/28/1 11:3	t https://pbs.twimg.com/profile_images/657330418	1	CODEED	i absolutely adore when louis starts the songs	NaN
3 81571922	9 False	finalized	3	10/26/15 23:10	male	1.0000	yes	1.0	6/11/0 22:3	https://pbs.twimg.com/profile_images/259703936	0	CODEED	Hi @JordanSpieth - Looking at the url - do you	NaN
4 81571923	0 False	finalized	3	10/27/15 1:15	female	1.0000	yes	1.0	4/16/1 13:2	t https://pbs.twimg.com/profile_images/564094871	0	0	Watching Neighbours on Sky+ catching up with t	NaN

5 rows × 26 columns

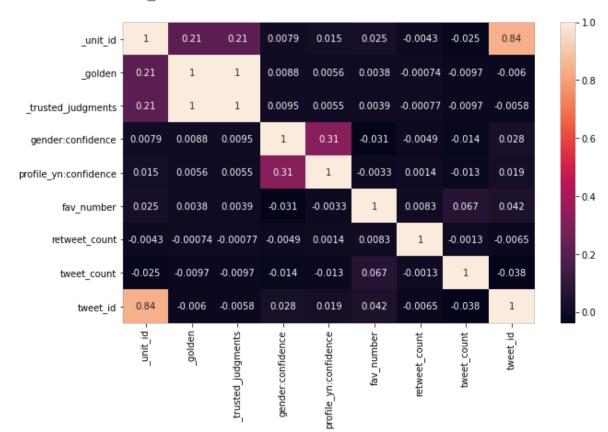
```
In [6]:
df.columns
Out[6]:
```

Feature Selection

```
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

```
In [9]:
fig = plt.figure(figsize=(10,6))
sns.heatmap(df.corr(),annot = True)
```

<matplotlib.axes. subplots.AxesSubplot at 0x16d773d0f40>



The above heatmap showcases the correlation between the numerical values which helps in choosing the features for further analysis.

Conclusions from the heatmap --

profile:confidence and gender confidence show some correlations so we took profile_yn as our feature. We eliminated unit_id and tweet_id from our dataframe as this doesnot make any sense. We included text and description columns as part of our analysis since it could be useful for natural language processing analysis for machine learning. Columns are selected as they are used to predict the gender column which is the target attribute.

```
In [10]:

df = df[['_unit_id', 'name', 'gender', 'gender: confidence', 'profile_yn', 'profile_yn: confidence', 'description', 'text']]
```

From above we have drawn some conclusions:

- 1. _unit_id: a unique id for user
- 2. _last_judgment_at: date and time of last contributor judgment; blank for gold standard observations
- 3. user_timezone: the timezone of the user
- 4. tweet_coord: if the user has location turned on, the coordinates as a string with the format "[latitude, longitude]"
- 5. tweet_created: when the random tweet (in the text column) was created

--> Attributes that do not provide useful information for Gender classification:

- 6. tweet_id: the tweet id of the random tweet
- 7. tweet_location: location of the tweet; seems to not be particularly normalized
- 8. profileimage: a link to the profile image
- 9. created: date and time when the profile was created
- --> Attributes that potentially provide useful information for Gender classification:
- 1. _golden: whether the user was included in the gold standard for the model; TRUE or FALSE 2. _unit_state: state of the observation; one of finalized (for contributor-judged) or golden (for gold standard observations)
- 3. _trusted_judgments: number of trusted judgments (int); always 3 for non-golden, and what may be a unique id for gold standard observations
- 4. gender: one of male, female, or brand (for non-human profiles)
- 5. gender:confidence: a float representing confidence in the provided gender
- 6. gender_gold: if the profile is golden, what is the gender?
- 7. profile_yn: "no" here seems to mean that the profile was meant to be part of the dataset but was not available when contributors went to judge it
- 8. profile_yn:confidence: confidence in the existence/non-existence of the profile
- 9. profile_yn_gold: whether the profile y/n value is golden
- 10. description: the user's profile description
- 11. fav_number: number of tweets the user has favorited
- 12. link_color: the link color on the profile, as a hex value
- 13. name: the user's name
- 14. retweet_count: number of times the user has retweeted (or possibly, been retweeted)
- 15. sidebar_color: color of the profile sidebar, as a hex value
- 16. text: text of a random one of the user's tweets
- 17. tweet_count: number of tweets that the user has posted

In [11]:

df.head()

Out[11]:

_unit_id	name	gender	gender:confidence	profile_yn	profile_yn:confidence	description	text
0 815719226	sheezy0	male	1.0000	yes	1.0	i sing my own rhythm.	Robbie E Responds To Critics After Win Against
1 815719227	DavdBurnett	male	1.0000	yes	1.0	I'm the author of novels filled with family dr	ÛÏIt felt like they were my friends and I was
2 815719228	lwtprettylaugh	male	0.6625	yes	1.0	louis whining and squealing and all	i absolutely adore when louis starts the songs
3 815719229	douggarland	male	1.0000	yes	1.0	Mobile guy. 49ers, Shazam, Google, Kleiner Pe	Hi @JordanSpieth - Looking at the url - do you
4 815719230	WilfordGemma	female	1.0000	yes	1.0	Ricky Wilson The Best FRONTMAN/Kaiser Chiefs T	Watching Neighbours on Sky+ catching up with t

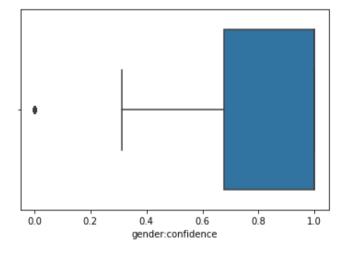
In [12]:

#Box plot used for data visualosation import seaborn as sns

In [13]:

sns.boxplot(df['gender:confidence'])

<matplotlib.axes._subplots.AxesSubplot at 0x16d7736aa30>



In [14]:

df = df[(df['profile_yn:confidence'] >= 0.6) | (df['gender:confidence'] >= 0.6)]

Profile_yn: Confidence having values greater than and equal to 0.6 are selected as this shows the confidence in the existence of the user's profile which might help us improve the quality of the dataset. Similarly for gender:confidence >= 0.6 is selected.

In [15]:

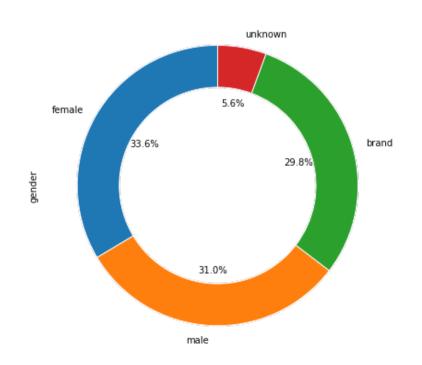
df.gender.unique()

Out[15]:

array(['male', 'female', 'brand', 'unknown', nan], dtype=object)

In [16]:

```
plt.figure(figsize=(7,7))
df['gender'].value_counts().plot(kind='pie', autopct='%1.1f%%',
                  startangle=90, wedgeprops=dict(width=0.3, edgecolor='w'))
plt.show()
```



Gender has values such as male, female, brand and unknown. For this prediction model only male and female gender values are used.

In [17]:

```
df = df[(df['gender'] == 'male') | (df['gender'] == 'female')]
```

In [18]:

df.profile yn.unique()

Out[18]:

```
array(['yes'], dtype=object)

In [19]:

df = df[df['profile_yn'] == 'yes']
```

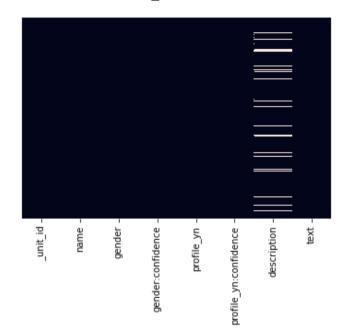
NULL VALUES

```
In [20]:
```

sns.heatmap(df.isnull(),yticklabels=False,cbar = False)

Out[20]:

<matplotlib.axes._subplots.AxesSubplot at 0x16d775a07f0>



In [21]:

```
df = df.dropna()
```

In [22]:

df.shape

111 [22].

Out[22]:

(11194, 8)

After cleaning the dataset is reduced from 20050 rows to 11194 rows and from 26 columns to 7 columns

```
In [23]:
```

```
df.info()
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11194 entries, 0 to 20049
Data columns (total 8 columns):
             Non-Null Count Dtype
# Column
                      -----
              11194 non-null int64
0 _unit_id
              11194 non-null object
11194 non-null object
1 name
2 gender
3 gender:confidence 11194 non-null float64
4 profile_yn 11194 non-null object
5 profile_yn:confidence 11194 non-null float64
6 description 11194 non-null object
                         11194 non-null object
dtypes: float64(2), int64(1), object(5)
```

In [24]:

memory usage: 787.1+ KB

```
df['text description'] = df['text'].str.cat(df['description'], sep=' ')
```

Text and description columns are here combined to add an extra layer of text data for classifying the gender based on the texting habits of the Twitter user.

```
In [25]:
```

df.head()

Out[25]:

_unit_id	name	gender	gender:confidence	profile_yn	profile_yn:confidence	description	text	text_description
0 815719226	sheezy0	male	1.0000	yes	1.0	i sing my own rhythm.	Robbie E Responds To Critics After Win Against	Robbie E Responds To Critics After Win Against
1 815719227	DavdBurnett	male	1.0000	yes	1.0	I'm the author of novels filled with family dr	ÛÏIt felt like they were my friends and I was	ÛÏIt felt like they were my friends and I was
2 815719228	lwtprettylaugh	male	0.6625	yes	1.0	louis whining and squealing and all	i absolutely adore when louis starts the songs	i absolutely adore when louis starts the songs
3 815719229	douggarland	male	1.0000	yes	1.0	Mobile guy. 49ers, Shazam, Google, Kleiner Pe	Hi @JordanSpieth - Looking at the url - do you	Hi @JordanSpieth - Looking at the url - do you
4 815719230	WilfordGemma	female	1.0000	yes	1.0 R	icky Wilson The Best FRONTMAN/Kaiser Chiefs T	Watching Neighbours on Sky+ catching up with t	Watching Neighbours on Sky+ catching up with t

In [26]:

```
#The individual text and description columns are dropped after combining the two text fields into one df= df.drop(['description','text'],axis=1)
```

In [27]:

df=df.reset_index(drop=True)

 $\textbf{Furture cleaning of text_description column is done below to remove the unwanted characters}$

```
In [28]:
```

```
import re
def cleaning(s):
   s = str(s)
   s = s.lower()
   s = s.replace(",","")
   s = re.sub('[!@#$_]', '', s)
   s = re.sub("\d+", "", s)
   s = re.sub('\s+','',s)
   s = s.replace('','')
   s = s.replace("co","")
   s = s.replace("https","")
   s = s.replace("http","")
   s = re.sub("[^a-zA-z]", "",s)
   return s
df['text description'] = [cleaning(s) for s in df['text description']]
df.head()
```

Out[28]:

	_unit_id	name	gender	gender:confidence	profile_yn	profile_yn:confidence	text_description
0	815719226	sheezy0	male	1.0000	yes	1.0	robbie e responds to critics after win against
1	815719227	DavdBurnett	male	1.0000	yes	1.0	it felt like they were my friends and i was
2	815719228	lwtprettylaugh	male	0.6625	yes	1.0	i absolutely adore when louis starts the songs
3	815719229	douggarland	male	1.0000	yes	1.0	hi jordanspieth looking at the url do you
4	815719230	WilfordGemma	female	1,0000	ves	1.0	watching neighbours on sky catching up with t

Q1) What are the most common emotions/words used by Males and Females?

In [32]:

In order to solve the above question two counters are created each for male and female. Male counter contains the words used by males and the number of times that particular word is used while the same is done for females. These counters contain the stopwords which are removed and the answers are found based on the filtered words.

```
from collections import Counter
wordsM = Counter()
wordsF = Counter()
for twit,gender in zip(df['text_description'],df['gender']):
    if gender == 'male':
        for x in twit.split(' '):
            wordsM[x] += 1
    else:
        for x in twit.split(' '):
             wordsF[x] += 1
wordsF.most common(5)
Out[32]:
[('', 59628), ('and', 5707), ('the', 5496), ('i', 4951), ('t', 3052)]
In [33]:
wordsM.most_common(5)
Out[33]:
[('', 51892), ('the', 6044), ('and', 5278), ('i', 3817), ('t', 3130)]
In [34]:
import nltk
nltk.download('stopwords')
[nltk_data] Downloading package stopwords to
                C:\Users\Muskaan\AppData\Roaming\nltk_data...
[nltk_data]
[nltk_data]
              Package stopwords is already up-to-date!
Out[34]:
True
In [35]:
from nltk.corpus import stopwords
stopwords = stopwords.words('english')
words_filteredM = Counter()
words_filteredF = Counter()
for x, y in wordsM.items():
    if not x in stopwords:
       words filteredM[x]=y
for x, y in wordsF.items():
    if not x in stopwords:
        words_filteredF[x]=y
words_filteredM.most_common(5)
Out[35]:
[('', 51892), ('love', 526), ('like', 480), ('get', 400), ('one', 372)]
In [36]:
words_filteredF.most_common(5)
Out[36]:
[('', 59628), ('love', 776), ('like', 601), ('life', 446), ('one', 433)]
From above we can hence conclude:
 1. The most common words used by males are : love, like, get
 2. The most common words used by females are :love, like, life
Q2) Which gender makes more typos in their tweets?
The Spell Correction library of python is being used to find the typos made by males and females. Since the length of the words used by males and females are greater in number it takes a greater amount of time to find the error in
words using this particular library.
In [37]:
wordsfemaletypo = []
wordsmaletypo = []
for key in wordsF:
   wordsfemaletypo.append(key)
for key in wordsM:
   wordsmaletypo.append(key)
In [38]:
len(wordsmaletypo)
Out[38]:
27082
In [40]:
from autocorrect import Speller
speller = Speller (lang = 'en')
In [41]:
wordmalesmall = wordsmaletypo[:101]
countmale = 0
for x in wordmalesmall:
    if (speller(x)!=x):
       countmale+=1
print('The typos done by males are: ',countmale)
The typos done by males are: 7
In [42]:
wordfemalesmall = wordsfemaletypo[:101]
countfemale = 0
for x in wordfemalesmall:
    if (speller(x)!=x):
       countfemale+=1
print('The typos done by Females are: ',countfemale)
```

Since the duration to get the output is long only limited words are used below but the answers using entire text_description is: The typos done by males are 7 and by females are 11. Therefore females make more typos when compared to males.

Ensemble Machine learning Modelling (3 Classification Algorithms : Logistic Regression, KNN, SVM)

The typos done by Females are: 11

```
In [43]:
from sklearn.feature_extraction.text import CountVectorizer
most_used = 5000 # Most used 5000 words in bios
```

```
cv = CountVectorizer(max_features=most_used, stop_words='english')
In [44]:
sparce matrix = cv.fit transform(df['text description']).toarray()
sparce_matrix.shape
Out[44]:
(11194, 5000)
Here the independent variable i.e.Text_description is converted into sparce matrix for prediction. Text_description is used for classifying the gender based on the texting habits of the Twitter user.
In [45]:
X = sparce_matrix
Y = df[['gender']].values
The target attribute is gender and the independent attribute is text_description(Text and description columns from the dataset are combined)
Logistic Regression
In [46]:
#Logsitic Regression
from sklearn.model selection import train test split
In [47]:
X train, X test, Y train, Y test = train test split(X, Y, train size = 0.8)
In [48]:
X_train.shape, X_test.shape, Y_train.shape, Y_test.shape
Out[48]:
((8955, 5000), (2239, 5000), (8955, 1), (2239, 1))
In [56]:
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
In [50]:
logReg = LogisticRegression()
In [51]:
logReg.fit(X_train, Y_train)
C:\Users\Muskaan\anaconda3\lib\site-packages\sklearn\utils\validation.py:73: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y
to (n_samples, ), for example using ravel().
  return f(**kwargs)
C:\Users\Muskaan\anaconda3\lib\site-packages\sklearn\linear model\ logistic.py:762: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
Increase the number of iterations (max iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
Out[51]:
LogisticRegression()
In [52]:
Y pred = logReg.predict(X test)
In [53]:
from sklearn.metrics import accuracy score
In [54]:
print("The accuracy from Logistic Regression model is :",accuracy_score(Y_pred, Y_test)*100)
The accuracy from Logistic Regression model is: 64.85037963376507
KNearest Neighbours (KNN)
In [65]:
#KNN
from sklearn.neighbors import KNeighborsClassifier
In [67]:
df.columns
Out[67]:
Index([' unit id', 'name', 'gender', 'gender:confidence', 'profile yn',
       'profile_yn:confidence', 'text_description'],
      dtype='object')
In [68]:
knn = KNeighborsClassifier(n_neighbors=5,metric='euclidean')
In [69]:
knn.fit(X train, Y train)
<ipython-input-69-b601c265607f>:1: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel
 knn.fit(X_train, Y_train)
Out[69]:
KNeighborsClassifier(metric='euclidean')
In [70]:
Y pred = knn.predict(X test)
In [71]:
print("The accuracy from KNN classification model is :",accuracy_score(Y_pred, Y_test)*100)
The accuracy from KNN classification model is: 53.10406431442608
Support Vector Machine
```

In [72]:

In [73]:

svc = SVC()

from sklearn.svm import SVC

svc.fit(X_train, Y_train)

#SVM

```
to (n_samples, ), for example using ravel().
  return f(**kwargs)
Out[73]:
SVC()
In [74]:
Y_pred = svc.predict(X_test)
In [75]:
print("The accuracy from SVM classification model is :",accuracy_score(Y_pred, Y_test)*100)
```

C:\Users\Muskaan\anaconda3\lib\site-packages\sklearn\utils\validation.py:/3: DataConversionWarning: A column-vector y was passed when a ld array was expected. Please change the shape of y

Conclusion: As we can see, our best classification algorithm for this dataset is SVM as it is having an accuracy of 66.64% which is greater than LR and KNN models which are having an accuracy of 64% and 53%

Ensemble Model used to predict gender

The accuracy from SVM classification model is: 66.636891469406

```
In [76]:
import statistics
from statistics import mode
def ensemble_model(test):
    11 = []
    11=[logReg.predict(test)[0], svc.predict(test)[0], knn.predict(test)[0]]
   print(mode(11))
In [77]:
#Actual Dataset showing gender values
df[4:10].gender
Out[77]:
     female
     female
```

#Prediction model showing the gender values ensemble_model([sparce_matrix[4]]) ensemble_model([sparce_matrix[5]]) ensemble model([sparce matrix[6]]) ensemble model([sparce matrix[7]]) ensemble_model([sparce_matrix[8]]) ensemble_model([sparce_matrix[9]])

male female female female

In [78]:

Name: gender, dtype: object

female female male female female female

The function ensemble_model here uses Logistic Regression, SVM and KNN to predict the gender and return the mode value among the three classification models.

SCOPE OF IMPROVEMENT

- 1. Text data could be used for natural language processing.
- 2. More exploratory data analysis could be possible.
- 3. The accuracy of the analysis can be improved by using other models.
- 4. Usage of 'autocorrect' can be avoided since it takes a lot of time. Many other libraries like pyspellchecker can be used.