SENTIMENT ANALYSIS IN MARKETING

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PHASE 5 : PROJECT SUBMISSION

PROJECTDEFINITION:

Sentiment Analysis:

The process of computationally identifying and categorizing opinions expressed in a piece of text, especially in order to determine whether the writer's attitude towards a particular topic, product,

1. It is a powerful tool for marketing professionals who want to understand their target audience, improve customer satisfaction, and optimize their marketing strategies.
2. In this blog post, we will present a project model for applying sentiment analysis in marketing using artificial intelligence (AI).

DesignThinking:

The project model consists of four main steps:

1. **Data collection:**
   The first step is to collect relevant text data from various sources, such as social media, online reviews, surveys, emails, etc. The data should be representative of the customer segments and the marketing objectives that we want to analyze.

2. **Data preprocessing**:
   The second step is to clean and prepare the data for analysis. This involves removing noise, such as punctuation, stopwords, emojis, etc., and transforming the data into a suitable format for the AI model, such as tokens, vectors, or matrices.

3. **Data analysis:**
   The third step is to apply the AI model to the preprocessed data and obtain the sentiment scores or labels. The AI model can be based on different techniques, such as rule-based methods, lexicon-based methods, or machine learning methods. The choice of the model depends on the type and complexity of the data, the accuracy and speed requirements, and the availability of resources and expertise.

4. **Data visualization and interpretation:**
   The final step is to present and interpret the results of the sentiment analysis. This can be done using various visualization tools, such as charts, graphs, dashboards, etc., that show the distribution and trends of the sentiments across different dimensions, such as time, location, product, topic, etc. The visualization should also provide insights and recommendations for improving the marketing performance and customer experience

SUMMARY :

- **Building The Sentiment Analysis Solution By Selecting An Appropriate Dataset And Pre-processing The Data**

- **Pre-processing The Text Data By Using Machine Learning Algorithm**

- **Data Preprocessing, Analysis, And Visualization For Building A Machine Learning Model**

BUILDING THE SENTIMENT ANALYSIS SOLUTION BY SELECTING AN APPROPRIATE DATASET AND PRE-PROCESSING THE DATA

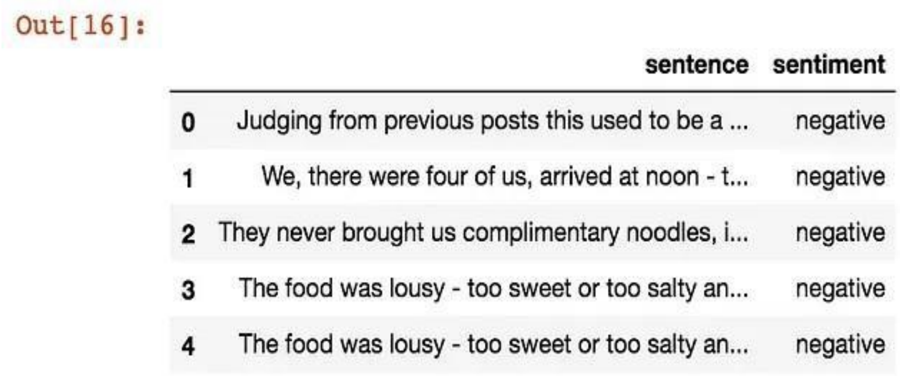
Sentiment analysis of reviews: Text Pre-processing

Training Data

To make a model you first need training data. I was able to find labeled training data for sentiment evaluation of restaurant reviews in New York from meta-share, a language data resource. It can be found here and can be freely downloaded as an xml file when signing up.

Lets first look at the data. I only extracting the data that is necessary for my model. The first column showing the polarity of the review and second column text of the review.

```
Import pandas as pd
Import numpy as np
Import xml.etree.ElementTree as ET
Xml_path = './NLP/ABSA15_RestaurantsTrain2/ABSA-15_Restaurants_Train_Final.xml'
Def parse_data_2015(xml_path):
  Container = []
  Reviews = ET.parse(xml_path).getroot()

  For review in reviews:
    Sentences = review.getchildren()[0].getchildren()
    For sentence in sentences:
      Sentence_text = sentence.getchildren()[0].text

      Try:
        Opinions = sentence.getchildren()[1].getchildren()

        For opinion in opinions:
          Polarity = opinion.attrib[“polarity”]
          Target = opinion.attrib[“target”]

          Row = {“sentence”: sentence_text, “sentiment”:polarity}
          Container.append(row)

      Except IndexError:
        Row = {“sentence”: sentence_text}
        Container.append(row)

  Return pd.DataFrame(container)
ABSA_df = parse_data_2015(xml_path)
ABSA_df.head()
```

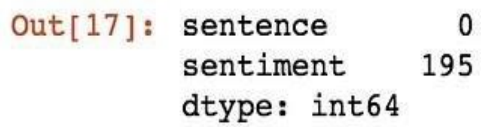


Out[16]:

	sentence	sentiment
0	Judging from previous posts this used to be a ...	negative
1	We, there were four of us, arrived at noon - t...	negative
2	They never brought us complimentary noodles, i...	negative
3	The food was lousy - too sweet or too salty an...	negative
4	The food was lousy - too sweet or too salty an...	negative

Before we start cleaning the text I wanted to ensure duplicates were dropped. Since we are using sentiment as our target (the variable we will be predicting) we cannot have any null values so these are dropped leaving the us with 1,201 rows.

ABSA_df.isnull().sum()



```
Out[17]: sentence       0
         sentiment    195
         dtype: int64
```

Print “Original:”, ABSA_df.shape

ABSA_dd = ABSA_df.drop_duplicates()

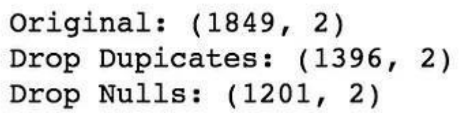
Dd = ABSA_dd.reset_index(drop=True)

Print “Drop Dupicates:”, dd.shape

Dd_dn = dd.dropna()

Df = dd_dn.reset_index(drop=True)

Print “Drop Nulls:”, df.shape



```
Original: (1849, 2)
Drop Dupicates: (1396, 2)
Drop Nulls: (1201, 2)
```

<u>Dirty dirty text</u>

Of all data, text is the most unstructured form and so means we have a lot of cleaning to do. These pre-processing steps help convert noise from high dimensional features to the low dimensional space to obtain as much accurate information as possible from the text.

Preprocessing data can consist of many steps depending on the data and the situation. To guide me through cleaning, I used a blogpost from analytics vidhya which shows the process of cleaning tweets. As we are dealing with reviews, some of the methods will not apply here.

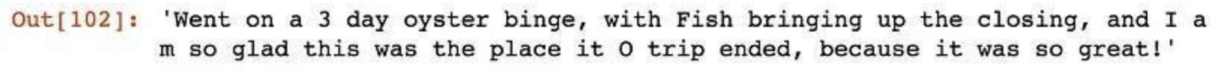
To further organise this process a blogpost from kdnuggets split it into categories of tokenization, normalization and substitution.

Preprocessing:

Tokenization

Tokenization is the process of converting text into tokens before transforming it into vectors. It is also easier to filter out unnecessary tokens. For example, a document into paragraphs or sentences into words. In this case we are tokenising the reviews into words.

Df.sentence[17]

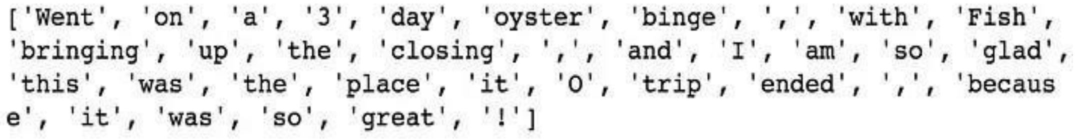


```
Out[102]: 'Went on a 3 day oyster binge, with Fish bringing up the closing, and I a
          m so glad this was the place it O trip ended, because it was so great!'
```

From nltk.tokenize import word_tokenize

Tokens = word_tokenize(df.sentence[17])

Print(tokens)



```
['Went', 'on', 'a', '3', 'day', 'oyster', 'binge', ',', 'with', 'Fish',
'bringing', 'up', 'the', 'closing', ',', 'and', 'I', 'am', 'so', 'glad',
'this', 'was', 'the', 'place', 'it', 'O', 'trip', 'ended', ',', 'becaus
e', 'it', 'was', 'so', 'great', '!']
```

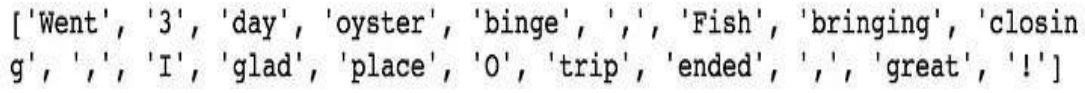
Stopwords

Stop words are the most commonly occuring words which are not relevant in the context of the data and do not contribute any deeper meaning to the phrase. In this case contain no sentiment. NLTK provide a library used for this.

From nltk.corpus import stopwords

Stop_words = stopwords.words('english')

Print [I for I in tokens if I not in stop_words]



```
['Went', '3', 'day', 'oyster', 'binge', ',', 'Fish', 'bringing', 'closin
g', ',', 'I', 'glad', 'place', 'O', 'trip', 'ended', ',', 'great', '!']
```

Preprocessing:

Normalization

Words which look different due to casing or written another way but are the same in meaning need to be process correctly. Normalisation processes ensure that these words are treated equally. For example, changing numbers to their word equivalents or converting the casing of all the text.

‘100’ → ‘one hundred’

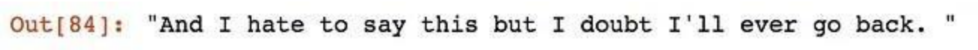
‘Apple’ → ‘apple’

The following normalisation changes are made:

1. **Casing the Characters**

Converting character to the same case so the same words are recognised as the same. In this case we converted to lowercase.

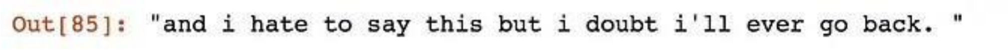
Df.sentence[24]



```
Out[84]: "And I hate to say this but I doubt I'll ever go back. "
```

Lower_case = df.sentence[24].lower()

Lower_case

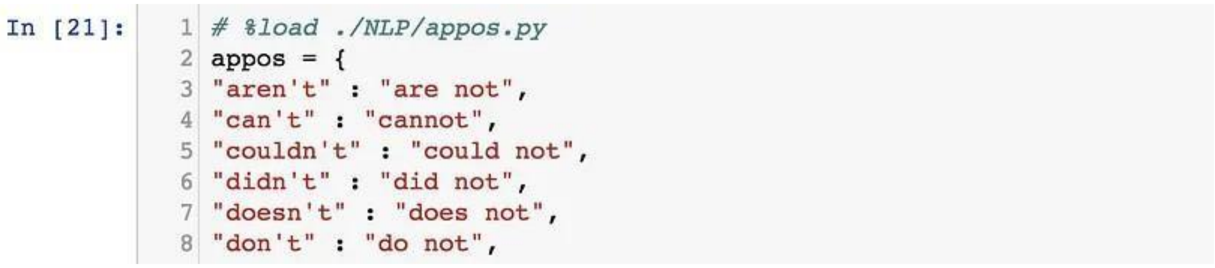


```
Out[85]: "and i hate to say this but i doubt i'll ever go back. "
```

2. Negation handling

Apostrophes connecting words are used everywhere, especially in public reviews. To maintain uniform structure it is recommended they should be converted into standard lexicons. The text will then follow the rules of context free grammar and helps avoids any word-sense disambiguation.

There was an apostrophe dictionary found from user comments on analytics vidhy blog which you can download here. The dictionary is in lowercase so the conversion will follow from the lower casing above.



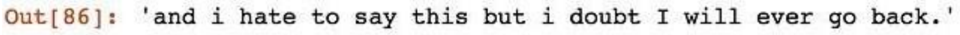
```
In [21]:  # %load ./NLP/appos.py
          appos = {
          "aren't" : "are not",
          "can't" : "cannot",
          "couldn't" : "could not",
          "didn't" : "did not",
          "doesn't" : "does not",
          "don't" : "do not",
```

Words = lower_case.split()

Reformed = [appos[word] if word in appos else word for word in words]

Reformed = “ “.join(reformed)

Reformed

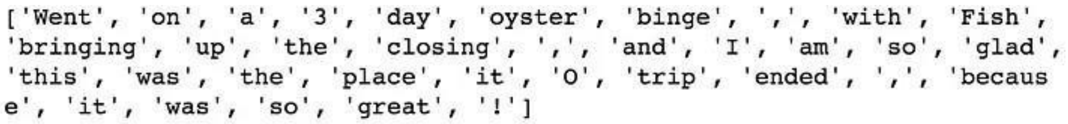


```
Out[86]: 'and i hate to say this but i doubt I will ever go back.'
```

3. Removing

Stand alone punctuations, special characters and numerical tokens are removed as they do not contribute to sentiment which leaves only alphabetic characters. This step needs the use of tokenized words as they have been split appropriately for us to remove.

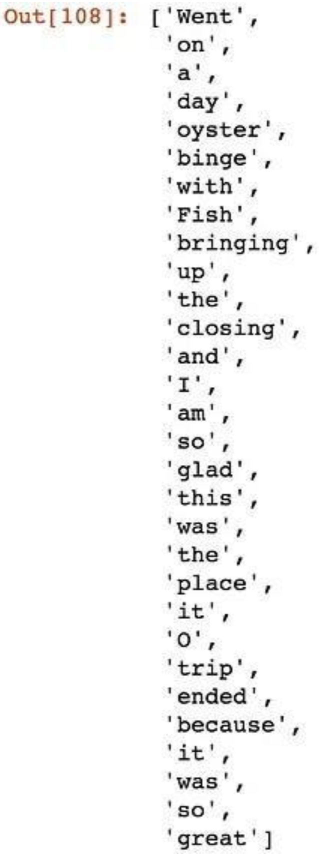
Tokens



```
['Went', 'on', 'a', '3', 'day', 'oyster', 'binge', ',', 'with', 'Fish',
'bringing', 'up', 'the', 'closing', ',', 'and', 'I', 'am', 'so', 'glad',
'this', 'was', 'the', 'place', 'it', 'O', 'trip', 'ended', ',', 'becaus
e', 'it', 'was', 'so', 'great', '!']
```

Words = [word for word in tokens if word.isalpha()]

Words



```
Out[108]: ['Went',
           'on',
           'a',
           'day',
           'oyster',
           'binge',
           'with',
           'Fish',
           'bringing',
           'up',
           'the',
           'closing',
           'and',
           'I',
           'am',
           'so',
           'glad',
           'this',
           'was',
           'the',
           'place',
           'it',
           'O',
           'trip',
           'ended',
           'because',
           'it',
           'was',
           'so',
           'great']
```

4. **Lemmatization**

This process finds the base or dictionary form of the word known as the lemma. This is done through the use of vocabulary (dictionary importance of words) and morphological analysis (word structure and grammar relations). This normalization is similar to stemming but takes into account the context of the word.

‘are’, ‘is’, ‘being’ → ‘be’

Gensim: Lemmatization

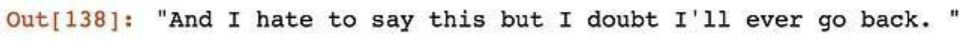
I used the lemmatize method from the Gensim package which took care of lower casing, removal of numerics, stand alone punctuation, special characters and stop words. It also identifies the words with part-of-speech tagging (POS- tagging) considering nouns/ NN, verbs/VB, adjectives/JJ and adverbs/RB.

The function uses the English lemmatizer from the pattern library to extract their lemmas. The words in a text are identified through word-category disambiguation where both its definition and context are taken into account to identify the specific POS- tag.

Tip1: This function is only available when the optional ‘pattern’ package is installed!

Tip2: This function only applies to UTF-8 encoded tokens.

Df.sentence[24]

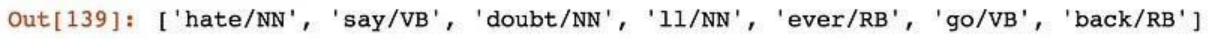


```
Out[138]: "And I hate to say this but I doubt I'll ever go back. "
```

From gensim.utils import lemmatize

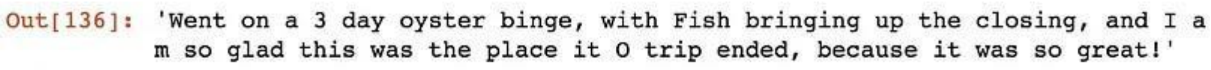
Lemm = lemmatize(df.sentence[24])

Lemm



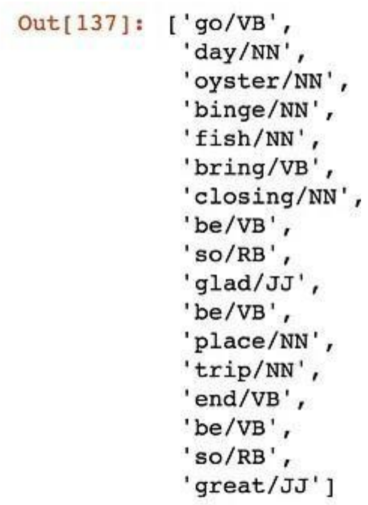
```
Out[139]: ['hate/NN', 'say/VB', 'doubt/NN', 'll/NN', 'ever/RB', 'go/VB', 'back/RB']
```

Df.sentence[17]



```
Out[136]: 'Went on a 3 day oyster binge, with Fish bringing up the closing, and I a
          m so glad this was the place it O trip ended, because it was so great!'
```

Lemmatize(df.sentence[17])



```
Out[137]: ['go/VB',
           'day/NN',
           'oyster/NN',
           'binge/NN',
           'fish/NN',
           'bring/VB',
           'closing/NN',
           'be/VB',
           'so/RB',
           'glad/JJ',
           'be/VB',
           'place/NN',
           'trip/NN',
           'end/VB',
           'be/VB',
           'so/RB',
           'great/JJ']
```

Preprocessing:

Substitution

This involves removing noise from text in its raw format. For example, the text is scrapped from the web it may contain HTML or XML wrappers or markups. Removal of these can be done through regular expressions. Fortunately our reviews do not apply to this as we were able to extract the exact review from the XML file.

Decoding

I found it difficult investigate what decoding means in the the NLP context however, I came across a comment from a stackoverflow question which helped me break down this section.

Text data is subject to different formats of decoding. For example, ASCII which contains english based letters, control characters, punctuation and numbers. When dealing with other languages with non-Latin characters another format may need to apply.

Unicode contains character sets including all languages by assigning every character to a unique number. It is recommended to use UTF-8. With its 1–4 bytes per character memory it widely accepts the majority of languages in the first 2 bytes and is memory efficient if dealing with mostly ASCII characters.

UTF-8 Character Bytes

1 byte: Standard ASCII

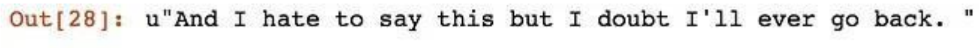
2 bytes: Arabic, Hebrew, most European scripts

3 bytes: BMP

4 bytes: All Unicode characters.

As we could be working with text it is advised to decode the utf-8 format ensuring they are all in the same format. The output presents a “u” before the string indicating it is Unicode.

```
Df.sentence[24].decode(“utf-8-sig”)
```



```
Out[28]: u"And I hate to say this but I doubt I'll ever go back. "
```

Defining a Cleaning Function

I created a cleaning function which will be applied to the whole dataset. It includes decoding, lowercasing (so the negation dictionary can apply), conversion with negation dictionary and lemmatization which includes lower casing, tokenising, removal of special characters, stand alone punctuation, stop words and POS tagging. The second function is to separate the tags and words.

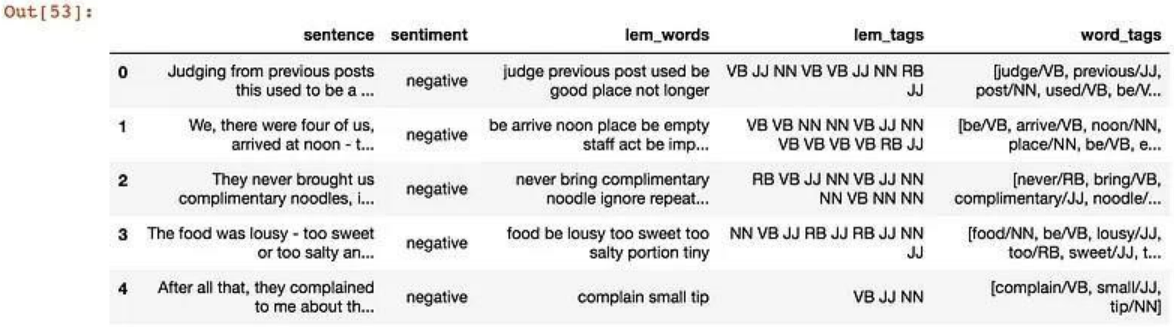
```
Def cleaning_function(tips):
    All_ = []
    For tip in tqdm(tips):
        Time.sleep(0.0001)

#       Decoding function
        Decode = tip.decode(“utf-8-sig”)

#       Lowercasing before negation
        Lower_case = decode.lower()
```

```
#       Replace apostrophes with words
        Words = lower_case.split()
        Split = [appos[word] if word in appos else word for word in words]
        Reformed = “ “.join(split)

#       Lemmatization
        Lemm = lemmatize(lower_case)
        All_.append(lemm)

    Return all_
Def separate_word_tag(df_lem_test):
    Words=[]
    Types=[]
    Df= pd.DataFrame()
    For row in df_lem_test:
        Sent = []
        Type_ =[]
        For word in row:
            Split   =   word.split(‘/’)
            Sent.append(split[0])
            Type_.append(split[1])
Words.append(‘   ‘.join(word   for   word   in   sent))
        Types.append(‘ ‘.join(word for word in type_))
Df[‘lem_words’]= words
    Df[‘lem_tag’]= types
    Return df
```

Cleaning Training Data

```
Word_tag = cleaning_function(df.sentence)
```

```
Lemm_df = separate_word_tag(word_tag)

# concat cleaned text with original

Df_training = pd.concat([df, lemm_df], axis=1)

Df_training[‘word_tags’] = word_tag

Df_training.head()
```



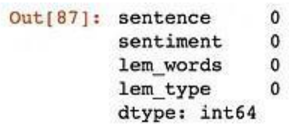
Out[53]:

	sentence	sentiment	lem_words	lem_tags	word_tags
0	Judging from previous posts this used to be a ...	negative	judge previous post used be good place not longer	VB JJ NN VB VB JJ NN RB JJ	[judge/VB, previous/JJ, post/NN, used/VB, be/V...
1	We, there were four of us, arrived at noon - t...	negative	be arrive noon place be empty staff act be imp...	VB VB NN NN VB JJ NN VB VB VB VB RB JJ	[be/VB, arrive/VB, noon/NN, place/NN, be/VB, e...
2	They never brought us complimentary noodles, i...	negative	never bring complimentary noodle ignore repeat...	RB VB JJ NN VB JJ NN NN VB NN NN	[never/RB, bring/VB, complimentary/JJ, noodle/...
3	The food was lousy - too sweet or too salty an...	negative	food be lousy too sweet too salty portion tiny	NN VB JJ RB JJ RB JJ NN JJ	[food/NN, be/VB, lousy/JJ, too/RB, sweet/JJ, t...
4	After all that, they complained to me about th...	negative	complain small tip	VB JJ NN	[complain/VB, small/JJ, tip/NN]

Check for null and empty values

There were no null values found because the cleaning process does not input nulls into empty values. Both were checked and the empty values were removed. It was identified that the text of the review was 3 reviews including “10”, “LOL” and “Why?” which has changed into null values during the cleaning process. I felt they did not contribute to the sentiment analysis so thought removing them is valid.

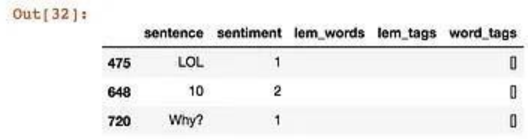
```
# reset index just to be safe

Df_training = df_training.reset_index(drop=True)

#check null values

Df_training.isnull().sum()
```



```
Out[87]: sentence     0
         sentiment    0
         lem_words    0
         lem_type     0
         dtype: int64
```

# empty values

Df_training[df_training['lem_words']=='']



Out[32]:

	sentence	sentiment	lem_words	lem_tags	word_tags
475	LOL	1			[]
648	10	2			[]
720	Why?	1			[]

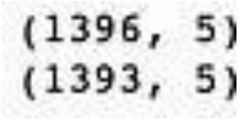
# drop these rows

Print df_training.shape

Df_training = df_training.drop([475, 648, 720])

Df_training = df_training.reset_index(drop=True)

Print df_training.shape



```
(1396, 5)
(1393, 5)
```

Cleaning Prediction Data

# load the data

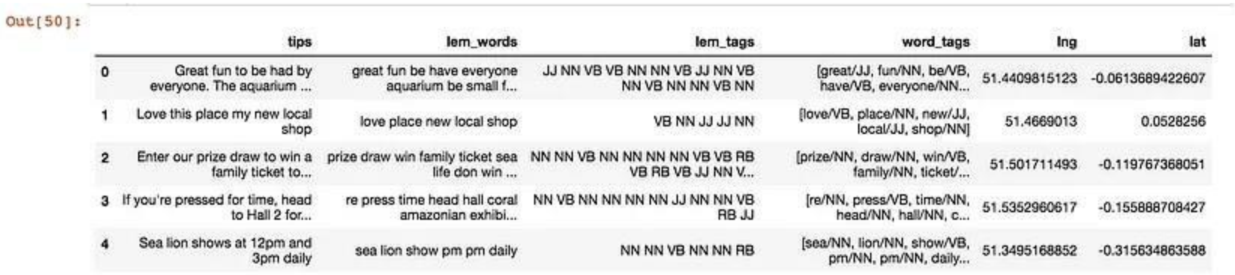
Fs = pd.read_csv('./foursquare/foursquare_csv/londonvenues.csv')

# use cleaning functions on the tips

Word_tag_fs = cleaning_function(fs.tips)

Lemm_fs = separate_word_tag(word_tag_fs)

```
# concat cleaned text with original

Df_fs_predict = pd.concat([fs, lemm_fs], axis=1)

Df_fs_predict[‘word_tags’] = word_tag_fs

# separate the long lat

Lng=[]

Lat=[]

For ll in df_fs_predict[‘ll’]:

    Lnglat = ll.split(‘,’)

     Lng.append(lnglat[0])

      Lat.append(lnglat[1])

 Df_fs_predict[‘lng’]  =lng

Df_fs_predict[‘lat’] =lat

#  drop the ll column

Df_fs_predict = df_fs_predict.drop([‘ll’], axis=1)

Df_fs_predict.head()
```

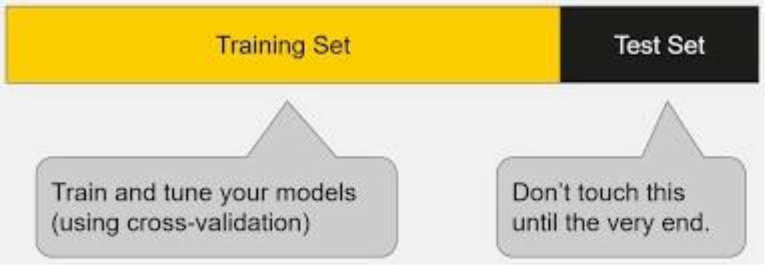


Out[50]:

	tips	lem_words	lem_tags	word_tags	lng	lat
0	Great fun to be had by everyone. The aquarium ...	great fun be have everyone aquarium be small f...	JJ NN VB VB NN NN VB JJ NN VB NN VB NN NN VB NN	[great/JJ, fun/NN, be/VB, have/VB, everyone/NN...	51.4409815123	-0.0613689422607
1	Love this place my new local shop	love place new local shop	VB NN JJ JJ NN	[love/VB, place/NN, new/JJ, local/JJ, shop/NN]	51.4669013	0.0528256
2	Enter our prize draw to win a family ticket to...	prize draw win family ticket sea life don win ...	NN NN VB NN NN NN NN VB VB RB VB RB VB JJ NN V...	[prize/NN, draw/NN, win/VB, family/NN, ticket/...	51.501711493	-0.119767368051
3	If you're pressed for time, head to Hall 2 for...	re press time head hall coral amazonian exhibi...	NN VB NN NN NN NN JJ NN NN VB RB JJ	[re/NN, press/VB, time/NN, head/NN, hall/NN, c...	51.5352960617	-0.155888708427
4	Sea lion shows at 12pm and 3pm daily	sea lion show pm pm daily	NN NN VB NN NN RB	[sea/NN, lion/NN, show/VB, pm/NN, pm/NN, daily...	51.3495168852	-0.315634863588

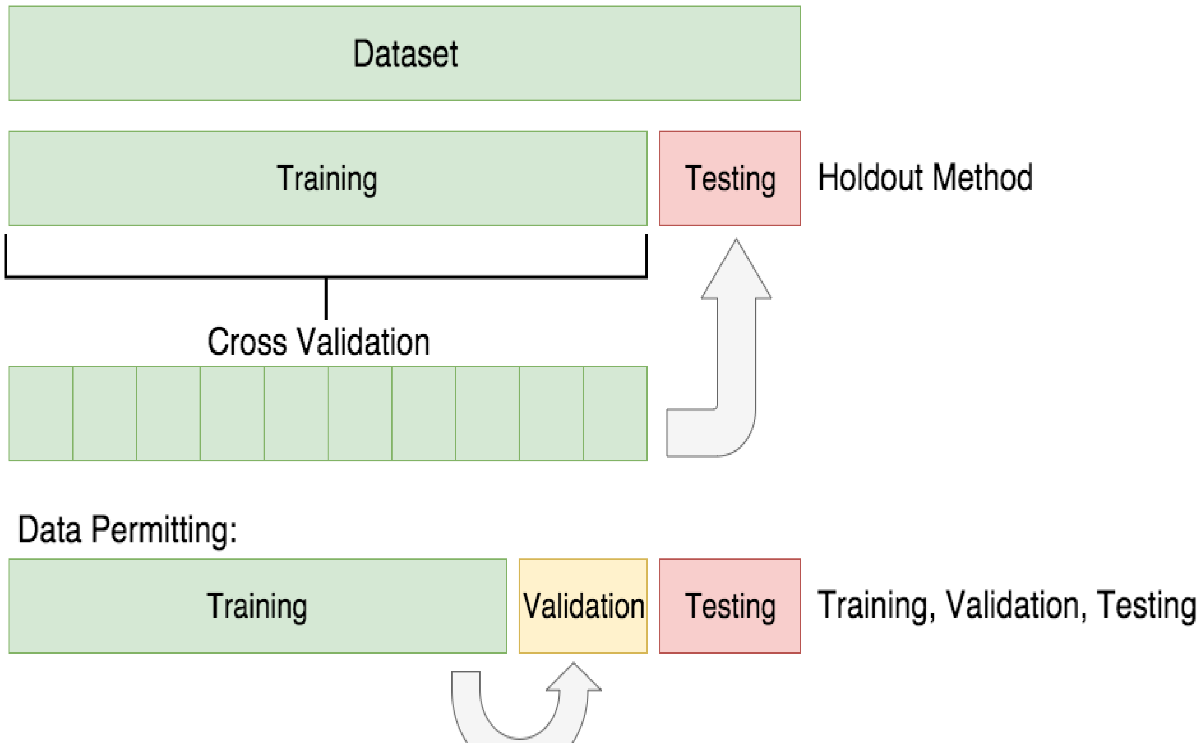
Train Test Split

To measure the accuracy of the model we are creating, the data needs to split into 2 parts. A training set to fit and tune our model and a testing set to create predictions on and evaluate the model at the very end.


Training Set
Test Set
Train and tune your models (using cross-validation)
Don't touch this until the very end.

Validation of the training data

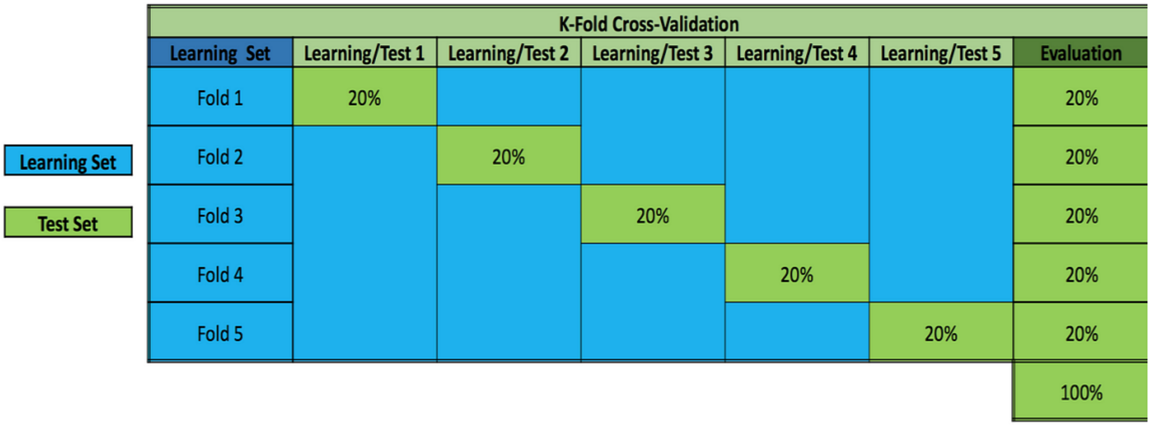
The training set is used to optimise the model using different models and parameters. Typically, it is further separated to train the model and validate on a section which is held out. After we have found the model with the best predictive score through cross validation and tuning parameters we test it against the test set.



K-Fold Cross Validation

K-fold CV represents the K number of folds/ subsets. Our training set is further split into k subsets where we train on k-1 and test on the subset that is held. This is done for each k fold with a k scores given as a result. We average the model against each of the folds to finalise our model.

By rotating through the subsets of training data it helps the resulting model to generalise (prevent overfitting and underfitting)



🟦 Learning Set

🟩 Test Set

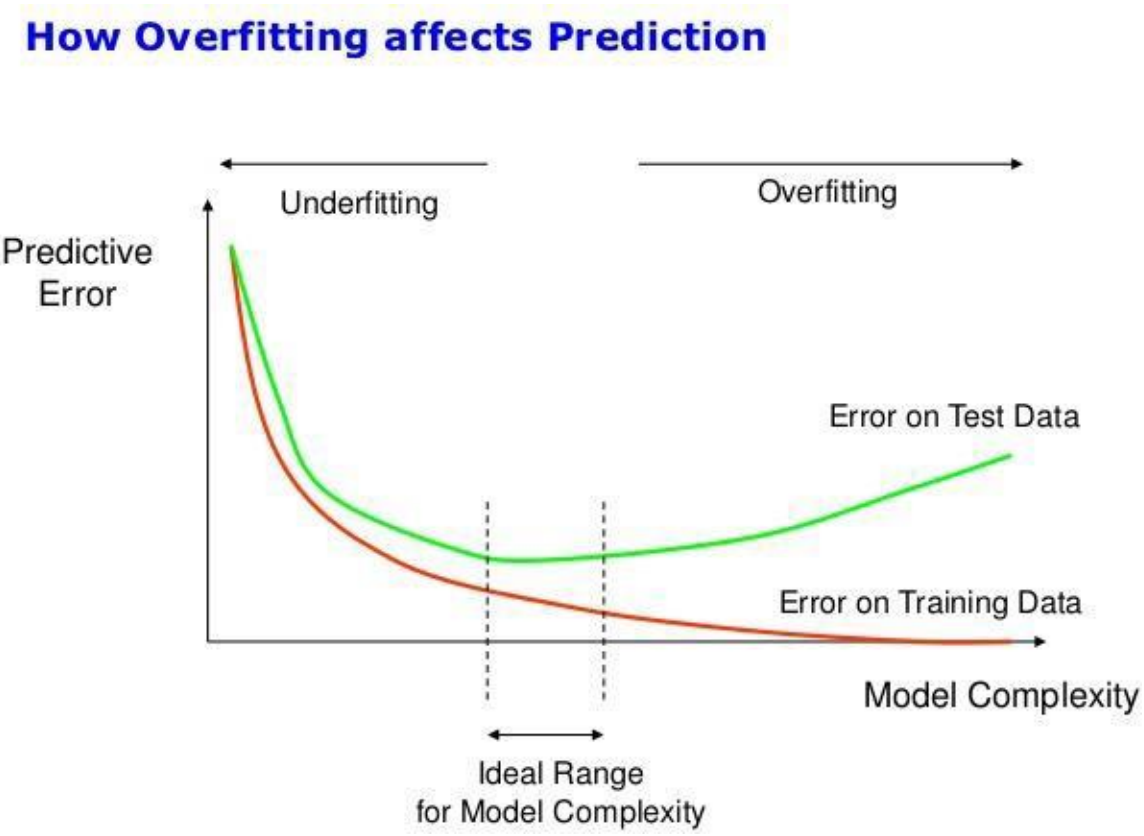
K-Fold Cross-Validation						
Learning Set	Learning/Test 1	Learning/Test 2	Learning/Test 3	Learning/Test 4	Learning/Test 5	Evaluation
Fold 1	20%					20%
Fold 2		20%				20%
Fold 3			20%			20%
Fold 4				20%		20%
Fold 5					20%	20%
						100%

What is Overfitting/Underfitting a Model?

A model that is ungeneralized means you can’t make accurate predictions on other data.

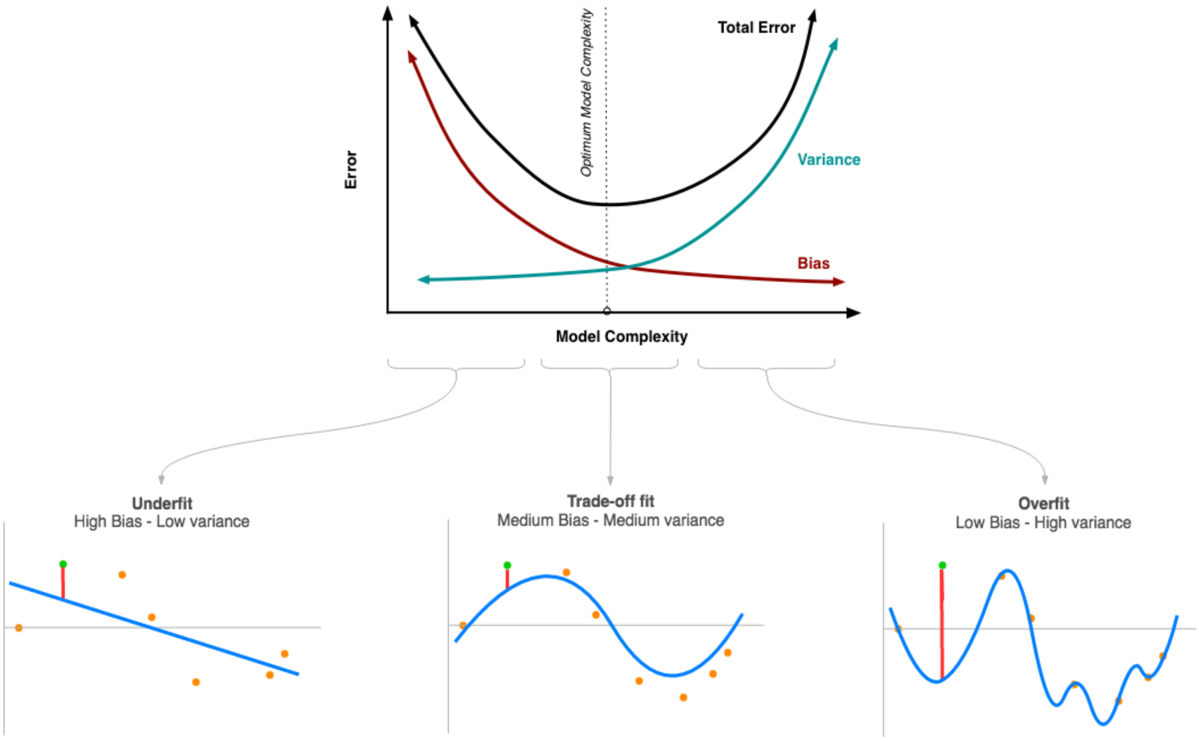
Overfitting is when the model is fit too closely to the training dataset. This is identified when the model is very accurate on the cross validated training data but not very accurate on testing, untrained or new data.

As shown in the image below, overfitting increase the error between the test and training increase. This can be caused by model complexity where there may be too many features/variables compared to the number of observations. Instead of the model learning the actual relationships between variables it learns the noise that is specific to the training set.



Underfitting is when the model does not fit the training data enough and therefore misses the trends in the data. This is identified by the model having a low accuracy score. It can be caused by not enough predictors being used to train the model and therefore is not complex enough. Also if the model chosen is too simple for the data. For example, fitting a linear regression to data that is not linear and so gives poor predictive ability on the training data.

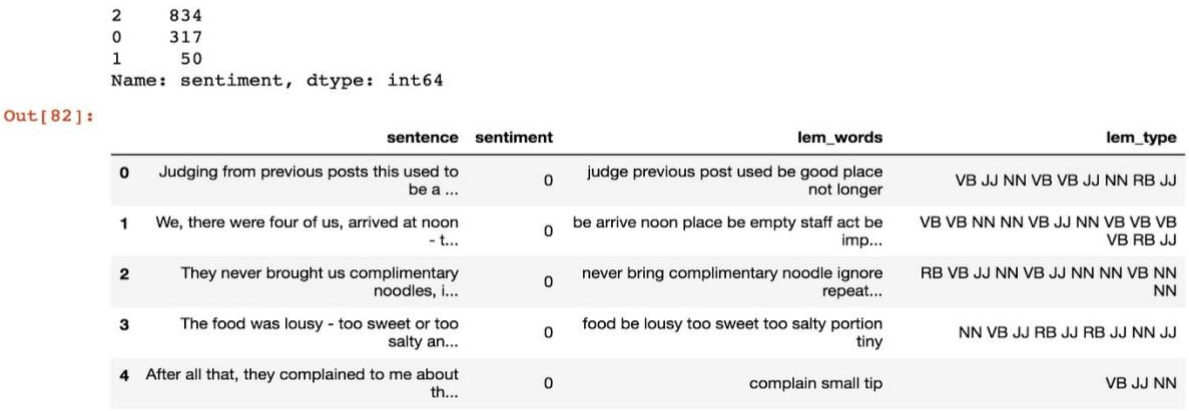
From the image below, you can see the trade off of over and underfitting. We need to create a model which balances both to ensure predictions are accurate.



Back to the Sentiment Classification

Our target variable we are predicting is sentiment.

```
# convert to numeric values
df_training['sentiment'] = df_training.sentiment.map(lambda x:
int(2) if x =='positive' else int(0) if x =='negative' else
int(1) if x == 'neutral' else np.nan)print
df_training['sentiment'].value_counts()
df_training.head()
```



```
2    834
0    317
1     50
Name: sentiment, dtype: int64
```

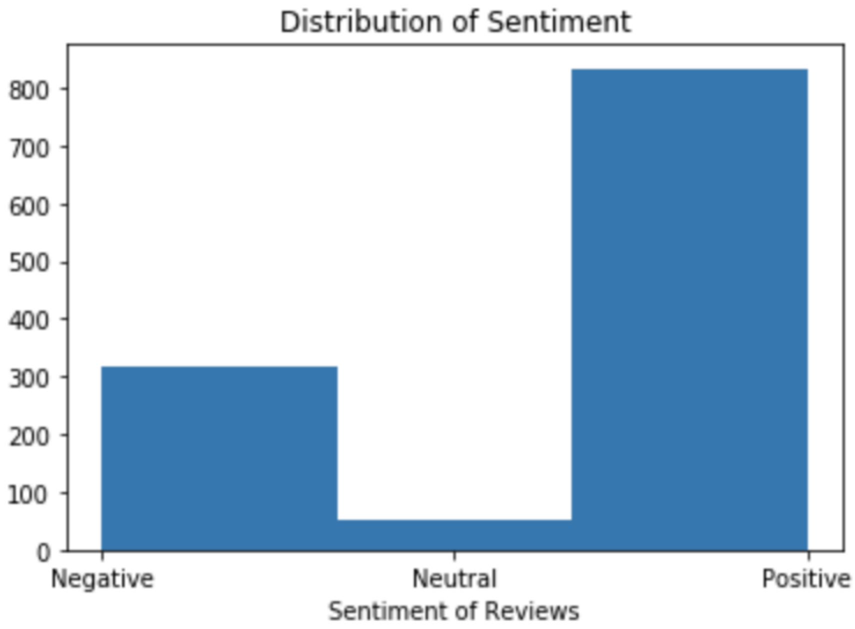
Out[82]:

	sentence	sentiment	lem_words	lem_type
0	Judging from previous posts this used to be a ...	0	judge previous post used be good place not longer	VB JJ NN VB VB JJ NN RB JJ
1	We, there were four of us, arrived at noon - t...	0	be arrive noon place be empty staff act be imp...	VB VB NN NN VB JJ NN VB VB VB VB RB JJ
2	They never brought us complimentary noodles, i...	0	never bring complimentary noodle ignore repeat...	RB VB JJ NN VB JJ NN NN VB NN NN
3	The food was lousy - too sweet or too salty an...	0	food be lousy too sweet too salty portion tiny	NN VB JJ RB JJ RB JJ NN JJ
4	After all that, they complained to me about th...	0	complain small tip	VB JJ NN

Distribution of Sentiment

I first chose to visualise the distribution of my target. The positive class is significantly lager than the other classes. Because of this imbalance, we will need to bootstrap to equalise the baseline accuracy between them. First, we will need to separate the data into training and test sets.

```
import matplotlib.pyplot as plt
plt.hist(df_training.sentiment, bins = 3, align= 'mid')
plt.xticks(range(3), ['Negative','Neutral', 'Positive'])
plt.xlabel('Sentiment of Reviews')
plt.title('Distribution of Sentiment')
plt.show()
```



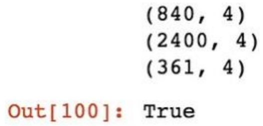
Train Test Split & Bootstrapping

To evaluate our model we split the data into Training and Testing sets. Here we are using the arguement of test_size = 0.3 which is a ratio of 70/30. The training data will then be used to tune our model through cross validation.

As seen above in the distribution of sentiment the classes are not balanced which can cause problems when measuring the accuracy as each class will have different baseline values. A resampling method with replacement is used, called bootstrapping. The smaller classes are upsampled and the remaining positive class is downsampled to 800 samples each.

```
from sklearn.model_selection import train_test_splittrain,
test = train_test_split(df_training, test_size=0.3,
random_state=1)t_1 =
train[train['sentiment']==1].sample(800,replace=True)
t_2 = train[train['sentiment']==2].sample(800,replace=True)
t_3 = train[train['sentiment']==0].sample(800,replace=True)
```

```
training_bs = pd.concat([t_1, t_2, t_3])print train.shape
print training_bs.shape
print test.shape# sanity check
df_training.shape[0] == (train.shape[0] + test.shape[0])
```

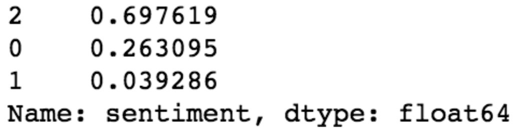


```
         (840, 4)
         (2400, 4)
         (361, 4)

Out[100]: True
```

Baseline Accuracy

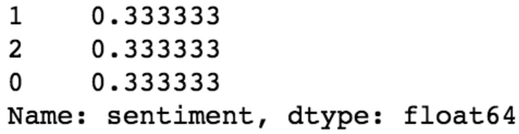
The baseline accuracy is the proportion of the majority class. Before bootstrapping ‘2’ which is positive sentiment gives us the baseline at 0.7. After Bootstrapping all the classes the accuracy to predict each of the classes balances so the baseline accuracy is 0.3 for each class.

```
print train['sentiment'].value_counts(normalize=True)
baseline = 0.3
```



```
2    0.697619
0    0.263095
1    0.039286
Name: sentiment, dtype: float64
```

```
print training_bs['sentiment'].value_counts(normalize=True)
baseline = 0.3
```



```
1    0.333333
2    0.333333
0    0.333333
Name: sentiment, dtype: float64
```

Save to csv file

The bootstrap training set and test set is then saved to a csv file, ready for modelling. This will continue in the next post.

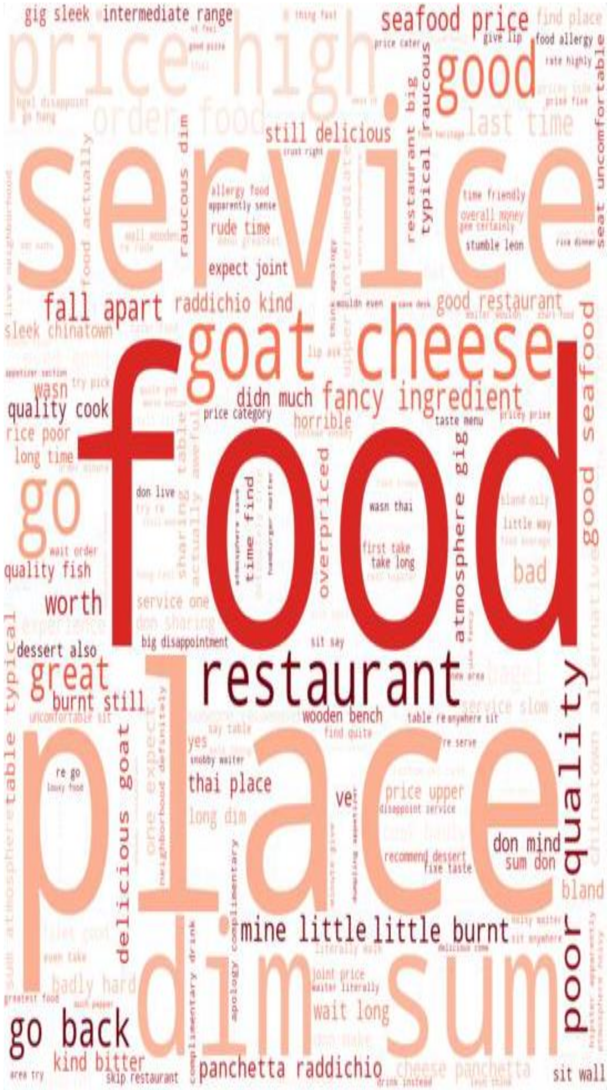
```
# reset index before savingtraining_bs =
training_bs.reset_index(drop=True)
training_bs.to_csv('./train_test_data/training_bs.csv',
header=True, index=False, encoding='UTF8')test =
test.reset_index(drop=True)
test.to_csv('./train_test_data/testing.csv', header=True,
index=False, encoding='UTF8')
```

Word Clouds

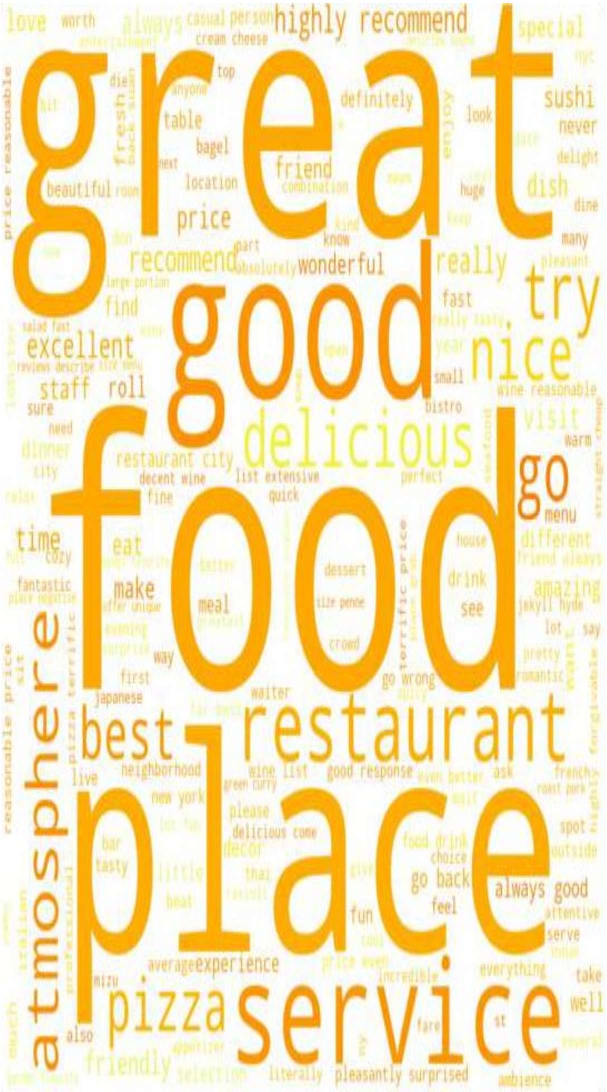
A worldcloud is a collage of randomly arranged words where the size of each word is proportional to its frequency in the corpus. It give us an idea of what words represent in the corpus of each class however, do not clearly indicate accurate information especially when comparing each class.

Just to have an idea of what my final training data looks like, I decided to visualise each class with word clouds. I imported the WordCloud library in python.

```
from wordcloud import WordCloud
import matplotlib.pyplot as plt# Polarity == 0 negative
train_s0 = training_bs[training_bs.sentiment ==0]all_text = ‘
‘.join(word for word in train_s0.lem_words)
wordcloud = WordCloud(colormap=’Reds’, width=1000,
height=1000, mode=’RGBA’,
background_color=’white’).generate(all_text)
plt.figure(figsize=(20,10))
plt.imshow(wordcloud, interpolation=’bilinear’)
plt.axis("off")
plt.margins(x=0, y=0)
plt.show()# Polarity == 1 neutral
train_s1 = training_bs[training_bs.sentiment ==1]all_text = '
'.join(word for word in train_s1.lem_words)
wordcloud = WordCloud(width=1000, height=1000,
colormap='Blues', background_color='white',
mode='RGBA').generate(all_text)
plt.figure( figsize=(20,10))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.margins(x=0, y=0)
plt.show()# Polarity == 2 positive
train_s2 = training_bs[training_bs.sentiment ==2]all_text = '
'.join(word for word in train_s2.lem_words)
wordcloud_p2 = WordCloud(width=1000, height=1000,
colormap='Wistia',background_color='white',
mode='RGBA').generate(all_text)
plt.figure(figsize=(20,10))
plt.imshow(wordcloud_p2, interpolation='bilinear')
plt.axis("off")
plt.margins(x=0, y=0)
plt.show()
```



nothing special
wasn thrill
potato stuff
way close
service person
ish kind
place diner
east village
eye start
price pay
try potato
food decent
sometimes good
downtown dinner
lemon salad
bit bigger
salad
restaurant nothing
companion trip
list simply
notice order
cheeseburger huge
typical italian
lower price
wait line small sparse
food decor
romantic simple start food
plate
exnect simple small
kind
foodgreat
decorplace
location ambienceprice bit
exceptio
mer
CL



In the negative cloud some neutral words are big like ‘service’, ‘food’ and ‘place’. Some of the mid sized words are ‘price’ , ‘high’, ‘goat cheese’, ‘dim sum’.

The neutral class larger words ‘food’ ‘okay’, ‘decent’, ‘sometimes’, ‘nothing special’. Giving me an idea of some of the mildly positive and mildly negative reviews.

The positive class has larger words ‘great’ , ‘good’ , ‘food’ and ‘place’. Mid size words that appear are ‘service’, ‘atmosphere’, ‘best restaurant’ and ‘pizza’. Smaller words ‘highly recommended’ , ‘good response’, ‘excellent’, ‘staff’.

‘food’ appears in negative, neutral and positive clouds as one of the biggest sizes. This suggests most people are highlighting their reviews based on the the food. The word ‘place’ is also one of the biggest in both positive and negative which suggests that most non neutral reviews are about the place.

PRE-PROCESSING THE TEXT DATA BY USING MACHINE LEARNING ALGORITHM

In [1]:

```
# This Python 3 environment comes with many helpful analytics libraries installed
# For example, here's several helpful packages to load in


import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
from sklearn.model_selection import train_test_split # function for splitting data to train and test sets


import nltk
from nltk.corpus import stopwords
from nltk.classify import SklearnClassifier


from wordcloud import WordCloud,STOPWORDS
import matplotlib.pyplot as plt
%matplotlib inline
```

```
# Input data files are available in the "../input/" directory.

# For example, running this (by clicking run or pressing Shift+Enter) w
ill list the files in the input directory



from subprocess import check_output
```

I decided to only do sentiment analysis on this dataset, therfore I dropped the unnecessary colunns, keeping only sentiment and text.

In [2]:

```
data = pd.read_csv('../input/Sentiment.csv')

# Keeping only the neccessary columns

 data = data[['text','sentiment']]
```

First of all, splitting the dataset into a training and a testing set. The test set is the 10% of the original dataset. For this particular analysis I dropped the neutral tweets, as my goal was to only differentiate positive and negative tweets.

In [3]:

```
#  Splitting  the  dataset  into  train  and  test  set

train, test = train_test_split(data,test_size = 0.1)

# Removing neutral sentiments

train = train[train.sentiment != "Neutral"]
```

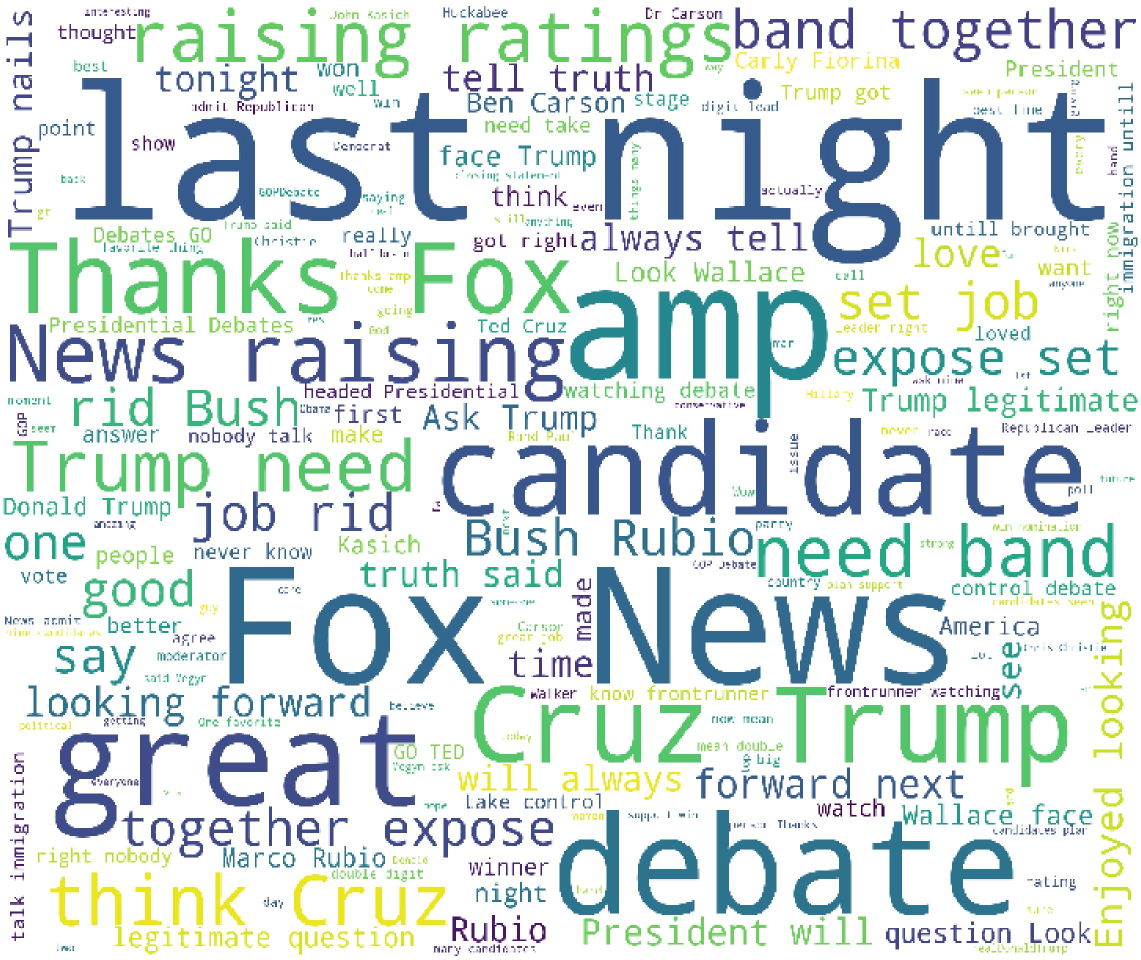
As a next step I separated the Positive and Negative tweets of the training set in order to easily visualize their contained words. After that I cleaned the text from hashtags, mentions and links. Now they were ready for a WordCloud visualization which shows only the most emphatic words of the Positive and Negative tweets.

In [4]:

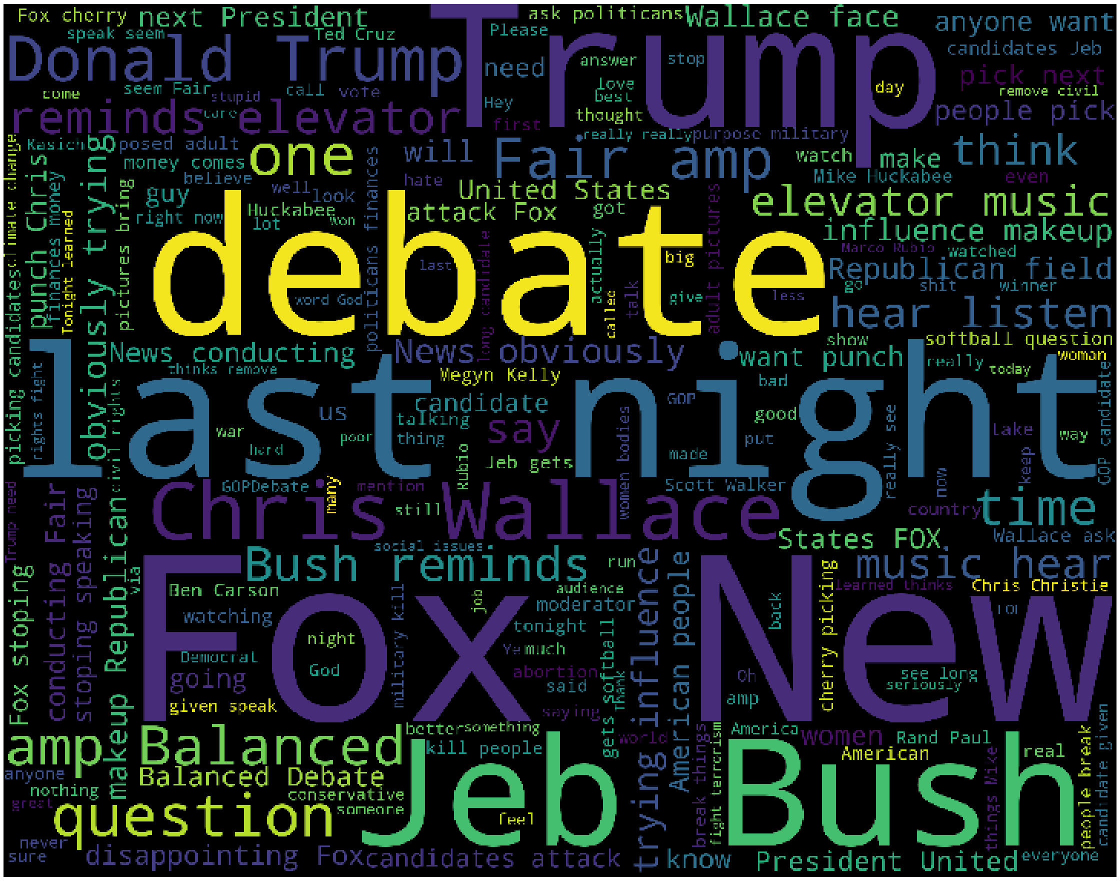
```
train_pos = train[ train['sentiment'] == 'Positive']
train_pos = train_pos['text']
train_neg = train[ train['sentiment'] == 'Negative']
train_neg = train_neg['text']


def wordcloud_draw(data, color = 'black'):
    words = ' '.join(data)
    cleaned_word = " ".join([word for word in words.split()
                            if 'http' not in word
                                and not word.startswith('@')
                                and not word.startswith('#')
                                and word != 'RT'
                            ])
    wordcloud = WordCloud(stopwords=STOPWORDS,
                      background_color=color,
                      width=2500,
                      height=2000
                     ).generate(cleaned_word)
    plt.figure(1,figsize=(13, 13))
    plt.imshow(wordcloud)
    plt.axis('off')
    plt.show()
```

```
print("Positive words")

wordcloud_draw(train_pos,'white')

print("Negative words")

wordcloud_draw(train_neg)
```

```
Positive words
```



Negative words



Interesting to notice the following words and expressions in the positive word set: truth, strong, legitimate, together, love, job

In my interpretation, people tend to believe that their ideal candidate is truthful, legitimate, above good and bad.

At the same time, negative tweets contains words like: influence, news, elevator music, disappointing, softball, makeup, cherry picking, trying

In my understanding people missed the decisively acting and considered the scolded candidates too soft and cherry picking.

After the vizualization, I removed the hashtags, mentions, links and stopwords from the training set.

Stop Word: Stop Words are words which do not contain important significance to be used in Search Queries. Usually these words are filtered out from search queries because they return vast amount of unnecessary information. (the, for, this etc.)

In [5]:

```
tweets = []
stopwords_set = set(stopwords.words("english"))


for index, row in train.iterrows():
    words_filtered = [e.lower() for e in row.text.split() if len(e) >
= 3]
    words_cleaned = [word for word in words_filtered
        if 'http' not in word
        and not word.startswith('@')
        and not word.startswith('#')
        and word != 'RT']
    words_without_stopwords = [word for word in words_cleaned if not
word in stopwords_set]
    tweets.append((words_without_stopwords, row.sentiment))


test_pos = test[ test['sentiment'] == 'Positive']
test_pos = test_pos['text']
test_neg = test[ test['sentiment'] == 'Negative']
test_neg = test_neg['text']
```

As a next step I extracted the so called features with nltk lib, first by measuring a frequent distribution and by selecting the resulting keys.

In [6]:

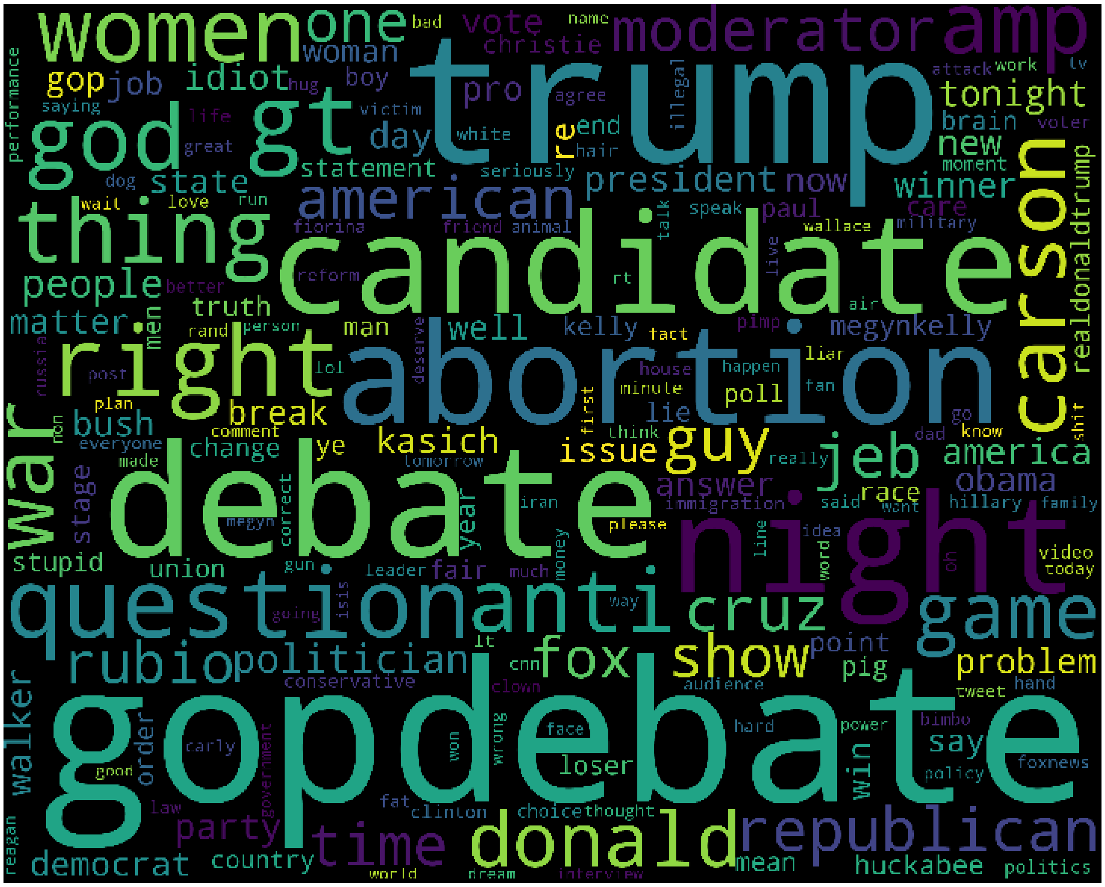
```
# Extracting word features
def get_words_in_tweets(tweets):
    all = []
    for (words, sentiment) in tweets:
        all.extend(words)
    return all


def get_word_features(wordlist):
    wordlist = nltk.FreqDist(wordlist)
    features = wordlist.keys()
    return features
w_features = get_word_features(get_words_in_tweets(tweets))
```

```
def extract_features(document):
    document_words = set(document)
    features = {}
    for word in w_features:
        features['contains(%s)' % word] = (word in document_words)
    return features
```

Hereby I plotted the most frequently distributed words. The most words are centered around debate nights.

In [7]:

```
wordcloud_draw(w_features)
```



Using the nltk NaiveBayes Classifier I classified the extracted tweet word features.

In [8]:

```
# Training the Naive Bayes classifier

training_set = nltk.classify.apply_features(extract_features,tweets)

classifier = nltk.NaiveBayesClassifier.train(training_set)
```

Finally, with not-so-intelligent metrics, I tried to measure how the classifier algorithm scored.

In [9]:

```
neg_cnt = 0

pos_cnt = 0

for obj in test_neg:

    res =  classifier.classify(extract_features(obj.split()))

    if(res == 'Negative'):

        neg_cnt = neg_cnt + 1

for obj in test_pos:

    res =  classifier.classify(extract_features(obj.split()))

    if(res == 'Positive'):

        pos_cnt = pos_cnt + 1


print('[Negative]: %s/%s '  % (len(test_neg),neg_cnt))

print('[Positive]: %s/%s '  % (len(test_pos),pos_cnt))
```

Output:

```
[Negative]: 842/795

[Positive]: 220/74
```

I was curious how well nltk and the NaiveBayes Machine Learning algorithm performs for Sentiment Analysis. In my experience, it works rather well for negative comments. The problems arise when the tweets are ironic, sarcastic has reference or own difficult context.

Consider the following tweet: "Muhaha, how sad that the Liberals couldn't destroy Trump. Marching forward." As you may already thought, the words sad and destroy highly influences the evaluation, although this tweet should be positive when observing its meaning and context.

Data Preprocessing, Analysis, and Visualization for building a Machine learning model

We are here to see the concept of Data Preprocessing, Analysis, and Visualization for building a Machine learning model. Business owners and organizations use Machine Learning models to predict their Business growth. But before applying machine learning models, the dataset needs to be preprocessed.

So, let’s import the data and start exploring it.

Importing Libraries and Dataset

We will be using these libraries :

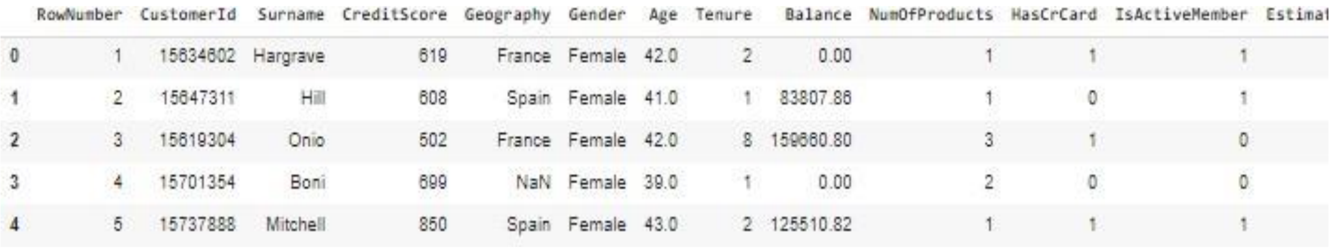
- Pandas library is used for data analysis.
- Numpy library is used for complex mathematical operations.
- Scikit-learn for model training and score evaluation.

```
import pandas as pd

import numpy as np

from sklearn.preprocessing import LabelEncoder

from sklearn.preprocessing import OneHotEncoder

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

dataset = pd.read_csv('Churn_Modelling.csv')
```

Now let us observe the dataset.

```
dataset.head()
```

Output :

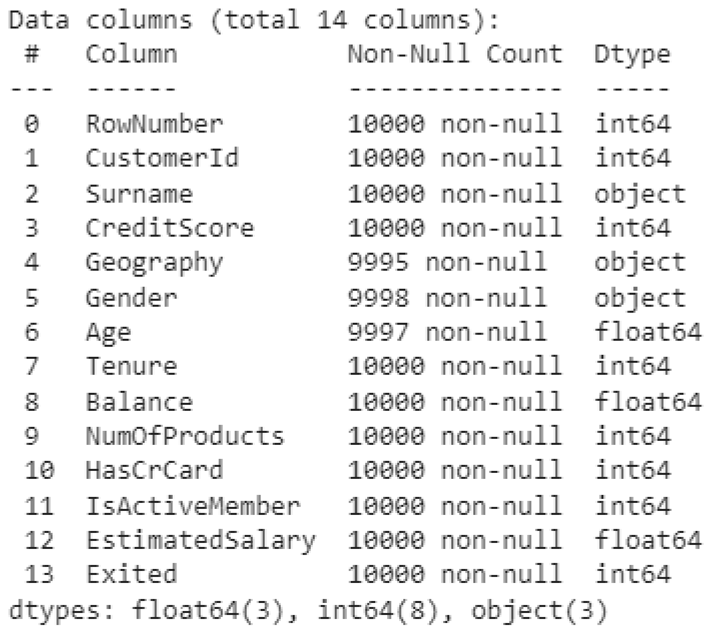


	RowNumber	CustomerId	Surname	CreditScore	Geography	Gender	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	Estimat
0	1	15634602	Hargrave	619	France	Female	42.0	2	0.00	1	1	1	
1	2	15647311	Hill	608	Spain	Female	41.0	1	83807.86	1	0	1	
2	3	15619304	Onio	502	France	Female	42.0	8	159660.80	3	1	0	
3	4	15701354	Boni	699	NaN	Female	39.0	1	0.00	2	0	0	
4	5	15737888	Mitchell	850	Spain	Female	43.0	2	125510.82	1	1	1	

Info() function retrieves the information about the dataset such as data type, number of rows and columns, etc.

```
dataset.info()
```

Output :



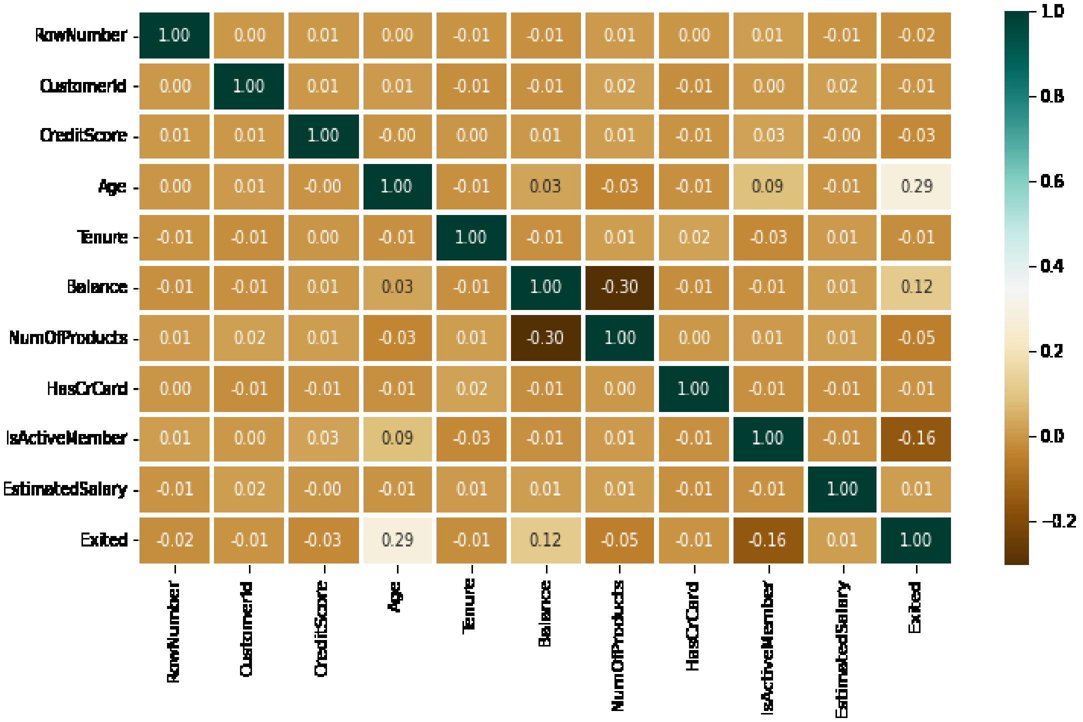
```
Data columns (total 14 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   RowNumber        10000 non-null  int64  
 1   CustomerId       10000 non-null  int64  
 2   Surname          10000 non-null  object 
 3   CreditScore      10000 non-null  int64  
 4   Geography        9995 non-null   object 
 5   Gender           9998 non-null   object 
 6   Age              9997 non-null   float64
 7   Tenure           10000 non-null  int64  
 8   Balance          10000 non-null  float64
 9   NumOfProducts    10000 non-null  int64  
 10  HasCrCard        10000 non-null  int64  
 11  IsActiveMember   10000 non-null  int64  
 12  EstimatedSalary  10000 non-null  float64
 13  Exited           10000 non-null  int64  
dtypes: float64(3), int64(8), object(3)
```

Exploratory data analysis and visualization

To find out the correlation between the features, Let’s make the headmap

```
plt.figure(figsize=(12,6))

sns.heatmap(dataset.corr(),

          cmap=’BrBG’,

            fmt=’.2f’,

            linewidths=2,

            annot=True)
```

Output :

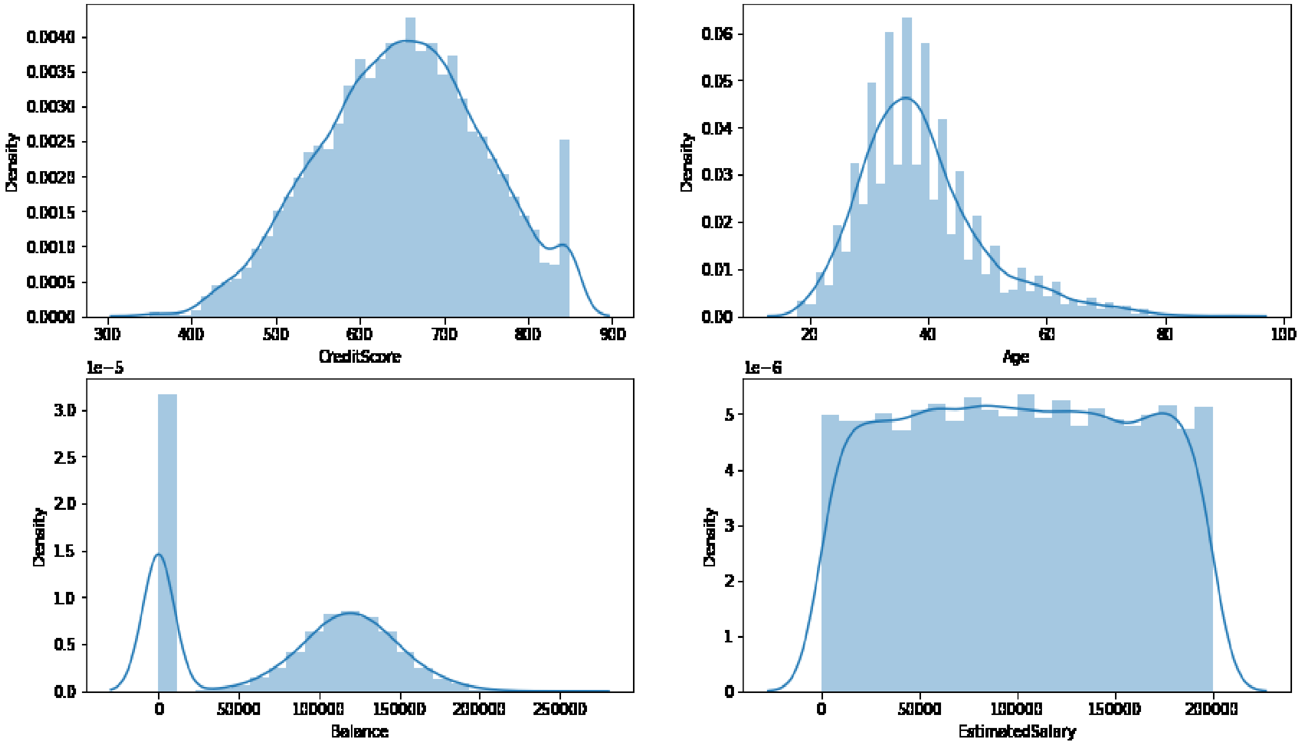


	RowNumber	CustomerId	CreditScore	Age	Tenure	Balance	NumOfProducts	HasCrCard	IsActiveMember	EstimatedSalary	Exited
RowNumber	1.00	0.00	0.01	0.00	-0.01	-0.01	0.01	0.00	0.01	-0.01	-0.02
CustomerId	0.00	1.00	0.01	0.01	-0.01	-0.01	0.02	-0.01	0.00	0.02	-0.01
CreditScore	0.01	0.01	1.00	-0.00	0.00	0.01	0.01	-0.01	0.03	-0.00	-0.03
Age	0.00	0.01	-0.00	1.00	-0.01	0.03	-0.03	-0.01	0.09	-0.01	0.29
Tenure	-0.01	-0.01	0.00	-0.01	1.00	-0.01	0.01	0.02	-0.03	0.01	-0.01
Balance	-0.01	-0.01	0.01	0.03	-0.01	1.00	-0.30	-0.01	-0.01	0.01	0.12
NumOfProducts	0.01	0.02	0.01	-0.03	0.01	-0.30	1.00	0.00	0.01	0.01	-0.05
HasCrCard	0.00	-0.01	-0.01	-0.01	0.02	-0.01	0.00	1.00	-0.01	-0.01	-0.01
IsActiveMember	0.01	0.00	0.03	0.09	-0.03	-0.01	0.01	-0.01	1.00	-0.01	-0.16
EstimatedSalary	-0.01	0.02	-0.00	-0.01	0.01	0.01	0.01	-0.01	-0.01	1.00	0.01
Exited	-0.02	-0.01	-0.03	0.29	-0.01	0.12	-0.05	-0.01	-0.16	0.01	1.00

Now we can also explore the distribution of CreditScore, Age, Balance, ExtimatedSalary using displot.

```
lis = [‘CreditScore’, ‘Age’, ‘Balance’, ‘EstimatedSalary’]

plt.subplots(figsize=(15, 8))

index = 1

for I in lis:

  plt.subplot(2, 2, index)

  sns.distplot(dataset[i])

  index += 1
```

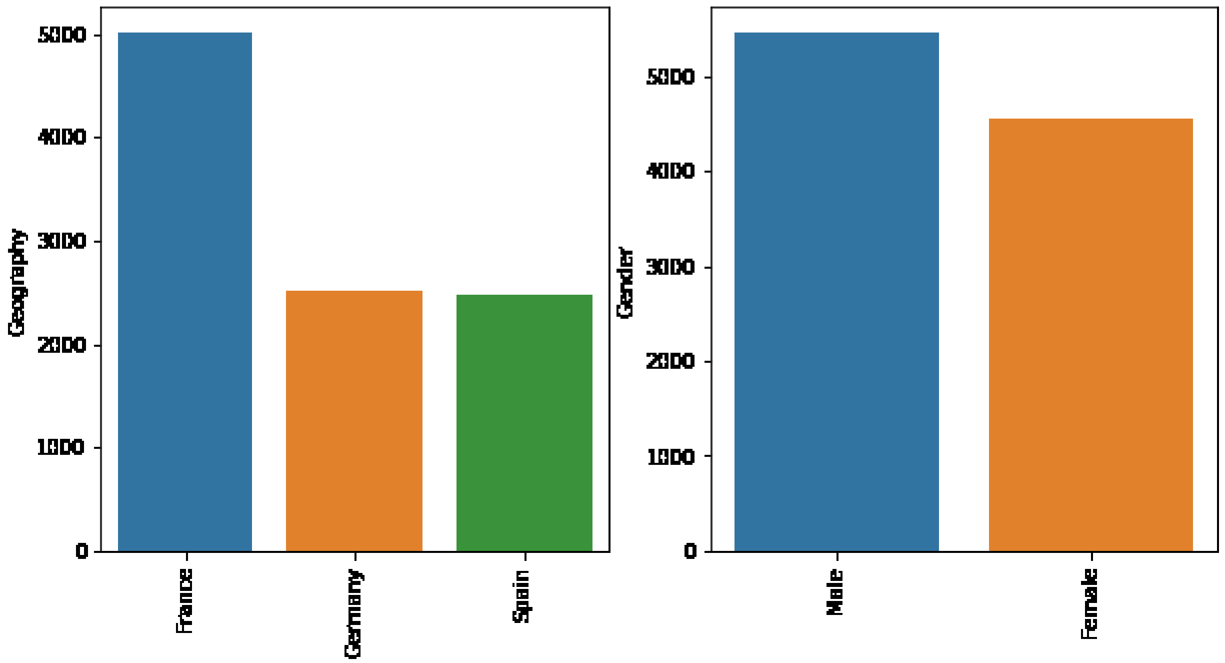
Output :



We can also check the categorical count of each category in Geography and Gender.

```
lis2 = [‘Geography’, ‘Gender’]
plt.subplots(figsize=(10, 5))
index = 1
for col in lis2:
   y = dataset[col].value_counts()
    plt.subplot(1, 2, index)
    plt.xticks(rotation=90)
    sns.barplot(x=list(y.index), y=y)
    index += 1
```

Output :



Data Preprocessing

Data preprocessing is used to convert raw data into a clear format. Raw data consist of missing values, noisy data, and raw data may be text, image, numeric values, etc.

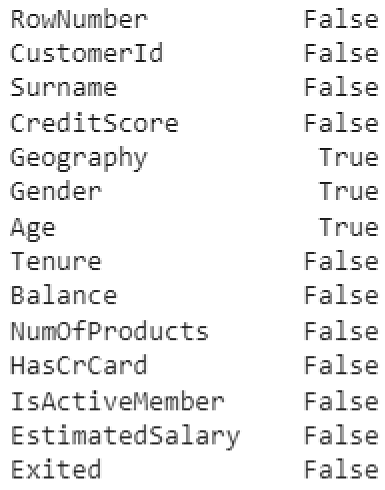
By the above definition, we understood that transforming unstructured data into a structured form is called data preprocessing. If the unstructured data is used in machine learning models to analyze or to predict, the prediction will be false because unstructured data contains missing values and unwanted data. So for good prediction, the data need to be preprocessed.

Finding Missing Values and Handling them

Let’s observe whether null values are present.

```
dataset.isnull().any()
```

Output :



```
RowNumber          False
CustomerId         False
Surname            False
CreditScore        False
Geography           True
Gender              True
Age                 True
Tenure             False
Balance            False
NumOfProducts      False
HasCrCard          False
IsActiveMember     False
EstimatedSalary    False
Exited             False
```

Here, True indicates a null value and False indicates there is no null value. We can observe that there are 3 columns containing null values. The 3 columns are Geography, Gender, and Age. Now we need to remove the null values, to do this there are 3 ways they are:

- Deleting rows
- Replacing null with custom values
- Replacing using Mean, Median, and Mode

In this scenario, we replace null values with Mean and Mode.

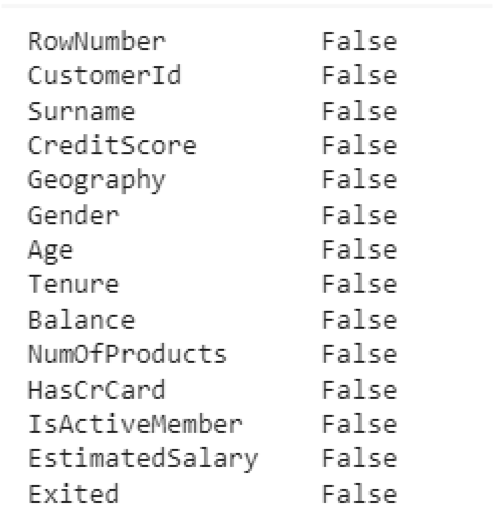
```
dataset[“Geography”].fillna(dataset[“Geography”].mode()[0],inplace = True)
dataset[“Gender”].fillna(dataset[“Gender”].mode()[0],inplace = True)
dataset[“Age”].fillna(dataset[“Age”].mean(),inplace = True)
```

As we know Geography and Gender is a Categorical columns we used mode and Age is an integer type so we used mean.

Note: By using “Inplace = True”, the original data set is modified.

Now once again let us check if any null values still exist.

```
Dataset.isnull().any()
```



```
RowNumber          False
CustomerId         False
Surname            False
CreditScore        False
Geography          False
Gender             False
Age                False
Tenure             False
Balance            False
NumOfProducts      False
HasCrCard          False
IsActiveMember     False
EstimatedSalary    False
Exited             False
```

Label Encoding

Label Encoding is used to convert textual data to integer data. As we know there are two textual data type columns which are “Geography” and “Gender”.

```
le = LabelEncoder()

dataset[‘Geography’] = le.fit_transform(dataset[“Geography”])

dataset[‘Gender’] = le.fit_transform(dataset[“Gender”])
```

First we initialized LabelEncoder() function, then transformed textual data to integer data with fit_transform() function.

So now, the “Geography” and “Gender” columns are converted to integer data types.

Splitting Dependent and Independent Variables

Dataset is split into x and y variables and converted to an array.

```
x = dataset.iloc[:,3:13].values

y = dataset.iloc[:,13:14].values
```

Here x is the independent variable and y is the dependent variable.

Splitting into Train and Test Dataset

```
x_train, x_test, y_train, y_test = train_test_split(x,y,

                                          test_size = 0.2,

                                          random_state = 0)
```

Here we split data into train and test sets.

Feature Scaling

Feature Scaling is a technique done to normalize the independent variables.

```
sc = StandardScaler()

x_train = sc.fit_transform(x_train)

x_test = sc.fit_transform(x_test)
```

We have successfully preprocessed the dataset. And now we are ready to apply Machine Learning models.

Model Training and Evaluation

As this is a Classification problem then we will be using the below models for training the data.

- K-Neighbors Classifier
- Random Forest Classifier
- SVC
- Logistic Regression

And for evaluation, we will be using Accuracy Score.

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression


from sklearn import metrics
knn = KNeighborsClassifier(n_neighbors=3)
rfc = RandomForestClassifier(n_estimators = 7,
                             criterion = ‘entropy’,
                             random_state =7)
svc = SVC()
lc = LogisticRegression()
# making predictions on the training set
for clf in (rfc, knn, svc,lc):
    clf.fit(x_train, y_train)
```

```
y_pred = clf.predict(x_test)

    Print("Accuracy score of ",clf._class_._name_,"=",

          100*metrics.accuracy_score(y_test, y_pred))
```

Output :

```
Accuracy score of  RandomForestClassifier = 84.5
Accuracy score of  KNeighborsClassifier = 82.5
Accuracy score of  SVC = 86.15
Accuracy score of  LogisticRegression = 80.75
```

CONCLUSION:

By following this project model, marketing professionals can leverage sentiment analysis in AI to gain a deeper understanding of their customers and their needs, preferences, and expectations. This can help them create more effective and personalized marketing campaigns that increase customer loyalty and retention