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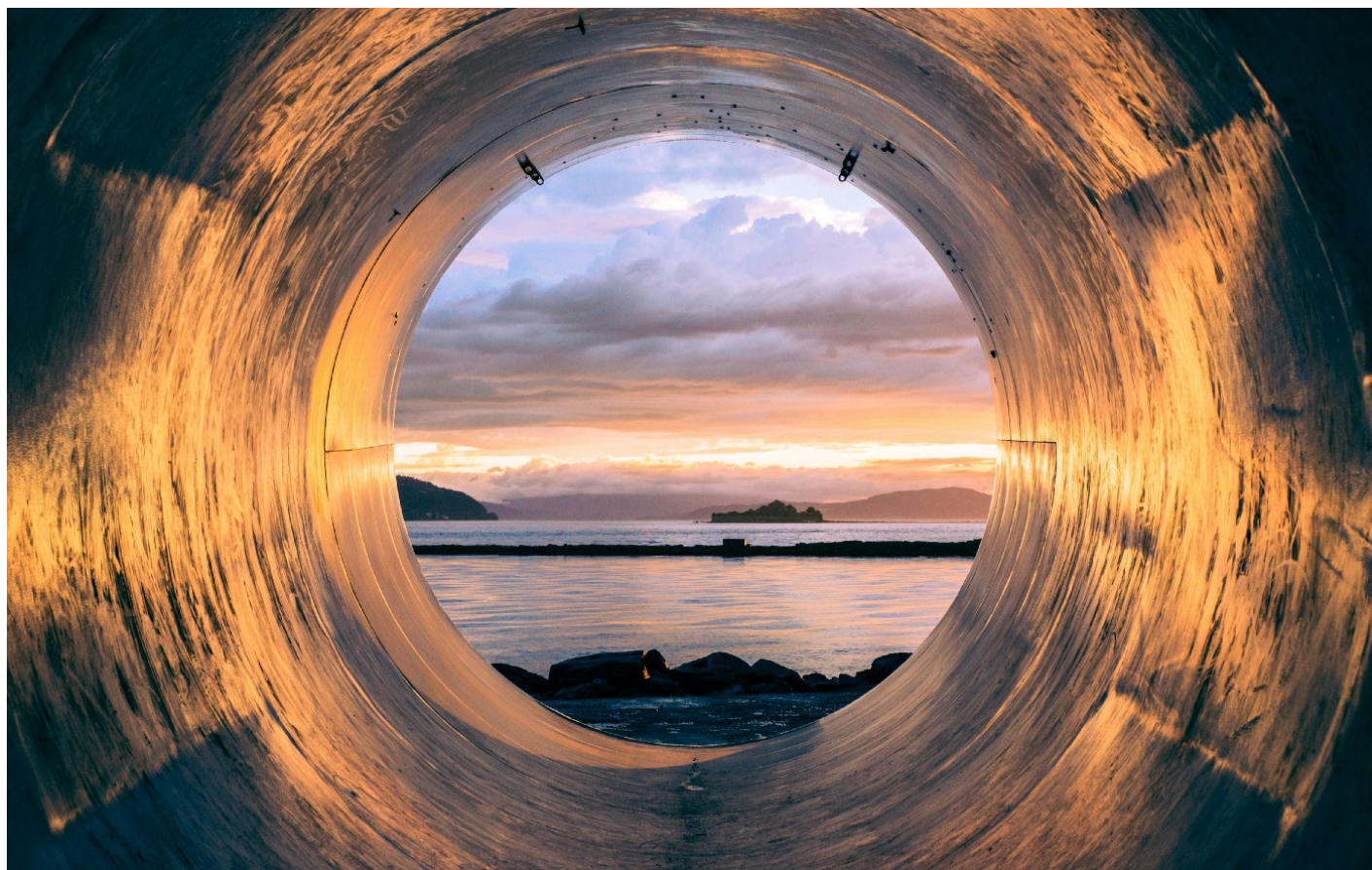
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## Building an ETL Pipeline in Python

### Introduction

In my last [post](#), I discussed how we could set up a script to connect to the Twitter API and stream data directly into a database. Today, I am going to show you how we can access this data and do some analysis with it, in effect creating a complete data pipeline from start to finish. Broadly, I plan to extract the raw data from our database, clean it and finally do some simple analysis using word clouds and an NLP Python library.

Let's think about how we would implement something like this. To make the analysis as general as possible I am going to take an object oriented approach by creating a **TweetObject** class and methods of this class to perform the tasks above. There are a few important libraries that we will use such as the NLTK (Natural Language Toolkit)





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Let's take our first look at the python code.

```
1  import mysql.connector
2  from mysql.connector import Error
3  import os
4  import re
5  import pandas as pd
6  from nltk.tokenize import word_tokenize
7  from nltk.corpus import stopwords
8  from nltk.stem.porter import PorterStemmer
9  from nltk.stem import WordNetLemmatizer
10 import nltk
11 from wordcloud import WordCloud, STOPWORDS
12 import numpy as np
13 import matplotlib.pyplot as plt
14 from textblob import TextBlob
15
16
17 class TweetObject():
18
19     def __init__(self, host, database, user):
20         self.password = os.environ['PASSWORD']
21         self.host = host
22         self.database = database
23         self.user = user
24
25
26
27     def MySQLConnect(self, query):
28         """
29         Connects to database and extracts
30         raw tweets and any other columns we
31         need
32         Parameters:
33         -----
34         arg1: string: SQL query
35         Returns: pandas dataframe
36         -----
37         """
38
39         try:
40             con = mysql.connector.connect(host = self.host, database = self.database, \
41                                           user = self.user, password = self.password, charset = 'utf8')
42
43             if con.is_connected():
44                 print("Successfully connected to database")
45
46                 cursor = con.cursor()
47                 query = query
48                 cursor.execute(query)
49
```





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```
55
56
57     except Error as e:
58         print(e)
59
60     cursor.close()
61     con.close()
62
63
64     return df
```

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First off, we import the necessary libraries. Like my previous post, we need to import the mysql-connector library to connect to our database. The TweetObject class will initialise some important parameters allowing us to connect to our database. The **MySQLConnect** method takes in a SQL query, executes it and returns a pandas data frame. Pandas is a really great library for any data analysis tasks and makes manipulating data really easy so I would recommend any aspiring data analysts/scientists get familiar with this library.

## Natural Language Processing: Cleaning the Tweets

Now that we have a method that queries our database and returns the data what are we going to do with it? Let's take a moment to talk a little bit about natural language processing (NLP). In general, text data requires some pre-processing before we can feed it to a machine learning algorithm. We need to put it into a format that an algorithm can understand. This generally involves some of the following tasks.

### Pre-Processing steps in NLP:

#### 1. Normalisation.



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#### 4. Lemmatisation

#### 5. TF-IDF.

This is certainly not an exhaustive list but these are the kinds of techniques that would apply to most NLP tasks. OK, let's explain what some of these concepts are and why we need to use them. Standardising words into lowercase is a normal step in NLP as we do not want our algorithm to consider PYTHON and python as two different words. Converting all words into the same case avoids these issues. Another step we want to take is to remove any irrelevant material from our text. One way to do this is to remove punctuation such as commas, full stops and stop words such as 'i', 'is', 'the'. A more detailed list of the stop words in the NLTK package can be seen [here](#). We should also think about **Tokenisation** which is a process that essentially splits up text into meaningful chunks or tokens (TextBlob does this for us automatically). The final pre-processing technique that we will use is **Lemmatisation**. This essentially converts a word into its 'canonical form'. In other words pythons will become python and walked becomes walk.

One technique that is quite useful but we do not use here is Term Frequency-Inverse Document Frequency or **TF-IDF**. It is an information retrieval technique which allows us to identify the relative importance of words in a document. Broadly speaking, if a word occurs many times in a document it is likely to be important. However, if it also appears frequently across multiple documents then it may just be a common word and not in fact very meaningful. TF-IDF tries to account for this and returns an overall score of importance for each word. It is a widely used technique when trying to quantify what a document is about and tends to be used with algorithms such as **Gaussian Mixture Models (GMM)**, **K-means** or **Latent Dirichlet Allocation (LDA)**.

There are many other techniques that we can employ that might improve our results such as stemming and n-grams for example but I will not go into these here. There are a number of resources online if you want to take a deeper dive into NLP.

Now let's get back to our code. The `clean_tweets` method below implements some of the techniques mentioned above. In particular, it normalises all words into lower case, splits the words, lemmatises, and only keeps words that are not in the stop words list. It also gets rid of some common HTML that tends to appear in tweets that won't really help our analysis.

```
1  def clean_tweets(self, df):
2
3      """
4      Takes raw tweets and cleans them
5      so we can carry out analysis
6      remove stopwords, punctuation,
7      lower case, html, emoticons.
8      This will be done using Regex
9      ? means option so colour?r matches
10     both color and colour.
11     """
12
13     # text preprocessing
```





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```
18         if len == None:
19             for i in range(0, len(df['tweet'])):
20                 # get rid of anything that isnt a letter
21
22                 exclusion_list = ['^a-zA-Z', 'rt', 'http', 'co', 'RT']
23                 exclusions = '|'.join(exclusion_list)
24                 text = re.sub(exclusions, ' ', df['tweet'][i])
25                 text = text.lower()
26                 words = text.split()
27                 words = [wordnet_lemmatizer.lemmatize(word) for word in words if not word in stopwords_list]
28                 # only use stem of word
29                 #words = [ps.stem(word) for word in words]
30                 df['clean_tweets'][i] = ' '.join(words)
31
32
33         # Create column with data length
34         df['len'] = np.array([len(tweet) for tweet in data["clean_tweets"]])
35
36
37
38         return df
```

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## Calculating Sentiment

Now that we have a method to clean our tweets, we can create a method to calculate sentiment. The TextBlob library makes sentiment analysis really simple in Python. All we need to do is pass our text into our TextBlob class, call the **sentiment.polarity** method on the object and it returns either 1, 0 or -1 corresponding to positive, neutral and negative sentiment respectively. The TextBlob class implements a number of text processing functions by default if no additional parameters are passed to it so let's have a quick look at these to understand what is going on under the hood.

There are four parameters, the **tokenizer**, **np\_extractor**, **pos\_tagger** and **analyser** that if left blank, default to certain methods. The tokenizer defaults to the **WordTokenizer** method which splits the text up into a list of words. The **FastNPEExtractor** method is called if we leave np\_extractor blank which according to the [documentation](#) returns a list of noun phrases which can be quite helpful in identifying what a particular sentence or tweet is about.



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Next, the `NLTK_tagger` is called which identifies parts of speech (POS) such as whether a word is a noun, verb or adjective. Finally, the analyser defaults to the pattern analyser which returns our polarity score. As we can see, the code for this sentiment calculation is really concise. The polarity score is returned on a scale from -1 to 1 which we convert into a sentiment score based on its value.

We also create methods which save our results to a CSV and create a word cloud. I really like using word clouds as they are an effective way of summarising text data. They provide a pretty visualisation of word counts in the text where the bigger words correspond to a higher count (word appears more often). This makes it much easier to get a feel for the kinds of things people are tweeting about.

```
1  def sentiment(self, tweet):
2      """
3          This function calculates sentiment
4          from our base on our cleaned tweets.
5          Uses textblob to calculate polarity.
6          Parameters:
7          -----
8          arg1: takes in a tweet (row of dataframe)
9          -----
10         Returns:
11             Sentiment:
12             1 is Positive
13             0 is Neutral
14             -1 is Negative
15         """
16
17         analysis = TextBlob(tweet)
18         if analysis.sentiment.polarity > 0:
19             return 1
20         elif analysis.sentiment.polarity == 0:
21             return 0
22         else:
23             return -1
24
25
26
27
28  def save_to_csv(self, df):
29      """
30          Save cleaned data to a csv for further
31          analysis.
32          Parameters:
33          -----
34          arg1: Pandas dataframe
35          """
36      try:
37          df.to_csv("clean_tweets.csv")
38          print("\n")
39          print("csv successfully saved. \n")
```





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```
45
46
47
48     def word_cloud(self, df):
49         """
50         Takes in dataframe and plots a wordcloud using matplotlib
51         """
52         plt.subplots(figsize = (12,10))
53         wordcloud = WordCloud(
54                                     background_color = 'white',
55                                     width = 1000,
56                                     height = 800).generate(" ".join(df['clean_tweets']))
57         plt.imshow(wordcloud)
58         plt.axis('off')
59         plt.show()
```

part7\_Twitter.py hosted with ❤ by GitHub

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## Main Method

Next up, we have our main method which creates our object and calls the appropriate methods. We first create an object of the TweetObject class and connect to our database, we then call our **clean\_tweets** method which does all of our pre-processing steps. The final steps create 3 lists with our sentiment and use these to get the overall percentage of tweets that are positive, negative and neutral. Before we run this we need to make sure our **SQL server is running**. Otherwise, we won't be able to connect to the database and retrieve our data.

```
1  if __name__ == '__main__':
2
3      t = TweetObject( host = 'localhost', database = 'twitterdb', user = 'root')
4
5      data = t.MySQLConnect("SELECT created_at, tweet FROM `TwitterDB`.`Golf`")
```



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```
11 pos_tweets = [tweet for index, tweet in enumerate(data["clean_tweets"]) if data["Sentiment"][index] > 0]
12 neg_tweets = [tweet for index, tweet in enumerate(data["clean_tweets"]) if data["Sentiment"][index] < 0]
13 neu_tweets = [tweet for index, tweet in enumerate(data["clean_tweets"]) if data["Sentiment"][index] == 0]
14
15 #Print results
16 print("percentage of positive tweets: {}".format(100*(len(pos_tweets)/len(data['clean_tweets']))))
17 print("percentage of negative tweets: {}".format(100*(len(neg_tweets)/len(data['clean_tweets']))))
18 print("percentage of neutral tweets: {}".format(100*(len(neu_tweets)/len(data['clean_tweets']))))
```

part8\_Twitter.py hosted with ❤ by GitHub

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## Results

OK, let's see what this code produced. As I said in my previous post, I am a bit of a golf fan so I decided to collect tweets during the final round of the masters in 2018. As we can see from the word cloud below, Patrick Reed is the most frequent name popping up which is probably not surprising given he won the tournament. We also see a few other golfers names such as Jordan Speith and Ricky Fowler who finished right behind Reed in the leaderboard. Although this isn't the most insightful graph in the world I really am a fan of using word clouds to try and draw some initial insights from data. It is not entirely obvious what the general sentiment of these tweets are looking at this word cloud but that is why we have the TextBlob library. Below this, we have the results from our sentiment calculation. In particular, we calculated the percentage of tweets that fall into the three categories above.

Our results from the sentiment score indicate that the majority of tweets are positive at around 48%. There is also a large group of people who seem to be quite neutral at 39%. Overall we can glean from this that the tweets are broadly positive but not by much. One weakness of the approach here is that we may have inadvertently grabbed tweets that aren't at all related to the golf tournament but simply contain some of our keywords. This is one thing to be wary of when doing any analysis like this.







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One disadvantage of the approach we have taken is that we have used an off the shelf algorithm. There is no guarantee that our results are very accurate and unfortunately no way to tell without going through the tweets we collected. One way we could handle this is to use a sentiment algorithm that was specifically trained on tweets which would likely give us improved results.

We could also take this analysis a step further and try some unsupervised learning methods such as clustering. This would help us find groups of tweets that are similar and could give us deeper insights into our dataset. GMM would also be an interesting technique to try. This algorithm attempts to do the same thing as clustering but has the added advantage of being more flexible by allowing us to assign tweets to multiple groups with certain probabilities. This is great as we can incorporate a level of uncertainty into our estimates. I will, however, leave these techniques for a future post.

*Recommended Course: [Data Engineering](#), [Big Data](#), and [Machine Learning on GCP](#)*

## Full Python Code

```
1  import mysql.connector
2  from mysql.connector import Error
3  import os
4  import re
5  import pandas as pd
6  from nltk.tokenize import word_tokenize
7  from nltk.corpus import stopwords
8  from nltk.stem import WordNetLemmatizer
9  import nltk
10 from wordcloud import WordCloud, STOPWORDS
11 import numpy as np
12 import matplotlib.pyplot as plt
13 from textblob import TextBlob
14
15
16
17 class TweetObject():
18
19
20     def __init__(self, host, database, user):
21         self.password = os.environ['PASSWORD']
22         self.host = host
23         self.database = database
24         self.user = user
25
26
27
28     def MySQLConnect(self, query):
29         """
30         Connects to database and extracts
31         raw tweets and any other columns we
32         need
```





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```
38         """
39
40         try:
41             con = mysql.connector.connect(host = self.host, database = self.database, \
42                                           user = self.user, password = self.password, charset = 'utf8')
43
44             if con.is_connected():
45                 print("Successfully connected to database")
46
47                 cursor = con.cursor()
48                 query = query
49                 cursor.execute(query)
50
51                 data = cursor.fetchall()
52                 # store in dataframe
53                 df = pd.DataFrame(data, columns = ['date', 'tweet'])
54
55
56
57         except Error as e:
58             print(e)
59
60         cursor.close()
61         con.close()
62
63         return df
64
65
66
67     def clean_tweets(self, df):
68
69         """
70         Takes raw tweets and cleans them
71         so we can carry out analysis
72         remove stopwords, punctuation,
73         lower case, html, emoticons.
74         This will be done using Regex
75         ? means option so colour matches
76         both color and colour.
77         """
78
79         # Do some text preprocessing
80         stopword_list = stopwords.words('english')
81         ps = PorterStemmer()
82         df["clean_tweets"] = None
83         df['len'] = None
84         for i in range(0, len(df['tweet'])):
85             # get rid of anything that isn't a letter
86
87             exclusion_list = ['^a-zA-Z', 'rt', 'http', 'co', 'RT']
88             exclusions = '|'.join(exclusion_list)
```





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```
94         #words = [ps.stem(word) for word in words]
95         df['clean_tweets'][i] = ' '.join(words)
96
97
98     # Create column with data length
99     df['len'] = np.array([len(tweet) for tweet in data["clean_tweets"]])
100
101
102
103     return df
104
105
106
107     def sentiment(self, tweet):
108         """
109         This function calculates sentiment
110         on our cleaned tweets.
111         Uses textblob to calculate polarity.
112         Parameters:
113         -----
114         arg1: takes in a tweet (row of dataframe)
115         """
116
117         # need to improve
118         analysis = TextBlob(tweet)
119         if analysis.sentiment.polarity > 0:
120             return 1
121         elif analysis.sentiment.polarity == 0:
122             return 0
123         else:
124             return -1
125
126
127
128
129     def save_to_csv(self, df):
130         """
131         Save cleaned data to a csv for further
132         analysis.
133         Parameters:
134         -----
135         arg1: Pandas dataframe
136         """
137         try:
138             df.to_csv("clean_tweets.csv")
139             print("\n")
140             print("csv successfully saved. \n")
141
142
143         except Error as e:
144             print(e)
```



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```
150     pos_tweets = [tweet for index, tweet in enumerate(data["clean_tweets"]) if data["Sentiment"][index] > 0]
151     wordcloud = WordCloud(
152         background_color = 'white',
153         width = 1000,
154         height = 800).generate(" ".join(df['clean_tweets']))
155     plt.imshow(wordcloud)
156     plt.axis('off')
157     plt.show()
158
159
160
161
162
163 if __name__ == '__main__':
164
165     t = TweetObject( host = 'localhost', database = 'twitterdb', user = 'root')
166
167     data = t.MySQLConnect("SELECT created_at, tweet FROM `TwitterDB`.`Golf`;")
168     data = t.clean_tweets(data)
169     data['Sentiment'] = np.array([t.sentiment(x) for x in data['clean_tweets']])
170     t.word_cloud(data)
171     t.save_to_csv(data)
172
173     pos_tweets = [tweet for index, tweet in enumerate(data["clean_tweets"]) if data["Sentiment"][index] > 0]
174     neg_tweets = [tweet for index, tweet in enumerate(data["clean_tweets"]) if data["Sentiment"][index] < 0]
175     neu_tweets = [tweet for index, tweet in enumerate(data["clean_tweets"]) if data["Sentiment"][index] == 0]
176
177     #Print results
178     print("percentage of positive tweets: {}".format(100*(len(pos_tweets)/len(data['clean_tweets']))))
179     print("percentage of negative tweets: {}".format(100*(len(neg_tweets)/len(data['clean_tweets']))))
180     print("percentage of neutral tweets: {}".format(100*(len(neu_tweets)/len(data['clean_tweets']))))
```

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