deletweet-deletion-times

April 3, 2017

1 DELETWEET DELETION TIMES

```
In [1]: import json
        import nltk
        import pandas
        import matplotlib
        from datetime import datetime
        from matplotlib import pyplot as plt
        from nltk.tokenize import TweetTokenizer

        %matplotlib inline
        matplotlib.rcParams['figure.figsize'] = [18.0, 12.0]
```

1.1 PARSE DATA

The Politwoops dataset came with two fields, 'created' and 'modified', that contain information about how long the tweet was live before it was deleted. The 'created' field corresponds to the time the tweet was originally created, whereas the 'modified' field corresponds to the last modification made to the tweet, which in this case is when it was deleted. To determine the time the tweet was live we take a simple difference between the two fields.

To achieve this we import the data and convert the two relevant fields into datetime objects, which allows for easy subtraction in python. Then we add a new column to our dataframe that represents the difference between the two.

```
In [2]: # import dataset
        deletweet = pandas.read_csv('../../deletweet/data/deleted_tweets_cleaned.csv')
```

```
In [3]: # convert time fields in dataframe to datetime objects for easier analysis
        deletweet['created'] = pandas.to_datetime(deletweet['created'])
        deletweet['modified'] = pandas.to_datetime(deletweet['modified'])
```

```
In [4]: # add new column to dataframe for the time difference from tweet creation to deletion
        deletweet['time_diff'] = deletweet['modified'] - deletweet['created']
```

1.2 PLOT AND ANALYSIS

Two different papers on tweet analysis (here and here) task themselves with determining for what reason a tweet has been deleted, based on the tweet's content and metadata. Both of them find that tweets that are deleted soon after their creation - as in a matter of seconds to several hours - are overwhelmingly deleted for aesthetic reasons, such as misspellings, improper formatting, broken or misdirected links, etc. They go on to say that tweets that are live several hours or more before being deleted are more likely to be classified as 'regrettable', and that anywhere from two hours to ten hours can be the threshold or decision boundary between regrettable and aesthetic.

The reasons for regret are varied, and determining them and their influence on decision making is a deeply philosophical question. However, given that this set of tweets is political in nature, it is safe to assume that they are likely to be in service of forming and supporting a positive public image for the politicians. In this context, regret can be more clearly expressed as a response to a tweet that is perceived as doing harm to this image or public opinion. While this is something to keep in mind, we will see below that it proves difficult to discern concrete differences that indicate that tweets deleted after 10 hours are more regrettable.

A look at the basic statistics of the 'time_diff' field show that the time for deletion varies greatly, from essentially instantly to over 5 years later. However the 50th percentile is only about 8 minutes, which means that over half the tweets have most likely been deleted for aesthetic reasons.

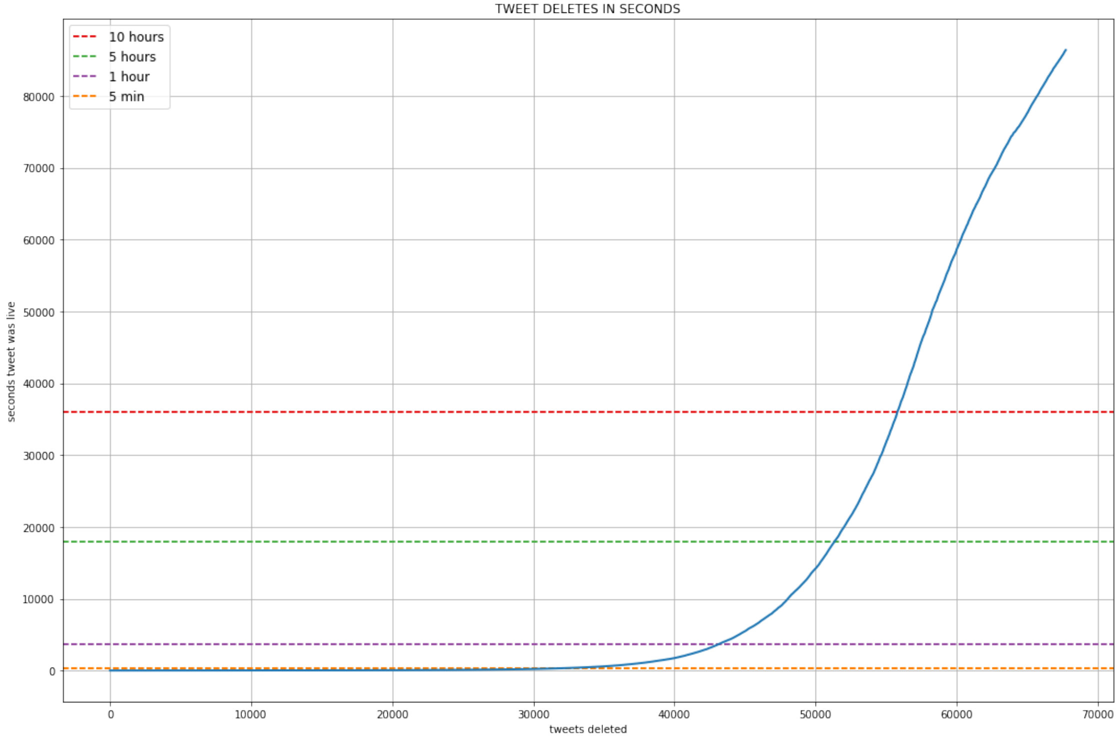
```
In [5]: deletweet['time_diff'].describe()
```

```
Out[5]: count                         67756
        mean       97 days 08:50:35.898990
        std       246 days 15:10:23.122675
        min                 0 days 00:00:00
        25%         0 days 00:00:33.750000
        50%                 0 days 00:07:54
        75%        19 days 21:19:45.750000
        max              1888 days 02:34:13
        Name: time_diff, dtype: object
```

```
In [6]: # make pandas series of time_diff column expressed as seconds for plotting
        seconds = pandas.Series([deletweet['time_diff'][i].seconds for i in range(len(deletweet))], \
                                index=[deletweet['id'][i] for i in range(len(deletweet))])
        seconds_sorted = sorted(seconds)
```

```
In [7]: plt.figure()
        plt.title('TWEET DELETES IN SECONDS')
        plt.xlabel('tweets deleted')
        plt.ylabel('seconds tweet was live')
        plt.grid(True)
        plt.yticks([0, 10000, 20000, 30000, 40000, 50000, 60000, 70000, 80000])
        plt.axhline(y=36000, linewidth=2, color = '#e41a1c', linestyle='dashed', label='10 hours')
        plt.axhline(y=18000, linewidth=2, color = '#4daf4a', linestyle='dashed', label='5 hours')
        plt.axhline(y=3600, linewidth=2, color = '#984ea3', linestyle='dashed', label='1 hour')
        plt.axhline(y=300, linewidth=2, color = '#ff7f00', linestyle='dashed', label='5 min')
        plt.legend(prop={'size':12})
        plt.plot(seconds_sorted, linewidth=2)
```

```
Out[7]: [<matplotlib.lines.Line2D at 0x112101198>]
```




```
In [8]: # make buckets to sort by time tweet was live before being deleted
        times = {'0-5 min': 300, '1-2 hrs': 7200, '15-30 min': 1800, '2-5 hrs': 18000, \
                 '30 min - 1 hr': 3600, '5-10 hrs': 36000, '5-15 min': 900, '>10hrs': 36000}
        times_list = ['0-5 min', '5-15 min', '15-30 min', '30 min - 1 hr', \
                      '1-2 hrs', '2-5 hrs', '5-10 hrs', '>10hrs']

        grouped = {key: [] for key in times.keys()}

        for tweet in seconds.iteritems():
            if tweet[1] <= times['0-5 min']:
                grouped['0-5 min'].append(tweet[0])
            elif tweet[1] <= times['5-15 min'] and tweet[1] > times['0-5 min']:
                grouped['5-15 min'].append(tweet[0])
            elif tweet[1] <= times['15-30 min'] and tweet[1] > times['5-15 min']:
                grouped['15-30 min'].append(tweet[0])
            elif tweet[1] <= times['30 min - 1 hr'] and tweet[1] > times['15-30 min']:
                grouped['30 min - 1 hr'].append(tweet[0])
            elif tweet[1] <= times['1-2 hrs'] and tweet[1] > times['30 min - 1 hr']:
                grouped['1-2 hrs'].append(tweet[0])
            elif tweet[1] <= times['2-5 hrs'] and tweet[1] > times['1-2 hrs']:
                grouped['2-5 hrs'].append(tweet[0])
            elif tweet[1] <= times['5-10 hrs'] and tweet[1] > times['2-5 hrs']:
                grouped['5-10 hrs'].append(tweet[0])
            elif tweet[1] > times['5-10 hrs']:
                grouped['>10hrs'].append(tweet[0])
```

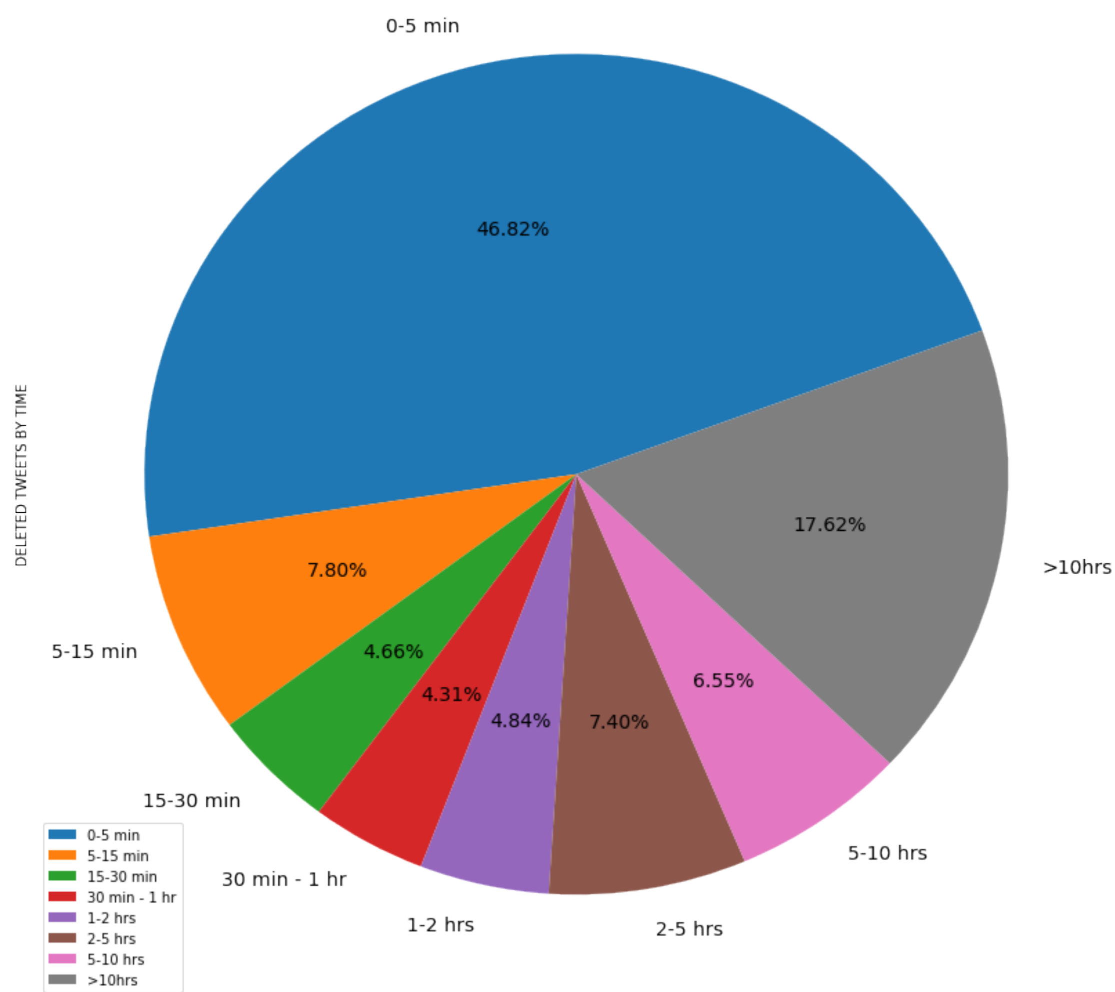
```
In [9]: # print number of tweets in each timeframe
```

```
        for time in times_list:
            print('{:,}: {}'.format(len(grouped[time]), time))
```

```
31,723: 0-5 min
5,282: 5-15 min
3,160: 15-30 min
2,917: 30 min - 1 hr
3,280: 1-2 hrs
5,012: 2-5 hrs
4,441: 5-10 hrs
11,941: >10hrs
```

```
In [10]: # transform into pandas series for plotting
         tweet_series = pandas.Series([len(grouped[times_list[i]]) for i in range(len(grouped))], \
                                      index=times_list, name='DELETED TWEETS BY TIME')
         tweet_series.plot.pie(figsize=(14, 14), fontsize=14, autopct='%.2f%%', \
                               startangle=20, legend=True)
```

```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1121076d8>
```



The graphs above indicate that close to half the tweets are deleted within 5 minutes of posting, and that almost 70% are deleted within 1 hour of posting. This is a good indication that the majority of this dataset is likely to have been deleted for aesthetic reasons.

1.3 SUBSETTING TWEETS DELETED AFTER 10 HOURS

In [11]:
```
# ids of the tweets that were deleted after 10 or more hours
subset_ids = grouped['>10hrs']
```

In [12]:
```
# construct a list of strings to hold the tweet text
tweet_text_raw = []

for thing in deletweet['id'].iteritems():
    if thing[1] in subset_ids:
        tweet_text_raw.append(deletweet['content'][thing[0]])
```

In [13]:
```
# number of tweets in the 10+ hour subset
len(tweet_text_raw)
```

Out[13]:
```
11941
```

In [14]:
```
# subset's % of total
print('{:.2%}'.format(len(tweet_text_raw) / len(deletweet)))
```

```
17.62%
```

In [15]:
```
# find number of retweets in the subset
retweet_count = 0

for thing in deletweet['id'].iteritems():
    if thing[1] in subset_ids:
        tweet = json.loads(deletweet['tweet'][thing[0]])
        if 'retweeted_status' in tweet.keys():
            retweet_count += 1

print('{:,}'.format(retweet_count))
```

```
4,826
```

In [16]:
```
# retweets as percentage of total tweets in 10+ hour subset
print('{:.2%}'.format(retweet_count / len(subset_ids)))
```

```
40.42%
```

Interestingly 40.42% of this subset consists of retweets, which is much higher than the original dataset's retweet percentage of 23.5%.

1.4 CONTENT ANALYSIS OF 10+ HOUR SUBSET

In [17]:
```
# tokenize with NLTK's tweet tokenizer and convert to NLTK text object
tweet_string = ' '.join(tweet_text_raw)

tknzr = TweetTokenizer(preserve_case=False, strip_handles=True, reduce_len=True)
tweet_tokenized = tknzr.tokenize(tweet_string)

text = nltk.Text(tweet_tokenized)
```

In [18]:
```
# remove stopwords, punctuation
stopwords = nltk.corpus.stopwords.words('english')
punctuation_etc = ['.', ':', ',', '!', '"', '-', '...', '...', \
                   "'", '?', '/', "'", '(', ')', '\', '"', '&', '%']
filtered = [w for w in tweet_tokenized if w.lower() not in stopwords]
filtered = [w for w in filtered if w.lower() not in punctuation_etc]

processed = []

# remove numbers
for i in range(len(filtered)):
    try:
        float(filtered[i])
    except ValueError:
        processed.append(filtered[i])


text_normalized = nltk.Text(processed)
```

In [19]:
```
# percentage of text remaining after normalizing
print('{:.2%}'.format(len(text_normalized) / len(text)))
```

```
55.89%
```

In [20]:
```
words_normalized = [w.lower() for w in text_normalized]
vocab_normalized = sorted(set(words_normalized))

# of unique words in normalized text
len(vocab_normalized)
```

Out[20]:
```
25146
```

In [21]:
```
# lexical diversity
print('{:.2%}'.format(len(vocab_normalized) / len(words_normalized)))
```

```
20.99%
```

In [22]:
```
# top 50 bigrams that frequently occur together
text_normalized.collocations(50)
```

```
added video; video playlist; #tg4lg #jobsnow; #mtsen #mtpol; looking
forward; #azgov #ducey2014; health care; hansen clarke; common sense;
renee ellmers; middle class; make sure; early voting; john mica;
colbert busch; president obama; last night; doug collins; town hall;
photo facebook; good luck; student loan; high school; little rock;
spread word; #flipadistrict #fl07; posted new; #ar2 #argop; #txsen
```

```
#ibleedtx; mike waite; minimum wage; tea party; http://t . ...; small
business; phone bank; don't forget; thoughts prayers; chamber
commerce; wall street; election day; new photo; south carolina; great
time; #betterknowachallenger #fl7; #colbertbump
#betterknowachallenger; midnight momentum; hard work; it's time; fox
news; monday midnight
```

```
In [23]: # 50 most common words
         fdist = nltk.FreqDist(text_normalized)
         common = fdist.most_common(50)
         pandas.Series([common[i][1] for i in range(len(common))], \
                       index=[common[i][0] for i in range(len(common))])
```

```
Out[23]: rt             5265
         today           906
         great           645
         support         499
         vote            498
         thank           437
         thanks          436
         us              431
         $               419
         time            403
         w               392
         day             391
         new             376
         get             372
         rep             369
         help            360
         house           337
         congress        315
         #tg4lg          313
         http            311
         tonight         304
         need            278
         #nc02           271
         join            270
         bill            268
         people          262
         video           262
         obama           260
         #ia03           250
         county          241
         i'm             240
         please          234
         work            230
         make            219
         campaign        218
         proud           217
         good            213
         see             213
         president       204
         tomorrow        200
         congressman     199
         it's            198
```

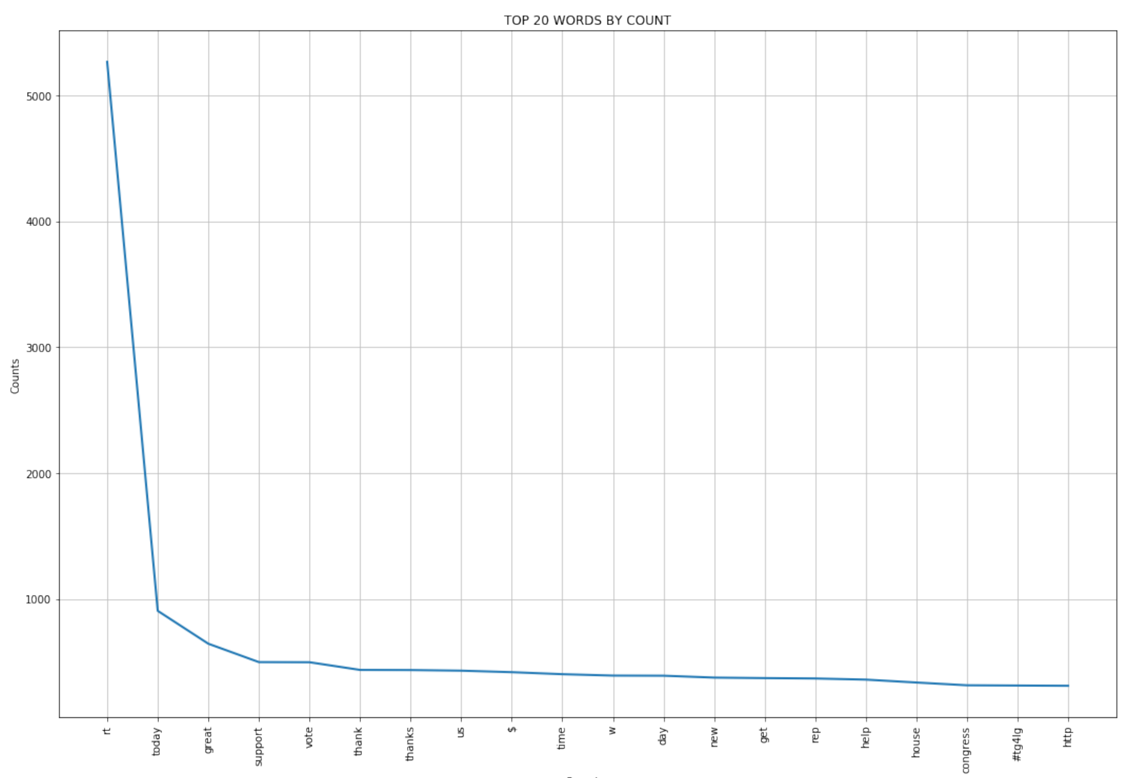
```
one             191
jobs            187
first           185
#obamacare      185
via             183
watch           182
state           181
women           179
dtype: int64
```

In [24]:
```
# words longer than 4 characters occurring more than 100 times
for frequent in sorted(word for word in set(text) if len(word) > 4 and fdist[word] > 100):
    print(frequent)
```

```
#ia03
#jobsnow
#nc02
#obamacare
#tg4lg
#txsen
added
america
american
better
budget
campaign
check
collins
congress
congressional
congressman
country
county
district
don't
election
ellmers
families
family
first
follow
friends
great
happy
health
honored
house
let's
meeting
morning
national
obama
office
people
playlist
```

```
please
president
proud
rehberg
right
senate
service
stand
state
support
talking
thank
thanks
today
tomorrow
tonight
veterans
video
voted
voting
washington
watch
women
working
would
years
```

In [25]:
```python
# plot frequencies of top 20 words
fdist.plot(20, title='TOP 20 WORDS BY COUNT')
```



In [26]:
```
# calculate 'rt's percentage of normalized text
print('{:.2%}'.format(fdist.freq('rt')))
```

```
4.39%
```

After analysis of the text, it appears difficult to classify the tweets that were deleted after 10 hours as more or less regrettable than the rest of the dataset. The content analysis of the subset is largely similar to that of the whole dataset, although there are some differences that are worth noting.

One area of difference is the collocations, or the frequently occuring bigrams. The presence of phrases such as 'added video', 'video playlist', 'photo facebook', 'new photo, 'last night', 'midgnight momentum', and 'fox news' may be indicative of tweets that contained content that was later determined to be regrettable. Also the presence of certain names may indicate that those people were at the center of contested issues, and tweets posted related to them may be contentious enough to be later deleted.

Another notable difference is the more frequent occurence of the hashtag '#obamacare', which is undoubtedly the subject of intense debate, and tweets that mention it may be subject to deletion based on response to the tweet, or potential harm done to the general constituency's perception of the politician.

1.5 MOST COMMON DELETION TIMES

Here we sort the tweets into buckets based on the hour and day they were created and deleted. We do this for both the entire dataset, and the subset of tweets deleted after 10 hours. There is little substantial difference between the distributions of the whole dataset and the subset.

Tweets in this dataset are overwhelming authored and deleted between the hours of 12PM - 1AM. The similarity between the range of the day that they are both created and deleted would seem to suggest that these are the hours that politicians are likely to be active on Twitter, rather than suggesting that tweets that are later deemed regrettable (for aesthetic reasons or otherwise) are likely to be authored at a particular time of day.

The same can be said for day of the week: tweets are likely to be authored and deleted Monday through Friday (0-5 on the x-axis), which corresponds to the traditional American work week.

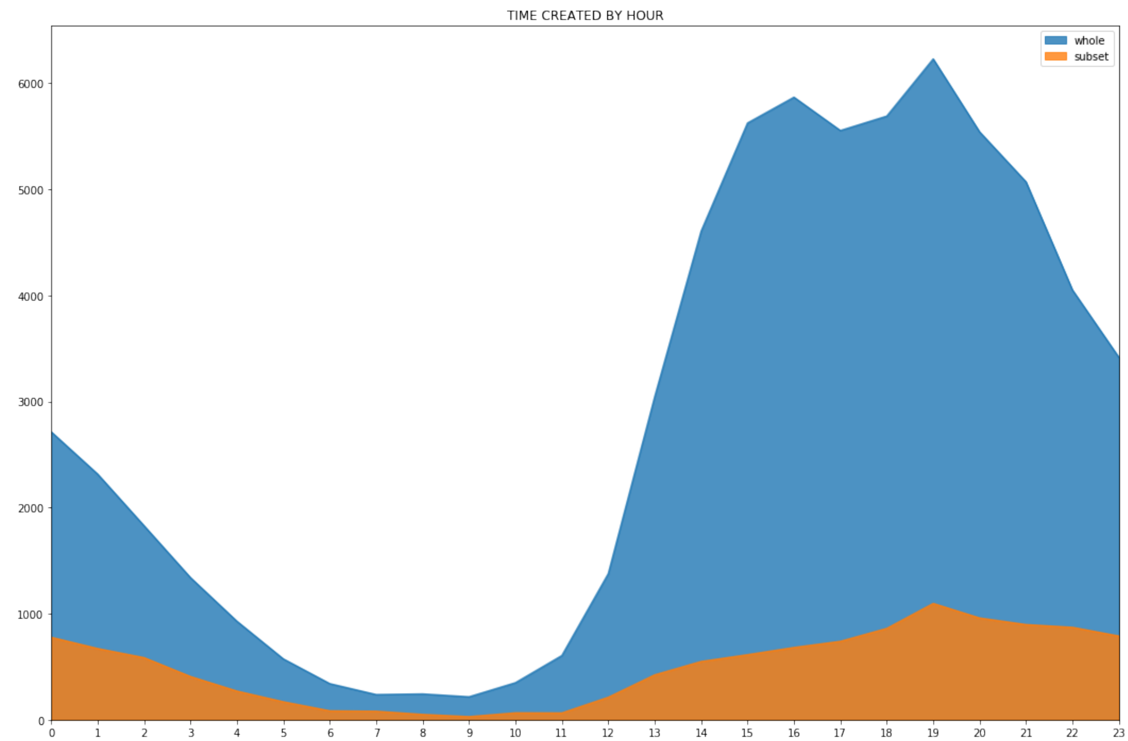
In [27]:
```
# sort tweets by hour and day they were created
created_hours = {i: [] for i in range(24)}
created_days = {i: [] for i in range(7)}

for i in range(len(deletweet)):
    created_hours[deletweet['created'][i].hour].append(deletweet['id'][i])
    created_days[deletweet['created'][i].weekday()].append(deletweet['id'][i])
```

In [28]:
```
# do the same for the 10+ hour subset
created_hours_subset = {i: [] for i in range(24)}
created_days_subset = {i: [] for i in range(7)}

for i in range(len(deletweet)):
    if deletweet['id'][i] in subset_ids:
        created_hours_subset[deletweet['created'][i].hour].append(deletweet['id'][i])
        created_days_subset[deletweet['created'][i].weekday()].append(deletweet['id'][i])
```

In [29]:
```
# create dataframes from hourly data for plotting
df_created_hours = pandas.DataFrame([len(created_hours[i]) \
                                     for i in range(24)], columns=['whole'])
df_created_hours['subset'] = pandas.Series([len(created_hours_subset[i]) \
```

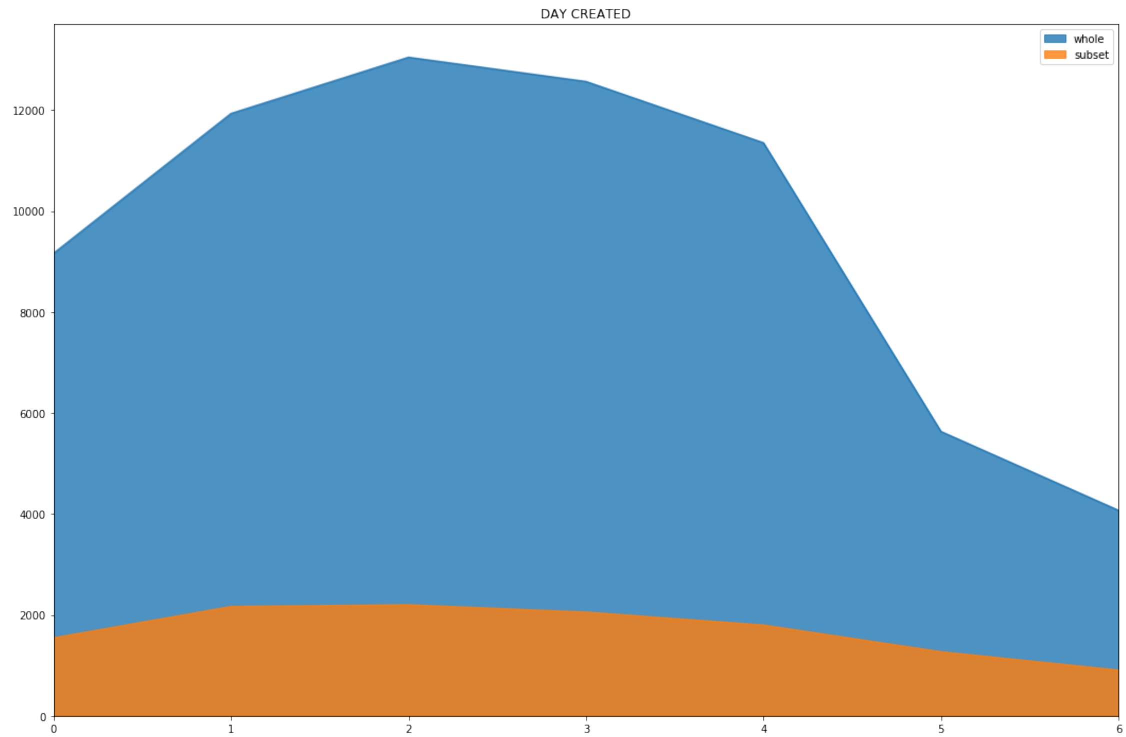
```
                                              for i in range(24)])
df_created_hours.plot.area(stacked=False, title='TIME CREATED BY HOUR', \
                           xticks=[i for i in range(24)], alpha=0.8)
```

Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x11236c630>



In [30]:
```
# create dataframes from daily data for plotting
df_created_days = pandas.DataFrame([len(created_days[i]) \
                                    for i in range(7)], columns=['whole'])
df_created_days['subset'] = pandas.Series([len(created_days_subset[i]) \
                                           for i in range(7)])
df_created_days.plot.area(stacked=False, title='DAY CREATED', \
                          xticks=[i for i in range(7)], alpha=0.8)
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x11402dac8>

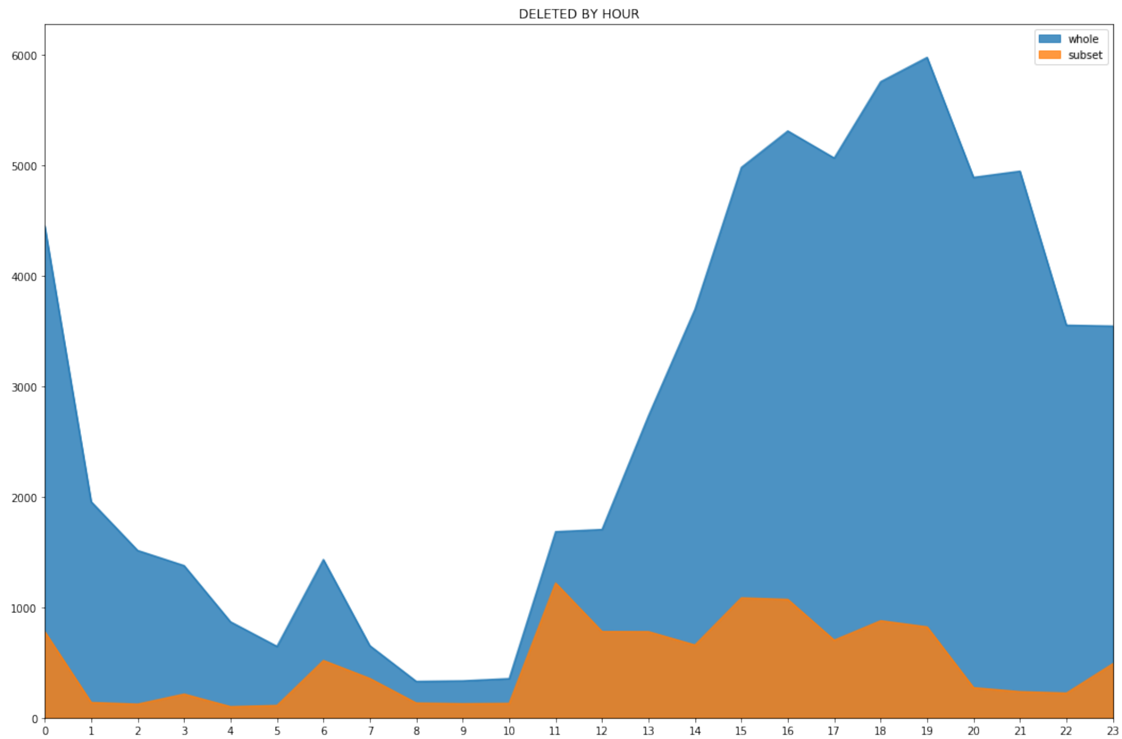



```
In [31]: # sort tweets by hour and day they were deleted
         deleted_hours = {i: [] for i in range(24)}
         deleted_days = {i: [] for i in range(7)}

         for i in range(len(deletweet)):
             deleted_hours[deletweet['modified'][i].hour].append(deletweet['id'][i])
             deleted_days[deletweet['modified'][i].weekday()].append(deletweet['id'][i])
```

```
In [32]: # do the same for the 10+ hour subset
         deleted_hours_subset = {i: [] for i in range(24)}
         deleted_days_subset = {i: [] for i in range(7)}

         for i in range(len(deletweet)):
             if deletweet['id'][i] in subset_ids:
                 deleted_hours_subset[deletweet['modified'][i].hour].append(deletweet['id'][i])
                 deleted_days_subset[deletweet['modified'][i].weekday()].append(deletweet['id'][i])
```

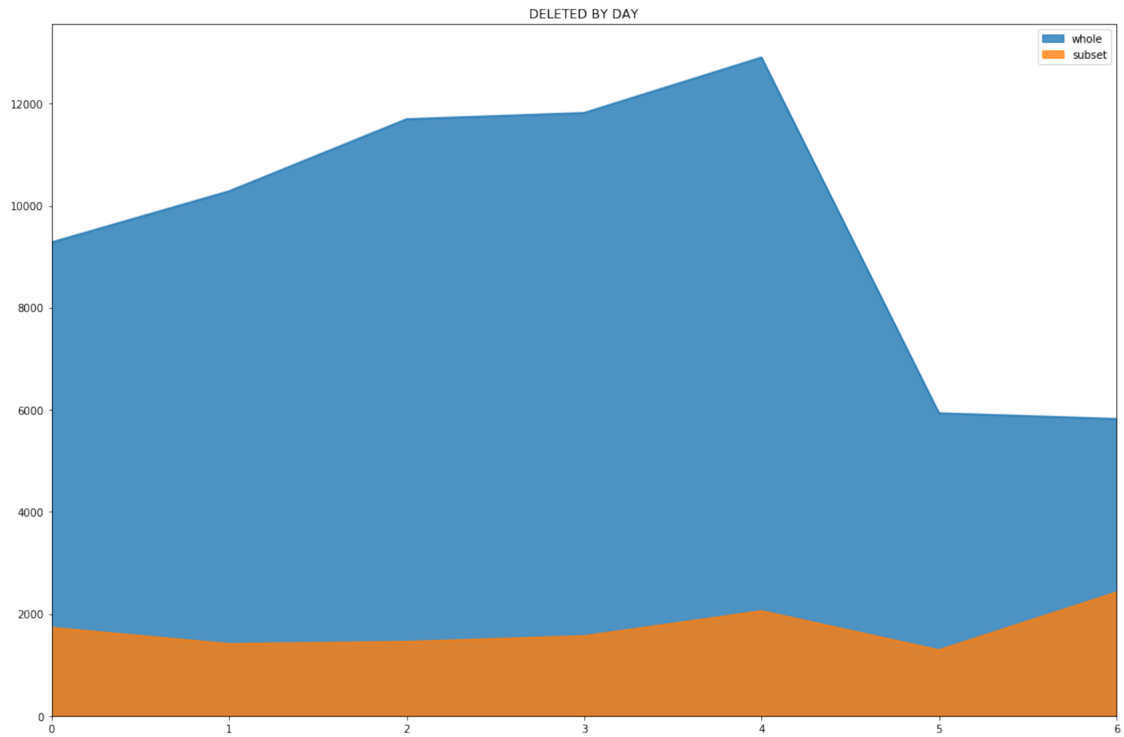
```
In [33]: # create dataframes from hourly data for plotting
         df_deleted_hours = pandas.DataFrame([len(deleted_hours[i]) \
                                              for i in range(24)], columns=['whole'])
         df_deleted_hours['subset'] = pandas.Series([len(deleted_hours_subset[i]) \
                                                     for i in range(24)])
         df_deleted_hours.plot.area(stacked=False, title='DELETED BY HOUR', \
                                    xticks=[i for i in range(24)], alpha=0.8)
```

```
Out[33]: <matplotlib.axes._subplots.AxesSubplot at 0x117690cc0>
```



In [34]:
```
# create dataframes from daily data for plotting
df_deleted_days = pandas.DataFrame([len(deleted_days[i]) \
                                   for i in range(7)], columns=['whole'])
df_deleted_days['subset'] = pandas.Series([len(deleted_days_subset[i]) \
                                          for i in range(7)])
df_deleted_days.plot.area(stacked=False, title='DELETED BY DAY', \
                          xticks=[i for i in range(7)], alpha=0.8)
```

Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x1180bf160>



1.6 CONCLUSION

It is difficult to extract concrete differences between the entire dataset and the subset of tweets that were deleted after 10+ hours, which are those that have more potential to be regrettable for reasons other than aesthetics. While there are some minor differences in common content between the datasets, it is clear that the vast majority of the tweets in the Politwoops dataset are likely deleted for aesthetic reasons such as misspellings, rather than the tweets being hotly contested, or damaging to the author's reputation or public image.

The most common times for both creation and deletion of tweets in this dataset are 12PM - 1AM, Monday - Friday. It would be interesting to compare this data with a dataset of these same politician's tweets that were not deleted to determine if these times are specific to tweets that are deleted, or if they are more simply the times that they are most active on Twitter.