Tweet Classifier: Detecting Disasters

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Problem

Can I build a machine learning model that can predict whether a tweet is referring to a disaster or not?

Why?

Disasters can strike at anytime and tweets provide real-time communication. It's important for local, state, and federal organizations that deal with disasters to be able to respond as quickly as possible. Being able to monitor social media for disasters would be one way to do this.

How?

I will apply various machine learning models on data that consists of over 10,000 tweets that have been classified as a relevant disaster tweet or not relevant.

Data

Data was downloaded from https://www.figure-eight.com/data-for-everyone/

This dataset consisted of 13 columns with 10,876. Out of 13, only 2 columns will be used.

```
tweets.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10876 entries, 0 to 10875
Data columns (total 13 columns):
_unit_id
                         10876 non-null int64
golden
                         10876 non-null bool
unit state
                         10876 non-null object
                         10876 non-null int64
trusted judgments
last judgment at
                         10792 non-null object
choose one
                         10876 non-null object
choose one:confidence
                         10876 non-null float64
                         87 non-null object
choose one gold
keyword
                         10789 non-null object
location
                         7238 non-null object
text
                         10876 non-null object
                         10876 non-null float64
tweetid
userid
                         10789 non-null float64
dtypes: bool(1), float64(3), int64(2), object(7)
memory usage: 1.0+ MB
```

```
tweets = tweets[['choose_one', 'text']]
tweets.head(5)
```

	choose_one	text
0	Relevant	Just happened a terrible car crash
1	Relevant	Our Deeds are the Reason of this #earthquake M
2	Relevant	Heard about #earthquake is different cities, s
3	Relevant	there is a forest fire at spot pond, geese are
4	Relevant	Forest fire near La Ronge Sask. Canada

Data Cleaning Steps

1. Target column had 3 unique values. One of the values was not significant so it was removed.

New DataFrame was created with the 2 columns: target and text.

3. Mapped 'Relevant' and 'Not Relevant' to 'Yes' and 'No'. This was a personal choice.

```
tweets.groupby('choose_one').count()

text
choose_one

Can't Decide 16

Not Relevant 6187
Relevant 4673
```

10/1		
Just happened a terrible car crash	Yes	0
Our Deeds are the Reason of this #earthquake M	Yes	1
Heard about #earthquake is different cities, s	Yes	2
there is a forest fire at spot pond, geese are	Yes	3
Forest fire near La Ronge Sask. Canada	Yes	4

Data Cleaning Steps cont.

- 4. Create text cleaning function
 - 4a. Remove URLs
 - 4b. Remove nametags (@)
 - 4c. Lowercase
 - 4d. Lemmatize
 - 4e. Remove symbols, punctuations and numbers
 - 4d. Remove stop words

```
#Remove stopwords
stop_words = stopwords.words('english')
#New words to add to the stopwords list. This contains
newWords = ['afaik', 'cc', 'cx', 'dm', 'ff', 'ht', 'icymi',
           'mm', 'mt', 'nsfw', 'oh', 'prt', 'rlrt', 'rt',
           'smh', 'tftf', 'til', 'tl', 'dr', 'tmb', 'tqrt', 'tt', 'w']
stop words.extend(newWords)
def text cleaning(text):
   """If applying on DataFrame column, use within an apply method.
        - text: text string"""
   text = re.sub(r'(www|http)\S+','',text) #Removes URLs
   text = re.sub(r'@\w+','', text) #Removes nametags
   text = text.lower() #lowercase all words
    def lemmatize(text):
       lemmatizer = WordNetLemmatizer()
        lemmatized_output = ' '.join(lemmatizer.lemmatize(x, 'v') for x in word_tokenize(text))
       return lemmatized output
   text = lemmatize(text)
    text = re.sub(r'[^a-z\s]',' ', text) #remove random symbols and numbers in string
   def remove stopwords(text):
        token = word tokenize(text)
        remove short = [x \text{ for } x \text{ in token if } len(x)>2] #remove words that are shorter than 2 letters
        #remove stopwords and put sentence back together
        remove_output = ' '.join(x for x in remove_short if x not in stop_words)
        return remove output
    text = remove stopwords(text)
    return text
```

Data Cleaning Steps cont.

5. Apply text cleaning function on text column

Forest fire near La Ronge Sask. Canada

Yes

```
#Test out the text cleaning function
clean2 = df.text[7958]
print('Original:',clean2)
print()
print('Cleaned:', text cleaning(clean2))
Original: Landslide caused by severe rainstorm kills 3 in ItalianåÉAlps https://t.co/8BhvxX2X19 http://t.co/4ou8s82Hx
Cleaned: landslide cause severe rainstorm kill italian alps
#Apply the text cleaning function to all of the texts
df['clean text'] = df['text'].apply(text cleaning)
df.head(5)
    target
                                                                               clean text
                       Just happened a terrible car crash
                                                                    happen terrible car crash
      Yes Our Deeds are the Reason of this #earthquake M...
                                                      deeds reason earthquake may allah forgive
             Heard about #earthquake is different cities, s... hear earthquake different cities stay safe eve...
              there is a forest fire at spot pond, geese are... forest fire spot pond geese flee across street...
```

forest fire near ronge sask canada



Feature Engineering

Tweet Length

```
#tweet length feature
df['tweet_length'] = df['clean_text'].str.len()

df.head()
```

target		text	clean_text	tweet_length	
0	Yes	Just happened a terrible car crash	happen terrible car crash	25	
1	Yes	Our Deeds are the Reason of this #earthquake M	deeds reason earthquake may allah forgive	41	
2	Yes	Heard about #earthquake is different cities, s	hear earthquake different cities stay safe eve	51	
3	Yes	there is a forest fire at spot pond, geese are	forest fire spot pond geese flee across street	51	
4	Yes	Forest fire near La Ronge Sask. Canada	forest fire near ronge sask canada	34	

Hashtag Count

```
#hashtag feature

def hashtag_count(text):
    words = text.split()
    hashtags = [word for word in words if word.startswith('#')]
    return len(hashtags)

df['hashtag_count'] = df['text'].apply(hashtag_count)

df.head()
```

	target	text	clean_text	tweet_length	num_words	hashtag_count
0	Yes	Just happened a terrible car crash	happen terrible car crash	25	4	0
1	Yes	Our Deeds are the Reason of this #earthquake M	deeds reason earthquake may allah forgive	41	6	1
2	Yes	Heard about #earthquake is different cities, s	hear earthquake different cities stay safe eve	51	7	1
3	Yes	there is a forest fire at spot pond, geese are	forest fire spot pond geese flee across street	51	9	0
4	Yes	Forest fire near La Ronge Sask. Canada	forest fire near ronge sask canada	34	6	0

Number of Words

```
#number of words feature

def word_count(text):
    words = text.split()
    return len(words)

df['num_words'] = df['clean_text'].apply(word_count)

df.head()
```

	target	text	clean_text	tweet_length	num_words
0	Yes	Just happened a terrible car crash	happen terrible car crash	25	4
1	Yes	Our Deeds are the Reason of this #earthquake M	deeds reason earthquake may allah forgive	41	6
2	Yes	Heard about #earthquake is different cities, s	hear earthquake different cities stay safe eve	51	7
3	Yes	there is a forest fire at spot pond, geese are	forest fire spot pond geese flee across street	51	9
4	Yes	Forest fire near La Ronge Sask. Canada	forest fire near ronge sask canada	34	6

Mention (@) Count

```
#montion feature

def mention_count(text):
   words = text.split()
   hashtags = [word for word in words if word.startswith('@')]
   return len(hashtags)

df['mention_count'] = df['text'].apply(mention_count)

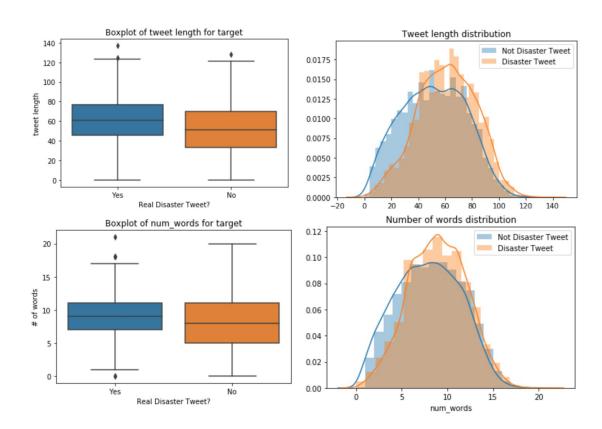
df.head()
```

. 8	target	text	clean_text	tweet_length	num_words	hashtag_count	mention_count
0	Yes	Just happened a terrible car crash	happen terrible car crash	25	4	0	0
1	Yes	Our Deeds are the Reason of this #earthquake M	deeds reason earthquake may allah forgive	41	6	1	0
2	Yes	Heard about #earthquake is different cities, s	hear earthquake different cities stay safe eve	51	7	1	0
3	Yes	there is a forest fire at spot pond, geese are	forest fire spot pond geese flee across street	51	9	0	0
4	Yes	Forest fire near La Ronge Sask. Canada	forest fire near ronge sask canada	34	6	0	0

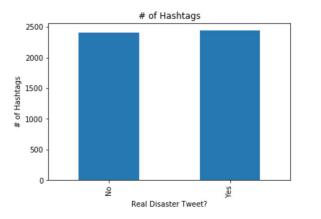


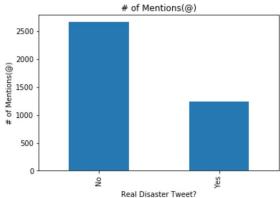
- Analysis

- Tweet lengths that relate to disasters are usually longer.
- Longer tweets = More words
- Describing situations to better inform public could be a reason.



EDA cont.





- There are similar amounts of hashtags for each case.
- More mentions are prevalent in tweet that are not related to a disaster than those that are.

EDA cont.

Not Disaster

[('get', 455), ('like', 413), ('new', 238), ('one', 187), ('make', 181), ('would', 170), ('body', 159), ('say', 158), ('think', 158), ('love', 155), ('see', 154), ('time', 151), ('bag', 151), ('come', 150), ('via', 142), ('know', 140), ('video', 135), ('want', 132), ('people', 132), ('burn', 130)]

<u>Unigram Analysis</u>

Frequent non-disaster tweets are general. 'Get' and 'Like' are the top 2 most common words

Unigram might be too simple for model to be successful

'California' is a common word for disaster tweets. Why?

Disaster

```
[('fire', 400),
('bomb', 259),
('news', 226),
('kill', 222),
('get', 183),
('via', 183),
('flood', 170),
 ('disaster', 166),
 ('attack', 166),
 ('suicide', 166),
 ('crash', 152),
('people', 151),
('police', 151),
('california', 150),
('train', 147),
 ('hiroshima', 146),
('like', 146),
 ('home', 137),
 ('storm', 137),
('build', 134)]
```



Bigram Analysis

Not Disaster

```
[(('body', 'bag'), 99),
 (('cross', 'body'), 53),
 (('like', 'video'), 51),
 (('look', 'like'), 47),
 (('full', 'read'), 42),
 (('feel', 'like'), 38),
 (('loud', 'bang'), 31),
 (('burn', 'build'), 29),
 (('first', 'responders'), 29),
 (('content', 'policy'), 28),
 (('china', 'stock'), 27),
 (('stock', 'market'), 27),
 (('market', 'crash'), 27),
 (('emergency', 'service'), 26),
 (('reddit', 'quarantine'), 26),
 (('quarantine', 'offensive'), 26),
 (('offensive', 'content'), 26),
 (('take', 'quiz'), 23),
 (('break', 'news'), 23),
 (('read', 'ebay'), 22)]
```

Bigram adds more context to the words.

'Body' and 'bag' in non-disaster tweets. Why?

California' a lot with 'wildfire'. This makes more sense than unigram.
California has been stricken with deadly wildfires in the past few years.

Disaster

```
[(('suicide', 'bomber'), 91),
(('atomic', 'bomb'), 67),
(('northern', 'california'), 57),
(('suicide', 'bomb'), 52),
(('oil', 'spill'), 50),
(('california', 'wildfire'), 46),
 (('bomber', 'detonate'), 46),
(('burn', 'build'), 44),
(('detonate', 'bomb'), 43),
(('pkk', 'suicide'), 43),
(('wild', 'fire'), 42),
(('year', 'old'), 41),
(('old', 'pkk'), 41),
(('mass', 'murder'), 40),
(('severe', 'thunderstorm'), 40),
(('home', 'raze'), 40),
(('latest', 'home'), 39),
(('raze', 'northern'), 39),
(('heat', 'wave'), 36),
(('bomb', 'turkey'), 36)]
```



EDA cont.

Not Disaster

```
[(('cross', 'body', 'bag'), 33),
(('china', 'stock', 'market'), 27),
(('stock', 'market', 'crash'), 27),
(('reddit', 'quarantine', 'offensive'), 26),
(('quarantine', 'offensive', 'content'), 25),
(('full', 'read', 'ebay'), 22),
(('break', 'news', 'unconfirmed'), 22),
 (('news', 'unconfirmed', 'hear'), 22),
 (('unconfirmed', 'hear', 'loud'), 22),
 (('hear', 'loud', 'bang'), 22),
 (('loud', 'bang', 'nearby'), 22),
 (('bang', 'nearby', 'appear'), 22),
(('nearby', 'appear', 'blast'), 22),
(('appear', 'blast', 'wind'), 22),
(('blast', 'wind', 'neighbour'), 22),
 (('wind', 'neighbour', 'ass'), 22),
(('reddit', 'new', 'content'), 22),
 (('new', 'content', 'policy'), 22),
(('content', 'policy', 'effect'), 21),
(('policy', 'effect', 'many'), 21)]
```

Trigram Analysis

Offers a lot more context, which could lead to better results.

'Cross', 'body', 'bag': that's a bag worn on one side of the body

'California', 'wildfire' from bigram now includes 'northern', Giving a better idea of where in California wildfires are taking place.

Disaster

```
[(('suicide', 'bomber', 'detonate'), 46),
 (('pkk', 'suicide', 'bomber'), 42),
 (('bomber', 'detonate', 'bomb'), 42),
 (('northern', 'california', 'wildfire'), 41),
 (('old', 'pkk', 'suicide'), 41),
 (('latest', 'home', 'raze'), 39),
 (('home', 'raze', 'northern'), 39),
 (('raze', 'northern', 'california'), 38),
 (('severe', 'thunderstorm', 'warn'), 36),
 (('families', 'affect', 'fatal'), 34),
 (('affect', 'fatal', 'outbreak'), 34),
(('watch', 'airport', 'get'), 34),
 (('airport', 'get', 'swallow'), 34),
(('get', 'swallow', 'sandstorm'), 34),
 (('swallow', 'sandstorm', 'minute'), 34),
 (('detonate', 'bomb', 'turkey'), 34),
(('bomb', 'turkey', 'army'), 34),
(('turkey', 'army', 'trench'), 34),
 (('families', 'sue', 'legionnaires'), 33),
(('wreckage', 'conclusively', 'confirm'), 33)]
```