

Text Classification of Tweets: Are they about a real disaster or not?

Project by Nicole Michaud, 12/30/2023

Business Problem

Data has been accumulated from a number of tweets, some of which are about disasters, some of which are not. By creating a model for Natural Language Processing (NLP), we can predict whether or not a given tweet is about a real disaster or not. This can benefit companies who wish to monitor twitter in the event of an emergency.

Data Understanding

Importing necessary packages, libraries, etc.:

```
In [1]: 1 import pandas as pd
        2 import numpy as np
        3 np.random.seed(42)
        4 import nltk
        5 nltk.download('punkt')
        6 import seaborn as sns
        7 import re
        8 import matplotlib.pyplot as plt
        9 from matplotlib.ticker import MaxNLocator
       10 %matplotlib inline
       11 from nltk.tokenize import word_tokenize, RegexpTokenizer
       12 from sklearn.metrics import f1_score, classification_report, confusion_matrix
       13 from sklearn.pipeline import Pipeline
       14 from sklearn import feature_extraction, linear_model, model_selection, preprocessing
       15 from sklearn.feature_extraction.text import TfidfVectorizer, CountVec
       16 from nltk.corpus import stopwords
       17 from sklearn.model_selection import train_test_split
       18 from nltk import FreqDist
       19 from sklearn.naive_bayes import MultinomialNB
       20 from nltk.stem.snowball import SnowballStemmer
       21 from sklearn.model_selection import GridSearchCV
       22 from nltk.corpus import stopwords, wordnet
       23 from nltk.stem import WordNetLemmatizer
       24
       25
```

```
[nltk_data] Downloading package punkt to
[nltk_data]      /Users/nicolemichaud/nltk_data...
[nltk_data]   Package punkt is already up-to-date!
```

Loading the data:

```
In [2]: 1 train_df = pd.read_csv("data/train.csv")
        2 test_df = pd.read_csv("data/test.csv")
```

Data Exploration:

Viewing and gaining understanding of the data, its features, number of rows, any missing values, and more so I can preprocess the data accordingly.

```
In [3]: 1 train_df.head()
```

Out [3]:

	id	keyword	location	text	target
0	1	NaN	NaN	Our Deeds are the Reason of this #earthquake M...	1
1	4	NaN	NaN	Forest fire near La Ronge Sask. Canada	1
2	5	NaN	NaN	All residents asked to 'shelter in place' are ...	1
3	6	NaN	NaN	13,000 people receive #wildfires evacuation or...	1
4	7	NaN	NaN	Just got sent this photo from Ruby #Alaska as ...	1

```
In [4]: 1 train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 5 columns):
#   Column      Non-Null Count  Dtype
---  -
0    id          7613 non-null   int64
1    keyword     7552 non-null   object
2    location    5080 non-null   object
3    text        7613 non-null   object
4    target      7613 non-null   int64
dtypes: int64(2), object(3)
memory usage: 297.5+ KB
```

```
In [5]: 1 test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3263 entries, 0 to 3262
Data columns (total 4 columns):
#   Column      Non-Null Count  Dtype
---  -
0    id          3263 non-null   int64
1    keyword     3237 non-null   object
2    location    2158 non-null   object
3    text        3263 non-null   object
dtypes: int64(1), object(3)
memory usage: 102.1+ KB
```

Dropping the 'keyword' and 'location' columns, as I won't be working with them. This project focuses on the text of the tweet. See miscellaneous notebook for investigation into the 'keyword' feature.

```
In [6]: 1 train_df = train_df.drop(columns = ['location', 'keyword'])
        2 test_df = test_df.drop(columns = ['location', 'keyword'])
        3 train_df.head()
```

Out [6]:

	id	text	target
0	1	Our Deeds are the Reason of this #earthquake M...	1
1	4	Forest fire near La Ronge Sask. Canada	1
2	5	All residents asked to 'shelter in place' are ...	1
3	6	13,000 people receive #wildfires evacuation or...	1
4	7	Just got sent this photo from Ruby #Alaska as ...	1

There doesn't appear to be any null values in the text column, but just to be sure I will drop null values in both the training and testing data.

```
In [7]: 1 train_df['text'].dropna(inplace=True)
        2 train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7613 entries, 0 to 7612
Data columns (total 3 columns):
#   Column  Non-Null Count  Dtype
---  -
0    id      7613 non-null     int64
1    text    7613 non-null     object
2    target  7613 non-null     int64
dtypes: int64(2), object(1)
memory usage: 178.6+ KB
```

```
In [8]: 1 test_df['text'].dropna(inplace=True)
        2 test_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3263 entries, 0 to 3262
Data columns (total 2 columns):
#   Column  Non-Null Count  Dtype
---  -
0    id      3263 non-null     int64
1    text    3263 non-null     object
dtypes: int64(1), object(1)
memory usage: 51.1+ KB
```

Previewing a random tweet from both datasets to get an idea of how they might look before cleaning:

```
In [9]: 1 # Example of what is NOT a disaster tweet:
        2 train_df[train_df["target"] == 0]["text"].values[6]
```

```
Out[9]: 'London is cool ;)'
```

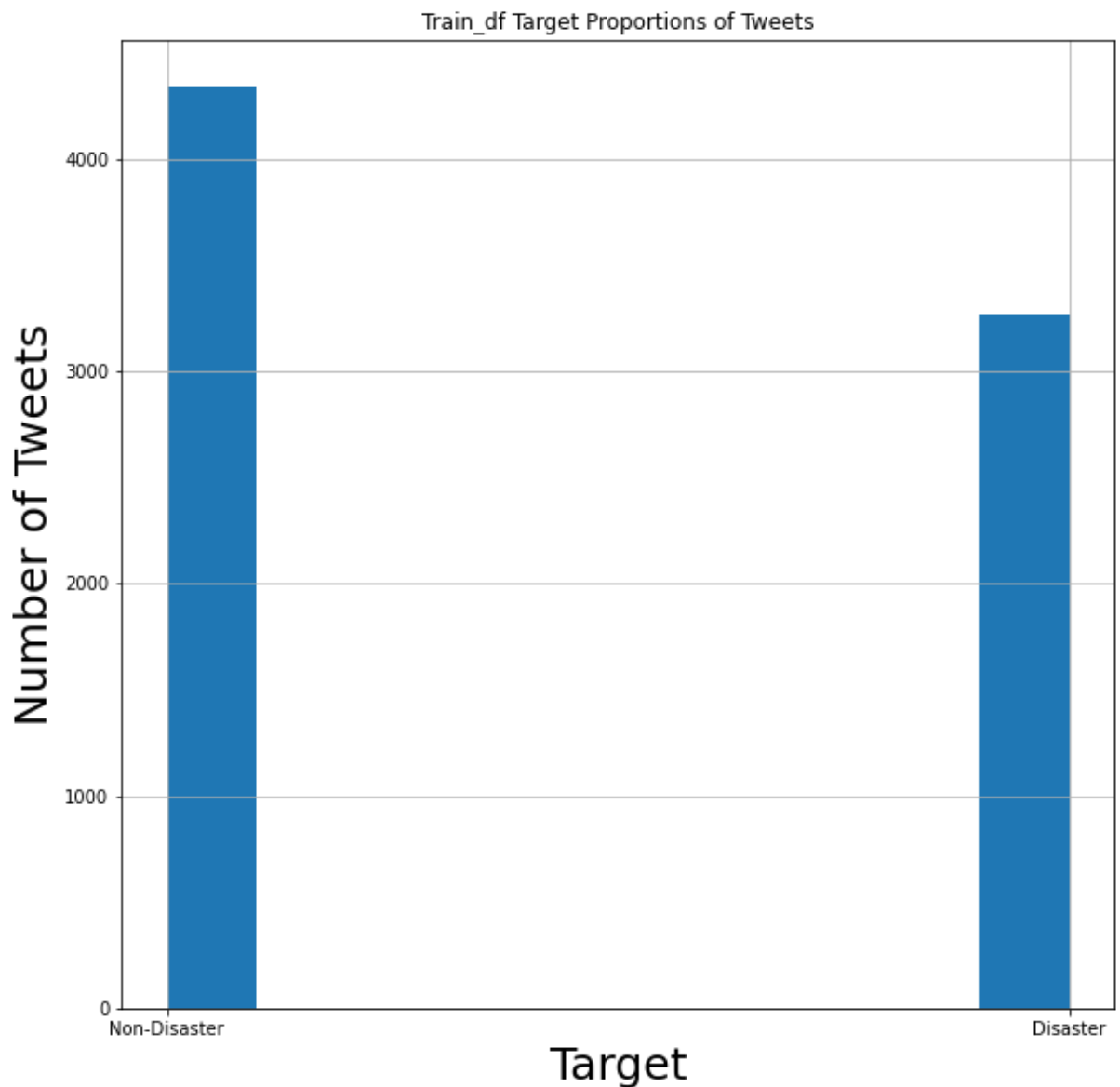
```
In [10]: 1 # Example of what IS a disaster tweet:
         2 train_df[train_df["target"] == 1]["text"].values[20]
```

```
Out[10]: 'Deputies: Man shot before Brighton home set ablaze http://t.co/gWNRhMS08k' (http://t.co/gWNRhMS08k)
```

Visualizing what proportion of the training data are disaster tweets and non-disaster tweets:

```
In [11]: 1 #from matplotlib import ticker
2 fig, ax = plt.subplots(figsize=(10,10))
3 proportions = train_df['target'].hist()
4
5 plt.locator_params(axis='x', nbins=2)
6
7 labels = [item.get_text() for item in ax.get_xticklabels()]
8 labels[1] = 'Non-Disaster'
9 labels[2] = 'Disaster'
10
11 ax.set_xticklabels(labels)
12
13 plt.xlabel('Target', fontsize=25)
14 plt.ylabel('Number of Tweets', fontsize=25)
15 plt.title('Train_df Target Proportions of Tweets');
16
```

<ipython-input-11-b887d99680f8>:11: UserWarning: FixedFormatter should only be used together with FixedLocator
ax.set_xticklabels(labels)



Calculating the probabilities of disaster and non-disaster tweets in the training data:

```
In [12]: 1 disaster_tweets = train_df[train_df['target']==1]
          2
          3 other_tweets = train_df[train_df['target']==0]
```

```
In [13]: 1 P_disasters = len(disaster_tweets) / (len(disaster_tweets)+len(other_
          2 P_non = len(other_tweets) / (len(other_tweets)+len(disaster_tweets))
          3 print(P_disasters)
          4 print(P_non)
```

```
0.4296597924602653
```

```
0.5703402075397347
```

This tells us that tweets in train_df have a higher probability of not being about a disaster.

Data Preparation

Cleaning text data: Remove urls, tags (contain @), stopwords, punctuation, etc.

```

In [14]: 1 # Creating a function to perform all these cleaning steps at once
2 stopwords_list = stopwords.words('english')
3
4 no_bad_chars = re.compile('[!\"#$%&()*+-./:;<=>?@[\\]^_`{|}~\\n - ]')
5 no_nums = re.compile('[\\d-]')
6
7 def clean_text(text):
8     text = no_nums.sub('', text)
9     #drop words '&' and 'via', see miscellaneous notebook for exp
10    text = re.sub("&", "", text)
11    text = re.sub("via", "", text)
12    text = re.sub("@[A-Za-z0-9]+", "", text) #Remove @ sign
13    text = re.sub(r"(?:\\@|http?\\:|https?\\:|www)\\S+", "", text) #
14    text = no_bad_chars.sub('', text)
15    text = text.replace("#", "").replace("_", " ") #Remove hashtag s
16    text = text.lower()
17    text = ' '.join(word for word in text.split() if word not in stop
18    return text
19
20
21 train_df_cleaned = train_df['text'].apply(clean_text)
22 test_df_cleaned = test_df['text'].apply(clean_text)
23 train_df_cleaned.head(10)
24
25
26

```

```

Out[14]: 0      deeds reason earthquake may allah forgive us
1      forest fire near la ronge sask canada
2      residents asked 'shelter place' notified offic...
3      people receive wildfires evacuation orders cal...
4      got sent photo ruby alaska smoke wildfires pou...
5      rockyfire update california hwy closed directi...
6      flood disaster heavy rain causes flash floodin...
7      i'm top hill see fire woods
8      there's emergency evacuation happening buildin...
9      i'm afraid tornado coming area
Name: text, dtype: object

```

Performing a train-test split on the **training data** to see how our models perform before applying them to our testing data and then applying the cleaning function to the split data:

```

In [15]: 1 X = train_df.text
2 y = train_df.target
3 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=

```

```

In [16]: 1 X_train_cleaned = X_train.apply(clean_text)
2 X_test_cleaned = X_test.apply(clean_text)

```

Modeling

Building a baseline model

```
In [17]: 1 # Baseline Multinomial Naive Bayes model vectorized with CountVectorizer
2 # no tuned parameters
3 baseline_model = Pipeline([('vect', CountVectorizer(max_features=None,
4                                                         tokenizer=word_tokenize,
5                                                         stop_words=stopwords))
6                               ('clf', MultinomialNB())
7                               ])
8 baseline_model.fit(X_train_cleaned, y_train)
9
10
11 y_pred = baseline_model.predict(X_test_cleaned)
12
13 print('Baseline model F1 %s' % f1_score(y_pred, y_test, average="macro"))
14 print(classification_report(y_test, y_pred))
```

/Users/nicolemichaud/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklearn/feature_extraction/text.py:383: UserWarning: Your stop_words may be inconsistent with your preprocessing. Tokenizing the stop words generated tokens ['d', 'll', 're', 's', 've', 'could', 'might', 'must', 'n't', 'need', 'sha', 'wo', 'would'] not in stop_words.
warnings.warn('Your stop_words may be inconsistent with ')

Baseline model F1 0.799114882744776

	precision	recall	f1-score	support
0	0.81	0.86	0.84	1091
1	0.80	0.73	0.76	813
accuracy			0.81	1904
macro avg	0.80	0.80	0.80	1904
weighted avg	0.81	0.81	0.80	1904

Stemming the text to see if it improves our model:

First, need to re-create the text cleaning function to not remove the stopwords, because we will want to have the stopwords stemmed as well before removal for consistency.


```
In [18]: 1 #Creating a function that cleans the text data without removing stop
2
3 def clean_text_nostop(text):
4     text = no_nums.sub('', text)
5     text = re.sub("@[A-Za-z0-9]+", "", text)
6     text = re.sub(r"(?:\@|http?\:\/\/|https?\:\/\/|www)\S+", "", text)
7     text = no_bad_chars.sub(' ', text)
8     text = text.replace("#", "").replace("_", " ")
9     text = text.lower()
10    return text
11
12 train_df_cleaned_nostop = train_df.copy()
13
14 train_df_cleaned_nostop['text'] = train_df_cleaned_nostop['text'].ap
15
16 X_nostop = train_df_cleaned_nostop.text
17 y_nostop = train_df_cleaned_nostop.target
18 X_train_nostop, X_test_nostop, y_train_nostop, y_test_nostop = train
19
```

```
In [19]: 1 #Initializing the stemmer and creating a list of stemmed stopwords
2 stemmer = SnowballStemmer(language="english")
3 tokenizer=word_tokenize
4
5 def stem_and_tokenize(document):
6     tokens = tokenizer(document)
7     return [stemmer.stem(token) for token in tokens]
8 stemmed_stopwords = [stemmer.stem(word) for word in stopwords_list]
```

```
In [20]: 1 #Stemmed data model
2
3 stem_model = Pipeline([('vect', CountVectorizer(
4                         stop_words=stemmed_stopwords,
5                         tokenizer=stem_and_tokenize)),
6                       ('clf', MultinomialNB()),
7                       ])
8 stem_model.fit(X_train_nostop, y_train_nostop)
9
10
11 y_pred_stem= stem_model.predict(X_test_nostop)
12
13 print('Stemmed model F1 %s' % f1_score(y_pred_stem, y_test_nostop, a
14 print(classification_report(y_test_nostop, y_pred_stem))
```

/Users/nicolemichaud/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklearn/feature_extraction/text.py:383: UserWarning: Your stop words may be inconsistent with your preprocessing. Tokenizing the stop words generated tokens ['"', "'d", 'could', 'might', 'must', "n't", 'need', 'r', 'sha', 'v', 'wo', 'would'] not in stop_words.

warnings.warn('Your stop_words may be inconsistent with '

Stemmed model F1 0.802174272578552

	precision	recall	f1-score	support
0	0.82	0.86	0.84	1091
1	0.80	0.74	0.77	813
accuracy			0.81	1904
macro avg	0.81	0.80	0.80	1904
weighted avg	0.81	0.81	0.81	1904

Stemming improved our model.

Conducting GridSearchCV to see if tuning the hyperparameters in our best model will improve it further:

```
In [21]: 1 # First, need to manually tokenize/vectorize data since we won't be
2
3 vectorizer = CountVectorizer()
4 X_train_vectorized = vectorizer.fit_transform(X_train_cleaned)
5 X_test_vectorized = vectorizer.transform(X_test_cleaned)
6
7 cv = CountVectorizer()
8 X_train_vec = cv.fit_transform(X_train_cleaned)
9 X_train_vec = pd.DataFrame.sparse.from_spmatrix(X_train_vec)
10 X_train_vec.columns = sorted(cv.vocabulary_)
11 X_train_vec.set_index(y_train.index, inplace=True)
12
13
14 X_test_vec = cv.transform(X_test_cleaned)
15 X_test_vec = pd.DataFrame.sparse.from_spmatrix(X_test_vec)
16 X_test_vec.columns = sorted(cv.vocabulary_)
17 X_test_vec.set_index(y_test.index, inplace=True)
```

Multinomial Naive Bayes doesn't have many tunable parameters. See miscellaneous notebook for explanation of the parameters and parameter values used here.

```
In [22]: 1 #GridSearchCV
2 alphas = [0.5, 1.0, 1.5, 2.0, 2.5]
3 p_grid_NB = {'alpha': alphas, 'fit_prior' : [True, False]}
4 NB_cls= MultinomialNB()
5
6 grid = GridSearchCV(estimator = NB_cls, param_grid = p_grid_NB, scoring='f1')
7 grid.fit(X_train_vec, y_train)
```

```
Out[22]: GridSearchCV(cv=3, estimator=MultinomialNB(),
                    param_grid={'alpha': [0.5, 1.0, 1.5, 2.0, 2.5],
                                'fit_prior': [True, False]},
                    scoring='f1')
```

```
In [23]: 1 grid.best_params_
```

```
Out[23]: {'alpha': 2.5, 'fit_prior': True}
```

Note: The GridSearch Determined the best value of alpha to be 2.5 and of fit_prior to be True. I ran the model below with alpha=2.5 and it did not perform as well as alpha=2.0. I'm not sure the reason for this, but this is why the value 2.0 is used instead.

```

In [24]: 1 tuned_model = Pipeline([('vect', CountVectorizer(
2     stop_words=stemmed_stopwords,
3     tokenizer=stem_and_tokenize,
4 )),
5
6         ('clf', MultinomialNB(alpha= 2.0, fit_prior =
7         ]))
8
9 tuned_model.fit(X_train_nostop, y_train_nostop)
10
11 y_pred_tuned= tuned_model.predict(X_test_nostop)
12
13 print('Tuned model F1 %s' % f1_score(y_pred_tuned, y_test_nostop, av
14
15 print(classification_report(y_test_nostop, y_pred_tuned))

```

/Users/nicolemichaud/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklearn/feature_extraction/text.py:383: UserWarning: Your stop words may be inconsistent with your preprocessing. Tokenizing the stop words generated tokens ['"', "'d", 'could', 'might', 'must', "n't", 'need', 'r', 'sha', 'v', 'wo', 'would'] not in stop_words.

warnings.warn('Your stop_words may be inconsistent with '

Tuned model F1 0.8022946797889032

	precision	recall	f1-score	support
0	0.81	0.86	0.84	1091
1	0.80	0.73	0.77	813
accuracy			0.81	1904
macro avg	0.81	0.80	0.80	1904
weighted avg	0.81	0.81	0.81	1904

Creating a visualization of the classification report:

In [25]:

```

1  # The following code is not mine, I adapted it from a stackoverflow
2
3  sns.set_context("poster")
4  final_clf_report = classification_report(y_test_nostop, y_pred_tuned)
5  def show_values(pc, fmt="%.2f", **kw):
6      '''
7      Heatmap with text in each cell with matplotlib's pyplot
8      Source: https://stackoverflow.com/a/25074150/395857
9      By HYRY
10     '''
11     pc.update_scalarmappable()
12     ax = pc.axes
13     #ax = pc.axes# FOR LATEST MATPLOTLIB
14     #Use zip BELOW IN PYTHON 3
15     for p, color, value in zip(pc.get_paths(), pc.get_facecolors(),
16                               pc.get_texts()):
17         x, y = p.vertices[:-2, :].mean(0)
18         if np.all(color[:3] > 0.5):
19             color = (0.0, 0.0, 0.0)
20         else:
21             color = (1.0, 1.0, 1.0)
22         ax.text(x, y, fmt % value, ha="center", va="center", color=color)
23
24  def cm2inch(*tupl):
25      '''
26      Specify figure size in centimeter in matplotlib
27      Source: https://stackoverflow.com/a/22787457/395857
28      By gns-ank
29      '''
30      inch = 2.54
31      if type(tupl[0]) == tuple:
32          return tuple(i/inch for i in tupl[0])
33      else:
34          return tuple(i/inch for i in tupl)
35
36
37  def heatmap(AUC, title, xlabel, ylabel, xticklabels, yticklabels, fig):
38      '''
39      Inspired by:
40      - https://stackoverflow.com/a/16124677/395857
41      - https://stackoverflow.com/a/25074150/395857
42      '''
43
44      # Plot it out
45      fig, ax = plt.subplots()
46      #c = ax.pcolor(AUC, edgecolors='k', linestyle='dashed', linewidth=1)
47      c = ax.pcolor(AUC, edgecolors='k', linestyle='dashed', linewidth=1)
48
49      # put the major ticks at the middle of each cell
50      ax.set_yticks(np.arange(AUC.shape[0]) + 0.5, minor=False)
51      ax.set_xticks(np.arange(AUC.shape[1]) + 0.5, minor=False)
52
53      # set tick labels
54      #ax.set_xticklabels(np.arange(1,AUC.shape[1]+1), minor=False)
55      ax.set_xticklabels(xticklabels, minor=False)
56      ax.set_yticklabels(yticklabels, minor=False)
57

```

```

58     # set title and x/y labels
59     plt.title(title, y=1.25)
60     plt.xlabel(xlabel)
61     plt.ylabel(ylabel)
62
63     # Remove last blank column
64     plt.xlim( 0, AUC.shape[1]) )
65
66     # Turn off all the ticks
67     ax = plt.gca()
68     for t in ax.xaxis.get_major_ticks():
69         t.tick1line.set_visible(False)
70         t.tick2line.set_visible(False)
71     for t in ax.yaxis.get_major_ticks():
72         t.tick1line.set_visible(False)
73         t.tick2line.set_visible(False)
74
75     # Add color bar
76     plt.colorbar(c)
77
78     # Add text in each cell
79     show_values(c)
80
81     # Proper orientation (origin at the top left instead of bottom l
82     if correct_orientation:
83         ax.invert_yaxis()
84         ax.xaxis.tick_top()
85
86     # resize
87     fig = plt.gcf()
88     #fig.set_size_inches(cm2inch(40, 20))
89     #fig.set_size_inches(cm2inch(40*4, 20*4))
90     fig.set_size_inches(cm2inch(figure_width, figure_height))
91
92
93
94 def plot_classification_report(classification_report, number_of_clas
95     '''
96     Plot scikit-learn classification report.
97     Extension based on https://stackoverflow.com/a/31689645/395857
98     '''
99     lines = classification_report.split('\n')
100
101     #drop initial lines
102     lines = lines[2:]
103
104     classes = []
105     plotMat = []
106     support = []
107     class_names = []
108     for line in lines[: number_of_classes]:
109         t = list(filter(None, line.strip().split(' ')))
110         if len(t) < 4: continue
111         classes.append(t[0])
112         v = [float(x) for x in t[1: len(t) - 1]]
113         support.append(int(t[-1]))
114         class_names.append(t[0])

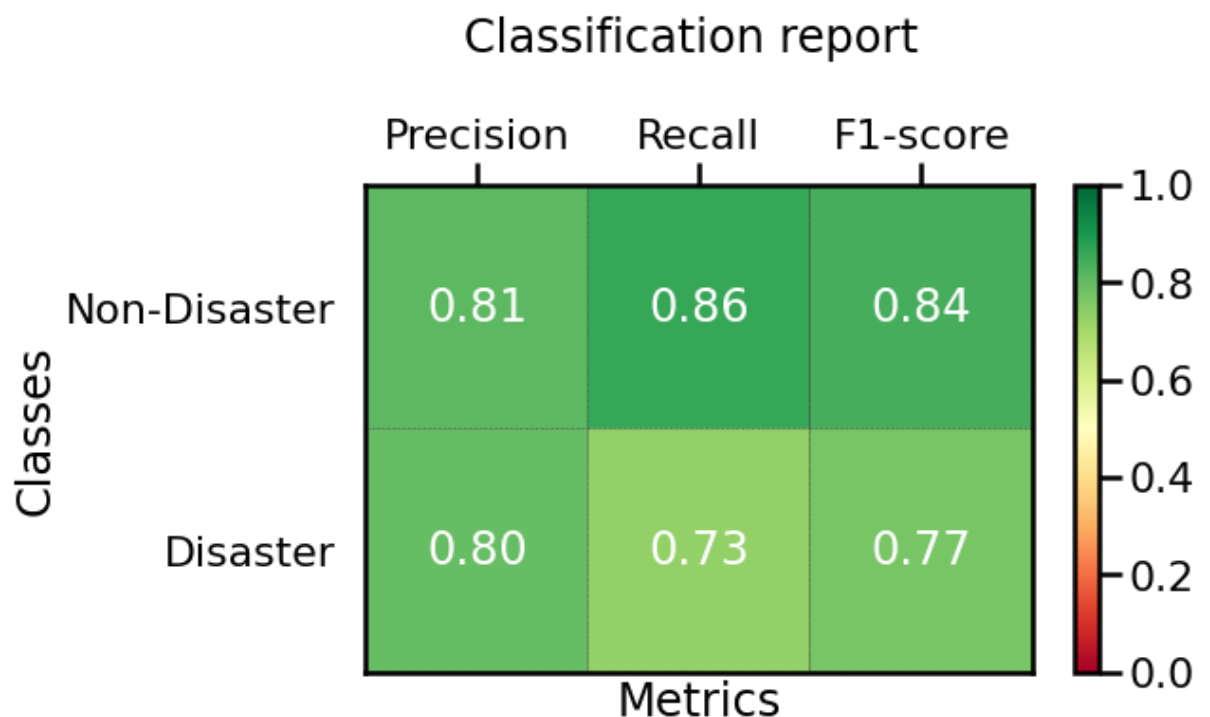
```

```

115         plotMat.append(v)
116
117
118         xlabel = 'Metrics'
119         ylabel = 'Classes'
120         xticklabels = ['Precision', 'Recall', 'F1-score']
121         yticklabels = ['Non-Disaster', 'Disaster']
122         #'{0} ({1})'.format(class_names[idx], sup) for idx, sup in enumerate(class_names)
123         figure_width = 20
124         figure_height = len(class_names) + 10
125         correct_orientation = True
126         heatmap(np.array(plotMat), title, xlabel, ylabel, xticklabels, yticklabels, plt.show())
127
128
129

```

In [26]: 1 plot_classification_report(final_clf_report)

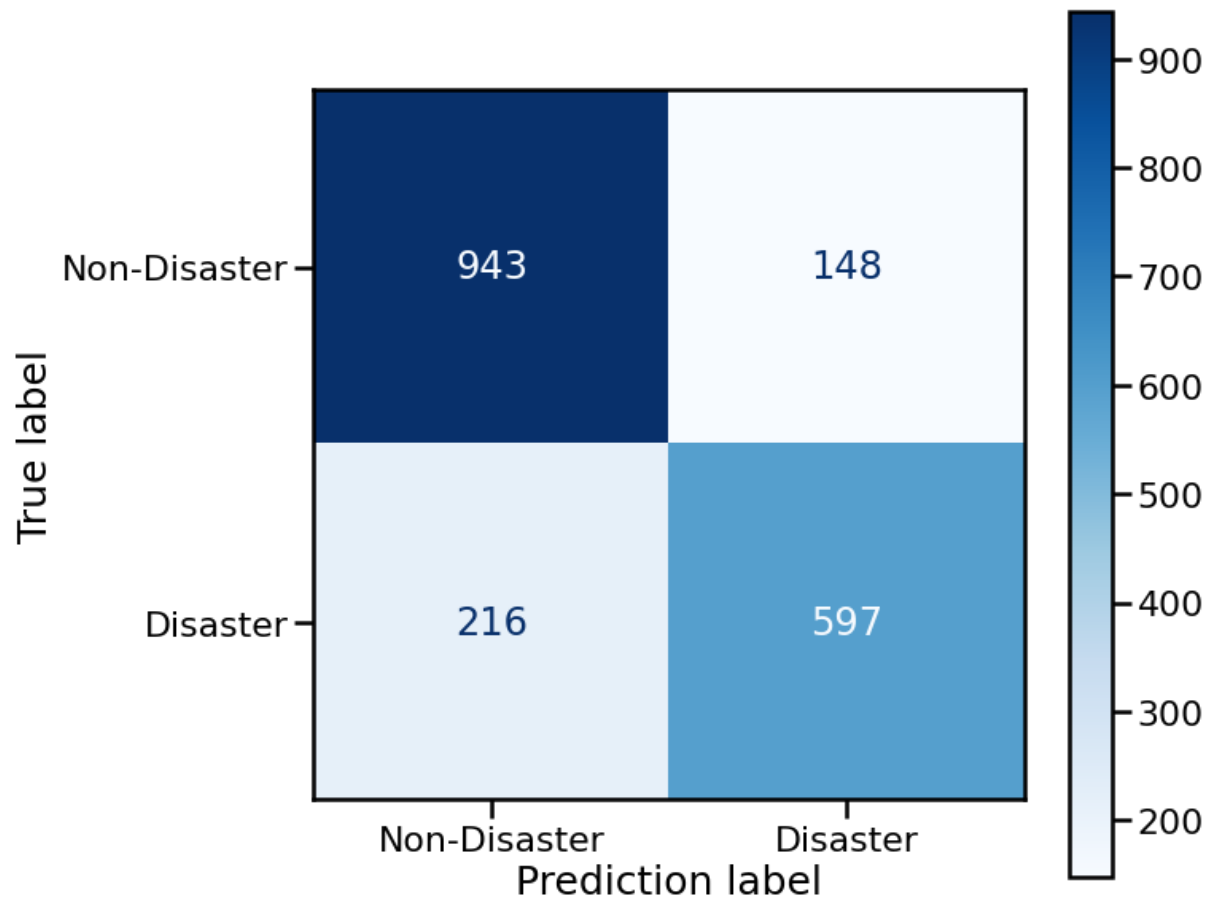


In [27]: 1 cnf_matrix = confusion_matrix(y_test_nostop, y_pred_tuned)
2 print('Confusion Matrix:\n', cnf_matrix)

Confusion Matrix:
[[943 148]
[216 597]]

Creating a visualization of this confusion matrix:


```
In [28]: 1 fig, ax = plt.subplots(figsize=(10,10))
2 cm_1 = ConfusionMatrixDisplay(confusion_matrix = cnf_matrix, display_
3 cm_1.plot(cmap=plt.cm.Blues, ax=ax)
4 plt.xlabel('Prediction label',fontsize=25)
5 plt.ylabel('True label',fontsize=25);
```



This model gave 943 True Negatives, 597 True Positives, 148 False Positives, and 216 False Negatives.

Both false negatives and false positives are costly in this instance.

Generating Predictions

```
In [29]: 1 sample_submission = pd.read_csv("data/sample_submission.csv")
```

```
In [30]: 1 sample_submission.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3263 entries, 0 to 3262
Data columns (total 2 columns):
#   Column  Non-Null Count  Dtype
---  ------  -
0    id      3263 non-null     int64
1   target  3263 non-null     int64
dtypes: int64(2)
memory usage: 51.1 KB
```

Before creating predictions on the sample submission csv, I want to try it on the test_df to make sure it works:

```
In [31]: 1 #Cleaning the test data:
2 def clean_text_nostop(text):
3     text = no_nums.sub('', text)
4     text = re.sub("@[A-Za-z0-9]+", "", text) #Remove @ sign
5     text = re.sub(r"(?:\@|http?\:\/\/|https?\:\/\/|www)\S+", "", text) #
6     text = no_bad_chars.sub(' ', text)
7     text = text.replace("#", "").replace("_", " ") #Remove hashtag s
8     text = text.lower()
9     return text
10
11 test_df_cleaned_nostop = test_df.copy()
12
13 test_df_cleaned_nostop['text'] = test_df_cleaned_nostop['text'].apply
14
```

```
In [32]: 1 test_df_cleaned_nostop.head()
```

Out[32]:

	id	text
0	0	just happened a terrible car crash
1	2	heard about earthquake is different cities s...
2	3	there is a forest fire at spot pond geese are...
3	9	apocalypse lighting spokane wildfires
4	11	typhoon soudelor kills in china and taiwan

```
In [33]: 1 test_df_sample = test_df_cleaned_nostop.copy()
2 test_df_sample['target'] = tuned_model.predict(test_df_sample['text'])
```

In [34]: 1 test_df_sample.head()

Out[34]:

	id	text	target
0	0	just happened a terrible car crash	1
1	2	heard about earthquake is different cities s...	1
2	3	there is a forest fire at spot pond geese are...	1
3	9	apocalypse lighting spokane wildfires	1
4	11	typhoon soudelor kills in china and taiwan	1

In [35]: 1 test_df_sample['target'].value_counts()

Out[35]: 0 2033
1 1230
Name: target, dtype: int64

This appears to have worked, so let's try it on the sample submission:

In [36]: 1 sample_submission["target"] = tuned_model.predict(test_df['text'])

In [37]: 1 sample_submission['target'].value_counts()

Out[37]: 0 2031
1 1232
Name: target, dtype: int64

Conclusion

Recommendations:

- Model should be deployed to monitor twitter for disaster tweets

Next Steps:

- Continue testing other models to see if performance can be improved
 - Use more tweets data
 - Use word embeddings
 - Flag top words/phrases of disaster tweets

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