Text Classification

In this project we will perform a text classification on the 20newsgroup text using both Naive Bayes and SVM. The package provided from the sklearn dataset provides a great introduction to text classification, and comes presplit, with little work required to get to point of analysis

The code, along with the files necessary and versions of packages in this instance can be found on this repo: [https://github.com/Benjamin-Siebold/MSDS-682-Text-Analytics (https://github.com/Benjamin-Siebold/MSDS-682-Text-Analytics)](https://github.com/Benjamin-Siebold/MSDS-682-Text-Analytics)

In [307]:
```
import numpy as np
import pandas as pd
import time

from sklearn.datasets import fetch_20newsgroups
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorize
from sklearn import svm
from sklearn.metrics import accuracy_score, classification_report
from sklearn.naive_bayes import MultinomialNB
import seaborn as sns
from wordcloud import WordCloud

from tqdm import tqdm
import nltk
import spacy
import re
from matplotlib import pyplot as plt

nlp = spacy.load('en_core_web_lg')
```

1 - Import and Prepare data

The first step in this analysis is to import the data in its train and test subgroups, remove excess information, and create our vectorizer and transforms for analysis

In [64]:
```
newsgroups_train = fetch_20newsgroups(subset='train', remove=('headers', 'f
newsgroups_test = fetch_20newsgroups(subset='test', remove=('headers', 'foo
```

In [104]:
```
def clean_from_articles(newsgroups):
    clean = []
    for i, a in enumerate(newsgroups['data']):
        cln1 = re.sub('^#>.*\n', '', a, flags=re.MULTILINE)
        clean.append(re.sub('\n*.*From article.*\n', '', cln1))

    return clean
```

In [72]:
```
clean_train = clean_from_articles(newsgroups_train)
```

In [73]:
```
clean_test = clean_from_articles(newsgroups_test)
```

In [205]:
```
vectorizer = TfidfVectorizer()
train_labels = newsgroups_train['target']
train_feats = vectorizer.fit_transform(clean_train)
test_labels = newsgroups_test['target']
test_feats = vectorizer.transform(clean_test)
```

In [200]:
```
test_feats.todense().shape
```

Out[200]:
```
(7532, 101631)
```

2 - Apply Models to text

The next step is to create both our NB and SVM models in order to find which classifier best suits this data. We can see from below using a MNB with no altercations only gives us a 60% accuracy score on our test data; however, by adjusting the alpha we are able to increase the models effeciency by 10%. In regards to the SVM model, following a linear model we achieve an accuracy score of 66, thus the NB model with an alpha of .01 is the best model of these tested

In [320]:
```
model = MultinomialNB()
model.fit(train_feats, train_labels)
```

Out[320]:
```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

In [321]:
```
model.score(train_feats,train_labels)
```

Out[321]:
```
0.8115608980024748
```

In [322]:
```
pred = model.predict(test_feats)
print(model.score(test_feats,test_labels))
```

```
0.6060807222517259
```

In [206]:
```
model = MultinomialNB(alpha=.01)
model.fit(train_feats, train_labels)
```

Out[206]:
```
MultinomialNB(alpha=0.01, class_prior=None, fit_prior=True)
```

In [207]:
```
model.score(train_feats,train_labels)
```

Out[207]:
```
0.9588120912144246
```

In [208]:
```
pred = model.predict(test_feats)
print(model.score(test_feats,test_labels))
```

```
0.7000796601168349
```

In [188]:
```
accuracy_score(pred, test_labels)
```

Out[188]:
```
0.7000796601168349
```

In [130]:
```
SVM = svm.SVC(C=1.0, kernel='linear', degree=2, gamma='auto')
```

In [131]:
```
SVM.fit(train_feats, train_labels)
```

...

In [132]:
```
start = time.time()
svm_predict = SVM.predict(test_feats)
end = time.time()
print('took', int(end-start), 'seconds')
```

```
took 76 seconds
```

In [133]:
```
rint("SVM Accuracy Score -> ",accuracy_score(svm_predict, test_labels)*100)
```

```
SVM Accuracy Score ->  66.25066383430695
```

3 - Build visuals of results

The next step is to build a classification report, and some visuals of our results. The dataframe of our classification report shows each of the classes almost evenly distributed, and the heatmap gives a quick visual that the model was really accurate with baseball classification, and had trouble around religion (atheism, religion christiantiy, religion).

In [232]:
```
t1 = []
t2 = []
for idx, cat in enumerate(newsgroups_train.target_names):
    t1.append(idx)
    t2.append(cat)
d = {'targets':t1, 'target_names':t2}
target_names_map = pd.DataFrame(d)
```

In [294]:
```
class_report = classification_report(test_labels, pred, target_names=target
```

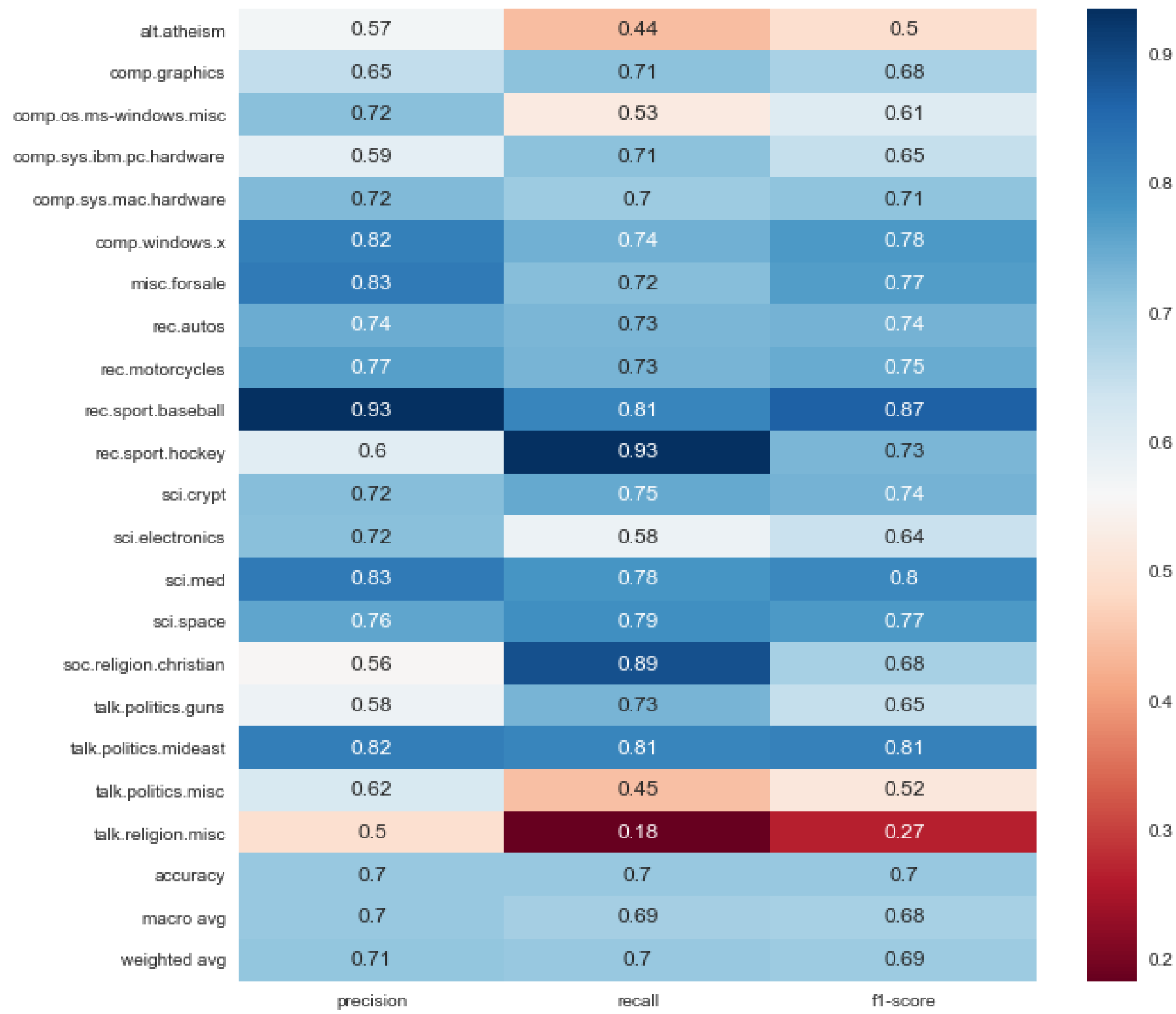
In [304]:
```
pd.DataFrame(class_report).transpose()
```

Out[304]:

	precision	recall	f1-score	support
alt.atheism	0.568548	0.442006	0.497354	319.00000
comp.graphics	0.650235	0.712082	0.679755	389.00000
comp.os.ms-windows.misc	0.716263	0.525381	0.606149	394.00000
comp.sys.ibm.pc.hardware	0.594883	0.711735	0.648084	392.00000
comp.sys.mac.hardware	0.724324	0.696104	0.709934	385.00000
comp.windows.x	0.815642	0.739241	0.775564	395.00000
misc.forsale	0.825959	0.717949	0.768176	390.00000
rec.autos	0.744845	0.729798	0.737245	396.00000
rec.motorcycles	0.766404	0.733668	0.749679	398.00000
rec.sport.baseball	0.933140	0.808564	0.866397	397.00000
rec.sport.hockey	0.600644	0.934837	0.731373	399.00000
sci.crypt	0.719807	0.752525	0.735802	396.00000
sci.electronics	0.716981	0.580153	0.641350	393.00000
sci.med	0.826203	0.780303	0.802597	396.00000
sci.space	0.758537	0.789340	0.773632	394.00000
soc.religion.christian	0.555730	0.889447	0.684058	398.00000
talk.politics.guns	0.579176	0.733516	0.647273	364.00000
talk.politics.mideast	0.818919	0.805851	0.812332	376.00000
talk.politics.misc	0.618834	0.445161	0.517824	310.00000
talk.religion.misc	0.500000	0.183267	0.268222	251.00000
accuracy	0.700080	0.700080	0.700080	0.70008
macro avg	0.701754	0.685546	0.682640	7532.00000
weighted avg	0.708057	0.700080	0.694175	7532.00000

In [298]:
```
.subplots(figsize=(10,10))
d.DataFrame(class_report).iloc[:-1, :].T, annot=True, ax=ax, cmap = 'RdBu')
```

Out[298]: <matplotlib.axes._subplots.AxesSubplot at 0x1a27d62550>

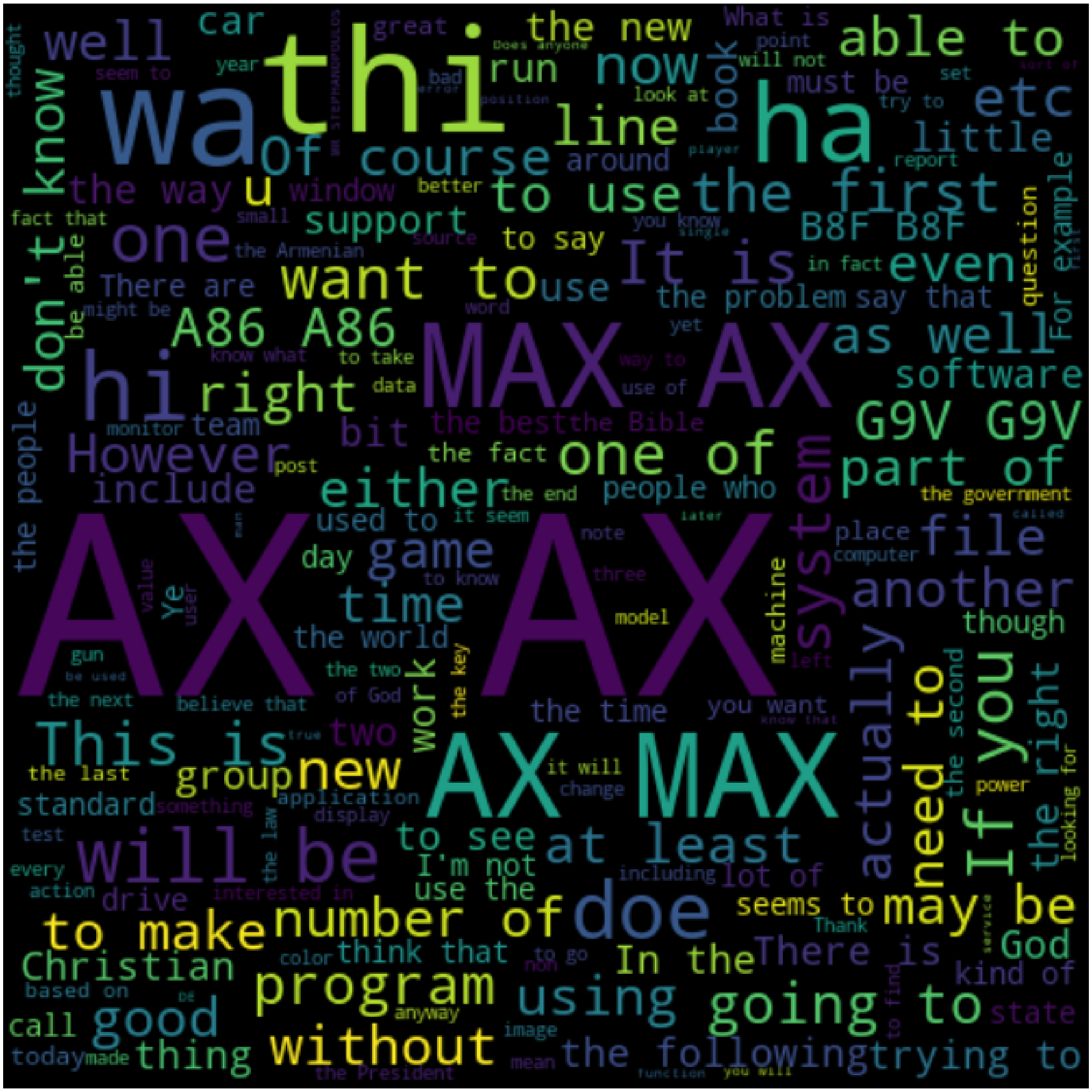


4 - Visualize datasets

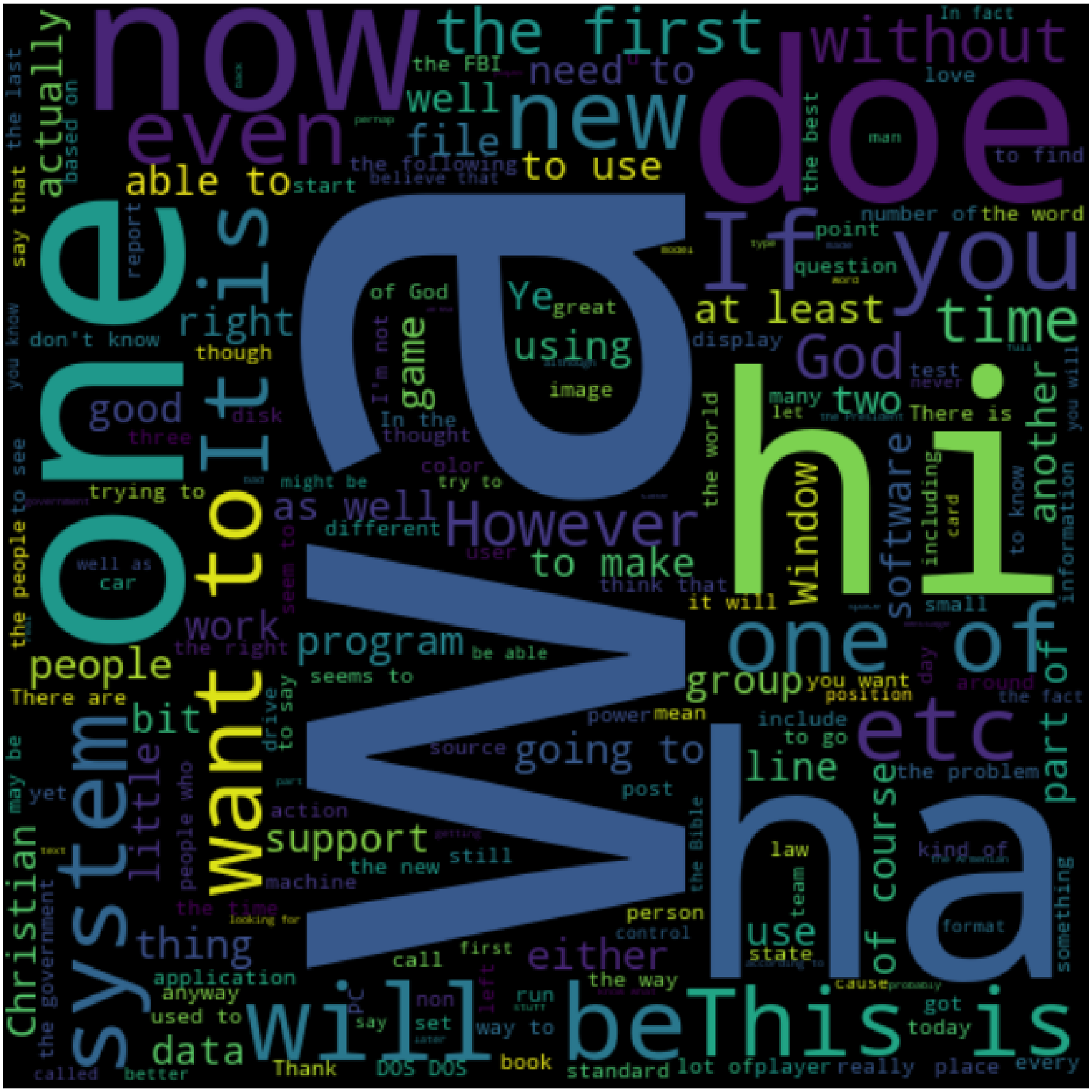
The last step in this analysis was a visualization of the two datasets (train and test) in order to see if it was possible to see overlap visually and easily.

In [318]:
```
clean_train_text = ' '.join(clean_train)
clean_test_text = ' '.join(clean_test)
```

In [317]:
```
fig = plt.figure(figsize=(12, 12))
wordcloud = WordCloud(width=500, height=500).generate(clean_train_text)
plt.imshow(wordcloud, interpolation='bilinear')
_ = plt.axis("off")
```



In [319]:
```
fig = plt.figure(figsize=(12, 12))
wordcloud = WordCloud(width=500, height=500).generate(clean_test_text)
plt.imshow(wordcloud, interpolation='bilinear')
_ = plt.axis("off")
```



From the above, the wordclouds of the data are not very beneficial. The wa, AX, ha, thi all being top words between the two show that the data is still messy even after cleaning it in regards to words/non real words in the text.