1 Introduction

Arxiv.org is a free open-access archive of scholarly articles. Articles on arxiv are not peer reviewed by the service, and articles are frequently published there before going through peer review of an actual academic research journal ostensibly to receive feedback before officially publishing. The service has papers from several different academic fields and as such has a user input category system to help researchers find papers relevant to their expertise.

The project is to use the abstracts of the paper to train a classifier to predict which categories a paper with a given abstract belongs to. This model could, in practice, be applied to summaries of other works to classify them in terms of Arxiv categories. For example, it could be used to identify what areas of research are being discussed in a news brief.

The first thing to do is to get the download the data set from https://www.kaggle.com/Cornell-University/arxiv for analysis. The dataset is in a json file, so we'll import the python json library in addition to some of the usual ones to clean the data.

```
import pandas as pd
import numpy as np
import json
from functools import reduce
from collections import defaultdict
```

As mention in the code comment below, the json file is too large to open in my systems memory. Fortunately each line in the file represents a unique entry in the data set, so we can loop through the file line by line and grab only the data we need and ut it into a pandas Dataframe.

```
l = list()
with open("arxiv-metadata-oai-snapshot.json", 'r',1) as f:
   """The data file is too large to open directly, but if we go through it line by line
   we can append the desired data into a list that we can hold in memory"""
   for line in f:
      d = json.loads(line)
      ap = dict()
      ap['id'] = d['id']
      ap['categories'] = d['categories']
      ap['title'] = d['title']
      ap['abstract'] = d['abstract']
      l.append(ap)
df = pd.DataFrame(l)
```

This is a language processing task, so we'll use be using nltk to create a corpus and create models based on a bag of words paradigm.

```
import nltk
from nltk.corpus.reader.plaintext import PlaintextCorpusReader
from nltk.stem import PorterStemmer
from nltk.corpus import stopwords
from string import punctuation
import re
from functools import reduce
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction import DictVectorizer
```

I used the following loop to put all the abstracts into text files for creating the corpus.

```
   for t, a in zip(df['id'], df['abstract']):
      t = t.replace('\n', '')
      t = t.replace('\\', '')
```

```
    t = t.replace('"', '')
    t = t.replace('<', '')
    t = t.replace('>', '')
    t = t.replace('?', '')
    t = t.replace('*', '')
    t = t.replace('^', '')
    t = t.replace('/', 'or')
    t = t.replace('|', '')
    t = t.replace(':', '')
    t = t.replace("'", '')
    t = t.replace('+', 'plus')
    t = t.replace('=', 'equal')
    t = t.replace(' ', '')
    t = t.replace('$', '')
    with open('data\\corpus\\'+t+'.txt', 'w', encoding='utf-8') as f:
      f.write(a)
```

These two functions are for creating the bags of words for each individual abstract. The variable ps is a globally defined PorterStemmer object.

```
def corpify(text):
  """This function takes a text input an converts it to a form where
  it has the has only the words recognized by the corpus. That is, it only has words
  in cp_final. Only works for documents in the corpus
  Must have defined punctuation and sw globally, and imported re"""
  words = [w.lower() for w in corpus._word_tokenizer.tokenize(text) if w.lower() not in sw]
  words_np = [w.lower() for w in words if w.lower() not in punctuation]
  pat = re.compile('[^a-zA-Z]')
  words_final = [(pat.sub('', w)) for w in words_np if pat.sub('',w)!='']
  words_final = list(map(ps.stem, words_final))
  return words_final

def dictify(words):
  return (dict(list(np.array(np.unique(words,return_counts=True)).transpose())))
```

In the end, there were too many categories for accurate categorization of the abstracts, so I generalized them in two steps. First an automated step that took advantage of a naming convention that put a '.' between a more general category and a sub category (ex: 'math.alg' would be the category for a paper on Algebra.) By removing the dot and everything after, we're left with a more general category that is still appropriate for the paper. This naming convention is used inconsistently on arxiv though, so as a second step I manually mapped some of the least common remaining categories to more general categories that in my own judgment were appropriate. This resulted in a variable 's' that contained the names of all categories to be used by the model and mapped the appropriate papers to their new categories.

The following code was used to create a sparse data frame object. A sparse data frame was need because in its dense form it would take nearly 300 GB of RAM to store in memory.

```
from collections import defaultdict
m = list()
for i in range(len(df)):
  d = defaultdict(lambda : 0)#, _id = df.iloc[i].id)
  for k in s:
    d  ['_'+k] = int(k in df.iloc[i].categories)
  ab = dictify(corpify(df.iloc[i].abstract))
  for k in ab.keys():
    d[k] = ab[k]
  m.append(d)
dv = DictVectorizer()
```

```
mat = dv.fit_transform(m)
col_dict = dict([(v,k) for k,v in dv.vocabulary_.items()])
cols = [col_dict[i] for i in range(len(col_dict))]
sp_df = pd.DataFrame.sparse.from_spmatrix(mat, columns = cols)
```

Printing sp_df.sparse.density yields 0.00048811985163166153 which means the vast majority of our data is zeros. Indicating that many of our papers use unique words.

below we import all models that I attempted to apply to the sparse data frame. I would have included a random forest classifier, but memory usage is a concern. I don't have enough RAM to train large amounts of decision trees, so the Gradient Boosting classifier was included instead.

```
from sklearn.naive_bayes import MultinomialNB
from sklearn.experimental import enable_hist_gradient_boosting#
from sklearn.ensemble import HistGradientBoostingClassifier#Does not work with sparse data
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import f1_score
from imblearn.over_sampling import RandomOverSampler #This didn't work and was abandoned.
```

Because an individual abstract can belong to multiple categories, an classifier needs to be trained for each category, training a Naive Bayes Classifier for each category yield an average f1 score of 0.240. We can improve upon this by training a GradientBoostingClassifier on the data and comparing it to the Naive Bayes; we then keep which ever one is performing better for each individual category. The loop also under-samples negative cases for categories that are uncommon, so that the classifiers don't overfit to always predicting not belonging to that category.

```
from random import sample
models = dict()
tscores = dict()

for col in y.columns:
   if y.sum()[col]<med:
      s = sample(range(len(X)), k=min(30000, 10*int(y.sum()[col])))
      s.extend(sp_df[sp_df[y.columns[0]]==1].index)
      X_train, X_test, y_train, y_test = train_test_split(X.iloc[s], y.iloc[s], test_size=0.2)
   else:
      X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
   nb = MultinomialNB()
   grad = GradientBoostingClassifier(n_iter_no_change=5)
   nb.fit(X_train, y_train[col])
   grad.fit(X_train, y_train[col])
   ns = f1_score(nb.predict(X_test), y_test[col])
   gs = f1_score(grad.predict(X_test), y_test[col])
   if ns < gs:
      models[col] = grad
      tscores[col] = gs
   else:
      models[col] = nb
      tscores[col] = ns

for key in models.keys():
   print(key, models[key], tscores[key])
```

The output of the print loop yields the following (although I did align it for readability.)

category	model	score	(1)
adap-org	$MultinomialNB()$	0.0	(2)
astro-ph	$MultinomialNB()$	0.8925676840834627	(3)
cond-mat	$MultinomialNB()$	0.7942148153586374	(4)
cs	$MultinomialNB()$	0.8282528762898826	(5)
econ	$MultinomialNB()$	0.0	(6)
eess	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.047244094488188897	(7)
gr-qc	$MultinomialNB()$	0.6378132118451024	(8)
hep-ex	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.31	(9)
hep-lat	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.2702702702702703	(10)
hep-ph	$MultinomialNB()$	0.7257037770547462	(11)
hep-th	$MultinomialNB()$	0.6220366379310345	(12)
math	$MultinomialNB()$	0.8300718006476138	(13)
math-ph	$MultinomialNB()$	0.198542172856647	(14)
nlin	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.07874015748031497	(15)
nucl-ex	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.32941176470588235	(16)
nucl-th	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.3278688524590164	(17)
physics	$MultinomialNB()$	0.5181849670938691	(18)
q-bio	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.20740740740740743	(19)
q-fin	$GradientBoostingClassifier(n_iter_no_change = 5)$	0.5555555555555556	(20)
quant-ph	$MultinomialNB()$	0.6092447587774691	(21)
stat	$MultinomialNB()$	0.46172289775646524	(22)
			(23)

The average f1 score of this set of models across the entire data set comes out to approximately 0.455 which is still lower than my target, but due to limitations of my machine I was unable to make further alterations to my models and training methods. Some of the models did do extremely well, while the least common categories still have models with scores of 0.

In its current form the category Identifier is undeployable. It does not evaluation threshold set at the beginning of the project is unreachable with available computing power.