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1 Project 2: Topic Classification

In this project, you'll work with text data from newsgroup postings on a variety of topics. You'll train classifiers to distinguish between the topics based on the text of the posts. Whereas with digit classification, the input is relatively dense: a 28x28 matrix of pixels, many of which are non-zero, here we'll represent each document with a "bag-of-words" model. As you'll see, this makes the feature representation quite sparse -- only a few words of the total vocabulary are active in any given document. The bag-of-words assumption here is that the label depends only on the words; their order is not important.

The SK-learn documentation on feature extraction will prove useful: http://scikit-learn.org/stable/modules/feature_extraction.html

Each problem can be addressed succinctly with the included packages -- please don't add any more. Grading will be based on writing clean, commented code, along with a few short answers.

As always, you're welcome to work on the project in groups and discuss ideas on the course wall, but please prepare your own write-up and write your own code.

In [1]:
```
# This tells matplotlib not to try opening a new window for each plot.
%matplotlib inline

# General libraries.
import re
import numpy as np
import matplotlib.pyplot as plt
import time

# SK-learn libraries for learning.
from sklearn.pipeline import Pipeline
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.model_selection import GridSearchCV

# SK-learn libraries for evaluation.
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import classification_report
```

```
# SK-learn library for importing the newsgroup data.
from sklearn.datasets import fetch_20newsgroups

# SK-learn libraries for feature extraction from text.
from sklearn.feature_extraction.text import *
from sklearn.feature_extraction.text import HashingVectorizer
```

1.0.1 Format Class

Created a class to add color or format print statements

```
In [2]: class bcolors:
            HEADER = '\033[95m'
            OKBLUE = '\033[94m'
            OKGREEN = '\033[92m'
            WARNING = '\033[93m'
            FAIL = '\033[91m'
            ENDC = '\033[0m'
            BOLD = '\033[1m'
            UNDERLINE = '\033[4m'
```

1.0.2 Load Data & Split

Load the data, stripping out metadata so that we learn classifiers that only use textual features. By default, newsgroups data is split into train and test sets. We further split the test so we have a dev set. Note that we specify 4 categories to use for this project. If you remove the categories argument from the fetch function, you'll get all 20 categories.

```
In [3]: categories = ['alt.atheism', 'talk.religion.misc', 'comp.graphics', 'sci.space']
        newsgroups_train = fetch_20newsgroups(subset='train',
                                              remove=('headers', 'footers', 'quotes'),
                                              categories=categories)
        newsgroups_test = fetch_20newsgroups(subset='test',
                                             remove=('headers', 'footers', 'quotes'),
                                             categories=categories)

        # Splitting the data into training, dev and test.
        num_test = len(newsgroups_test.target)
        test_data, test_labels = newsgroups_test.data[int(num_test/2):], newsgroups_test.targe
        dev_data, dev_labels = newsgroups_test.data[:int(num_test/2)], newsgroups_test.target[
        train_data, train_labels = newsgroups_train.data, newsgroups_train.target

        print('training label shape:', train_labels.shape)
        print('test label shape:', test_labels.shape)
        print('dev label shape:', dev_labels.shape)
        print('labels names:', newsgroups_train.target_names)
```

```
training label shape: (2034,)
test label shape: (677,)
dev label shape: (676,)
labels names: ['alt.atheism', 'comp.graphics', 'sci.space', 'talk.religion.misc']
```

- Training dataset has around 2000 examples while dev and test are split into around 676 example each.

1.0.3 Histogram

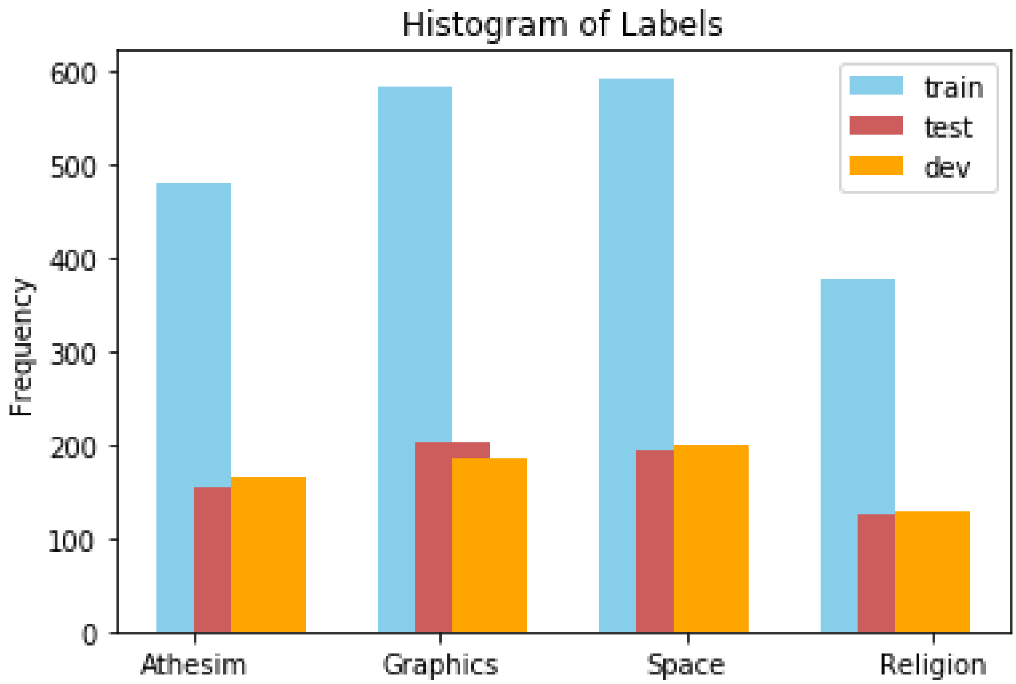
Lets look at the distribution of the data within the various classes.

```
In [4]: fig, ax = plt.subplots()

        rects1 = ax.hist(train_labels,
                         color='SkyBlue', label='train', align = 'left')
        rects2 = ax.hist(test_labels,
                         color='IndianRed', label='test', align = 'mid')
        rects3 = ax.hist(dev_labels,
                         color='orange', label='dev', align = 'right')

        # Add some text for labels, title and custom x-axis tick labels, etc.
        ax.set_ylabel('Frequency')
        ax.set_title('Histogram of Labels')
        ax.set_xticks(np.arange(4))
        ax.set_xticklabels(('Athesim', 'Graphics', 'Space', 'Religion'))
        ax.legend()
```

```
Out[4]: <matplotlib.legend.Legend at 0x1a27864a90>
```



- The data looks to be distributed evenly across all the labels for training, test and development datasets.

```
In [5]: print (newsgroups_train.data[1].splitlines(), newsgroups_train.target_names[1])
```

```
['', '', 'Seems to be, barring evidence to the contrary, that Koresh was simply', 'another dera
```

1.0.4 Sample Data

(1) For each of the first 5 training examples, print the text of the message along with the label.

```
In [5]: def P1(num_examples=5):
            for i in np.arange(num_examples):
                print (train_data[i], '\n')
                print (bcolors.HEADER, 'Label: ' , train_labels[i] , bcolors.ENDC)
                print ('--------------------------------------------------', '\n')
            return


        P1()
```

```
Hi,

I've noticed that if you only save a model (with all your mapping planes
```

positioned carefully) to a .3DS file that when you reload it after restarting 3DS, they are given a default position and orientation. But if you save to a .PRJ file their positions/orientation are preserved. Does anyone know why this information is not stored in the .3DS file? Nothing is explicitly said in the manual about saving texture rules in the .PRJ file. I'd like to be able to read the texture rule information, does anyone have the format for the .PRJ file?

Is the .CEL file format available from somewhere?

Rych

Label: 1

Seems to be, barring evidence to the contrary, that Koresh was simply another deranged fanatic who thought it neccessary to take a whole bunch of folks with him, children and all, to satisfy his delusional mania. Jim Jones, circa 1993.

Nope - fruitcakes like Koresh have been demonstrating such evil corruption for centuries.

Label: 3

>In article <1993Apr19.020359.26996@sq.sq.com>, msb@sq.sq.com (Mark Brader)

MB> So the
MB> 1970 figure seems unlikely to actually be anything but a perijove.

JG>Sorry, _perijoves_...I'm not used to talking this language.

Couldn't we just say periapsis or apoapsis?

Label: 2

I have a request for those who would like to see Charley Wingate respond to the "Charley Challenges" (and judging from my e-mail, there appear to be quite a few of you.)

```
It is clear that Mr. Wingate intends to continue to post tangential or
unrelated articles while ingoring the Challenges themselves.  Between
the last two re-postings of the Challenges, I noted perhaps a dozen or
more posts by Mr. Wingate, none of which answered a single Challenge.

It seems unmistakable to me that Mr. Wingate hopes that the questions
will just go away, and he is doing his level best to change the
subject.  Given that this seems a rather common net.theist tactic, I
would like to suggest that we impress upon him our desire for answers,
in the following manner:

1. Ignore any future articles by Mr. Wingate that do not address the
Challenges, until he answers them or explictly announces that he
refuses to do so.

--or--

2. If you must respond to one of his articles, include within it
something similar to the following:

    "Please answer the questions posed to you in the Charley Challenges."

Really, I'm not looking to humiliate anyone here, I just want some
honest answers.  You wouldn't think that honesty would be too much to
ask from a devout Christian, would you?

Nevermind, that was a rhetorical question.

 Label:  0
--------------------------------------------------

AW&ST  had a brief blurb on a Manned Lunar Exploration confernce
May 7th  at Crystal City Virginia, under the auspices of AIAA.

Does anyone know more about this?  How much, to attend????

Anyone want to go?

 Label:  2
--------------------------------------------------
```

1.0.5 Vectorize data

(2) Use CountVectorizer to turn the raw training text into feature vectors. You should use the fit_transform function, which makes 2 passes through the data: first it computes the vocabulary ("fit"), second it converts the raw text into feature vectors using the vocabulary

("transform").

The vectorizer has a lot of options. To get familiar with some of them, write code to answer these questions:

a. The output of the transform (also of fit_transform) is a sparse matrix: http://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.sparse.csr_matrix.html. What is the size of the vocabulary? What is the average number of non-zero features per example? What fraction of the entries in the matrix are non-zero? Hint: use "nnz" and "shape" attributes.

b. What are the 0th and last feature strings (in alphabetical order)? Hint: use the vectorizer's get_feature_names function.

c. Specify your own vocabulary with 4 words: ["atheism", "graphics", "space", "religion"]. Confirm the training vectors are appropriately shaped. Now what's the average number of non-zero features per example?

d. Instead of extracting unigram word features, use "analyzer" and "ngram_range" to extract bigram and trigram character features. What size vocabulary does this yield?

e. Use the "min_df" argument to prune words that appear in fewer than 10 documents. What size vocabulary does this yield?

f. Using the standard CountVectorizer, what fraction of the words in the dev data are missing from the vocabulary? Hint: build a vocabulary for both train and dev and look at the size of the difference.

```
In [76]: def P2(data, vocab,analyzer, min_df, ngram_range , details, preprocessor, stop_words)
             feat_vect = CountVectorizer(vocabulary=vocab, analyzer = analyzer, min_df= min_df
                                         ngram_range = ngram_range, preprocessor = preprocesso
             print (feat_vect)
             feat_vect.fit(data)
             dtm_train = feat_vect.transform(data)
             if details == 'Y':
                 print (bcolors.BOLD + '\n The size of the vocabulary is:', dtm_train.shape[1]
                 print('\n Average length of each example: %.2f' % (dtm_train.nnz /dtm_train.s
                 print ('\n Amount of Non-Zero occurences: ', dtm_train.nnz)
                 print ('\n sparsity: %.2f%%' % (100.0 * dtm_train.nnz /
                                                 (dtm_train.shape[0] * dtm_train.shape[1])))
                 print ('\n First Feature string: ', feat_vect.get_feature_names()[0])
                 print ('\n Last Feature string: ', feat_vect.get_feature_names()[dtm_train.sha
             return feat_vect, dtm_train



         # Using the vocabulary from the corpus of words within the text
         P2(train_data, None, 'word', 1, (1,1), 'Y', None, None)
         print ('-------------------------------')
         # Using the vocabulary from the corpus of words within the text
```

```
P2(train_data, ["atheism", "graphics", "space", "religion"], 'word', 1, (1,1), 'Y', No
print ('-------------------------------')
# Using the vocabulary from the corpus of words while using the character with word b
# 2-gram character
P2(train_data, None, 'char_wb', 1, (2,2), 'Y', None, None)
print ('-------------------------------')
# Using the vocabulary from the corpus of words while using the character with word b
# 3-gram character
P2(train_data, None, 'char_wb', 1, (3,3), 'Y', None, None)
print ('-------------------------------')
# Using the vocabulary from the corpus of words while looking for words that appear i
feat_vec_1, dtm_train_1 = P2(train_data, None, 'word', 10, (1,1), 'Y', None, None)
print ('-------------------------------')
# Count of Vocabular for dev data
feat_vec_1, dtm_train_1 = P2(train_data, None, 'word', 1, (1,1), 'Y', None, None)
feat_vec_2, dtm_train_2 = P2(dev_data, None, 'word', 1, (1,1), 'Y', None, None)
print ('\n Total words that are in the dev data vocabulary but not in training data a
       len(np.unique(list(set(feat_vec_2.get_feature_names()) - set(feat_vec_1.get_fea
print ('-------------------------------')
```

```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
 The size of the vocabulary is: 26879 Average length of each example: 96.71 Amount of Non-Zero
```

Answers:

a. The output of the transform (also of fit_transform) is a sparse matrix: http://docs.scipy.org/doc/scipy-0.14.0/reference/generated/scipy.sparse.csr_matrix.html. What is the size of the vocabulary? What is the average number of non-zero features per example? What fraction of the entries in the matrix are non-zero? Hint: use "nnz" and "shape" attributes.

   The size of the vocabulary is: 25864

   Average length of each example: 371.46

   Amount of Non-Zero occurences: 755559

   sparsity: 1.44%

b. What are the 0th and last feature strings (in alphabetical order)? Hint: use the vectorizer's get_feature_names function.

   First Feature string: 00

   Last Feature string: zyxel

c. Specify your own vocabulary with 4 words: ["atheism", "graphics", "space", "religion"]. Confirm the training vectors are appropriately shaped. Now what's the average number of non-zero features per example?

The size of the vocabulary is: 4

Average length of each example: 0.27

- It is worth nothing that due to limited vocabulary, the length of each example is very low.

d. Instead of extracting unigram word features, use "analyzer" and "ngram_range" to extract bigram and trigram character features. What size vocabulary does this yield?

- For N-Gram of (2,2) > **The size of the vocabulary is: 3090**

Average length of each example: 201.12

Amount of Non-Zero occurences: 409075

sparsity: 6.51%

- For N-Gram of (3,3) > **The size of the vocabulary is: 25864**

Average length of each example: 371.46

Amount of Non-Zero occurences: 755559

sparsity: 1.44%

e. Use the "min_df" argument to prune words that appear in fewer than 10 documents. What size vocabulary does this yield? > **The size of the vocabulary is: 3064**

Average length of each example: 72.68

f. Using the standard CountVectorizer, what fraction of the words in the dev data are missing from the vocabulary? Hint: build a vocabulary for both train and dev and look at the size of the difference. > **Total words that are in the dev data vocabulary but not in training data are: 4027**

(3) Use the default CountVectorizer options and report the f1 score (use metrics.f1_score) for a k nearest neighbors classifier; find the optimal value for k. Also fit a Multinomial Naive Bayes model and find the optimal value for alpha. Finally, fit a logistic regression model and find the optimal value for the regularization strength C using l2 regularization. A few questions:

a. Why doesn't nearest neighbors work well for this problem?

b. Any ideas why logistic regression doesn't work as well as Naive Bayes?

c. Logistic regression estimates a weight vector for each class, which you can access with the coef_ attribute. Output the sum of the squared weight values for each class for each setting of the C parameter. Briefly explain the relationship between the sum and the value of C.

```
In [30]: def P3_knn(data, labels, k_value, ngram_range, preprocessor, validation_ind, stop_word
             feat_vec, dtm_train = P2(data, vocab, analyzer , min_df, ngram_range, 'N', preproc
             dtm_dev = feat_vec.transform(dev_data)
             model = KNeighborsClassifier()
             if validation_ind == 'N':
                 model.fit(dtm_train, labels)
                 print("*** Model Metrics ***")
                 print(classification_report(dev_labels, model.predict(dtm_dev)))
                 print ("Model Score: %3f" % model.score(dtm_dev, dev_labels))
             if validation_ind == 'Y':
                 gcv = GridSearchCV(model, param_grid = k_value, n_jobs=-1, cv = 5)
                 gcv.fit(dtm_train, labels)
                 print(bcolors.BOLD + 'Best score for KNN Classifier :', gcv.best_score_)
                 print('Best parameters for KNN Classifier :', gcv.best_params_)
                 print(bcolors.ENDC)
             return

         def P3_MNB(data, labels, alphas, ngram_range, preprocessor, validation_ind, stop_words
             feat_vec, dtm_train = P2(data, vocab, analyzer, min_df, ngram_range, 'N', preproce
             dtm_dev = feat_vec.transform(dev_data)
             model = MultinomialNB()
             if validation_ind == 'N':
                 model.fit(dtm_train, labels)
                 print("*** Model Metrics ***")
                 print(classification_report(dev_labels, model.predict(dtm_dev)))
                 print ("Model Score: %3f" % model.score(dtm_dev, dev_labels))
             if validation_ind == 'Y':
                 gcv = GridSearchCV(model, param_grid = alphas, n_jobs=-1, cv = 5)
                 gcv.fit(dtm_train, labels)
                 print(bcolors.BOLD + 'Best score for Naive Bayes Classifier :', gcv.best_score
                 print('Best parameters for Naive Bayes Classifier :', gcv.best_params_)
                 print('Best Score for Naive Bayes Classifier on Train Data :', gcv.score(dtm_d
                 print(bcolors.ENDC)
             return

         def P3_LogReg(penalty, data, labels, Cs, ngram_range, preprocessor, validation_ind, st
             feat_vec, dtm_train = P2(data, vocab, analyzer, min_df, ngram_range, 'N', preproce
             dtm_dev = feat_vec.transform(dev_data)
             model = LogisticRegression(penalty = penalty, C = 0.1 )
             if validation_ind == 'N':
                 model.fit(dtm_train, labels)
                 print("*** Model Metrics ***")
                 print(classification_report(dev_labels, model.predict(dtm_dev)))
                 print ("Model Score: %3f" % model.score(dtm_dev, dev_labels))
             if validation_ind == 'Y':
                 gcv = GridSearchCV(model, param_grid = Cs, n_jobs=-1, cv = 10)
                 gcv.fit(dtm_train, labels)
                 print(bcolors.BOLD + 'Best score for Logistic Regression Classifier :', gcv.be
```

```
        print('Best parameters for Logistic Regression Classifier :', gcv.best_params_
        print('Best Score for Logistic Regression Classifier on Train Data :', gcv.sco
    return

def P3_LogReg_weights(penalty, data, labels, c_values, print_ind, ngram_range, prepro
                      tolerance, max_iter):
    weights = [0 for i in c_values]
    feat_vec, dtm_train = P2(data, vocab, analyzer, min_df, ngram_range, 'N', preproce
    dtm_dev = feat_vec.transform(dev_data)
    for i in np.arange(len(c_values)):
        model = LogisticRegression(penalty = penalty, C = c_values[i],
                                   tol = tolerance, max_iter= max_iter)
        model.fit(dtm_train, labels)
        print ("Model Score: %3f" % model.score(dtm_dev, dev_labels))
        if print_ind == 'Y' :
            print(bcolors.BOLD + 'C values: %3f Weights :%3f '% (c_values[i], np.squa
        weights[i] = np.square(model.coef_).sum(axis=1).sum()
    print(bcolors.ENDC)
    if print_ind == 'Y':
        plt.bar(c_values, weights)
    return model, feat_vec



k_values = {'n_neighbors': [1,2,3,4,5,6,7,8,9, 10]}
P3_knn(train_data, train_labels, k_values, (1,1), None, 'Y', None,'word',1, None)

alphas = {'alpha': [0.0, 0.0001, 0.001, 0.01, 0.1, 0.5, 1.0, 2.0, 10.0]}
P3_MNB(train_data, train_labels, alphas, (1,1), None, 'Y', None, 'word',1, None)

Cs = {'C': [0.01, 0.1, 1.0,2.0,3.0,4.0,5.0,6.0,7.0,8.0,9.0, 10.0]}
c_values = [0.01, 0.1, 1.0,2.0,3.0,4.0,5.0,6.0,7.0,8.0,9.0, 10.0]
P3_LogReg('l2', train_data, train_labels, Cs, (1,1), None, 'Y', None, 'word',1, None)
P3_LogReg_weights('l2', train_data, train_labels, c_values, 'Y', (1,1), None, None, 'w
```

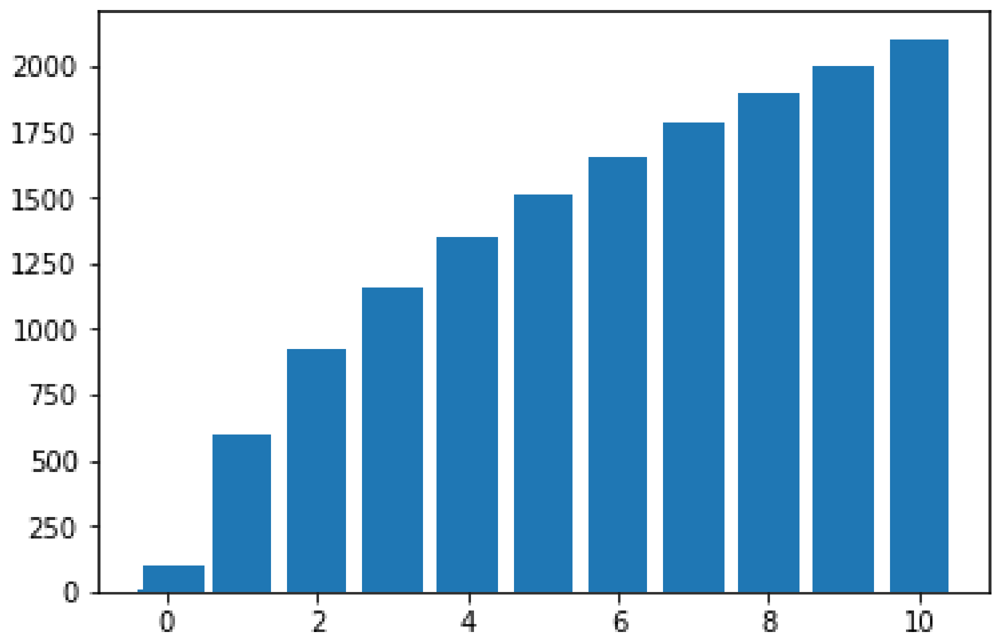
```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
Best score for KNN Classifier : 0.436086529006883Best parameters for KNN Classifier : {'n_neig
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

```
Best score for Naive Bayes Classifier : 0.828416912487709Best parameters for Naive Bayes Class
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)


/Users/sniggie/Desktop/conda/anaconda2/envs/python3/lib/python3.6/site-packages/sklearn/linear_
  FutureWarning)
/Users/sniggie/Desktop/conda/anaconda2/envs/python3/lib/python3.6/site-packages/sklearn/linear_
  "this warning.", FutureWarning)


Best score for Logistic Regression Classifier : 0.7846607669616519Best parameters for Logistic


Out[30]: (LogisticRegression(C=10.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='warn',
                   n_jobs=None, penalty='l2', random_state=None, solver='warn',
                   tol=0.0001, verbose=0, warm_start=False),
          CountVectorizer(analyzer='word', binary=False, decode_error='strict',
                  dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
                  lowercase=True, max_df=1.0, max_features=None, min_df=1,
                  ngram_range=(1, 1), preprocessor=None, stop_words=None,
                  strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
                  tokenizer=None, vocabulary=None))
```



ANSWER: - KNN does not work well due to high dimentionality of the data - We see that the model generalizes better for Naive Bayes, this could be due to the fact that the data supports the independence of the features better which can explain the fact that the decrease in performance from train to dev data for Naive Bayes is a lot less compared to that we see for Logistic Regression. - As the value of C increases the sum of the weights increases, this can be attributed to the fact that as C increases the intesity of regularization decreases and so the value of co-efficients increases. This can be found in the plot between C and the coefficient weights.

(4) Train a logistic regression model. Find the 5 features with the largest weights for each label -- 20 features in total. Create a table with 20 rows and 4 columns that shows the weight for each of these features for each of the labels. Create the table again with bigram features. Any surprising features in this table?

```
In [229]: def P4(c_values, stop_words, preprocessor, penalty, ngram_range, analyzer, min_df):
              logreg_model, feat_vect = P3_LogReg_weights(penalty, train_data, train_labels, c
                                                    stop_words, analyzer, min_df, None, (
              top_features_idx = np.argsort(-logreg_model.coef_)[:,:5].reshape(-1)
              j = 0
              k=0
              l=0
              top_features = np.chararray(top_features_idx.shape, itemsize=10)
              top_weights = np.zeros((4,20))
              for i in np.nditer(top_features_idx):
                  top_features[j] = feat_vect.get_feature_names()[i]
                  for l in np.arange(4):
                      top_weights[l,j] = logreg_model.coef_[l,i ]
                  j += 1
              dash = '-' * 100
              for i in np.arange(21):
                  if i == 0:
                    print(dash)
                    print('{:<20s}{:>20s}{:>20s}{:>20s}{:>20s}'.format('Label', newsgroups_tra
                                                                      newsgroups_train.target_
                                                                      newsgroups_train.target_

                    print(dash)
                  else:
                    print('{:<20s}{:>20.4f}{:>20.4f}{:>20.4f}{:>20.4f}'.format(top_features[i-
                                                                              top_weights[0,i-
                                                                          top_weights[1,i-1],t
                                                                          top_weights[3,i-1])

              return

          c_values = [0.1]
          P4(c_values, 'english', None, 'l2', (1,1), 'word',1)
          c_values = [0.1]
          P4(c_values, 'english', None, 'l2', (2,2), 'word',1)
          P4(c_values, 'english', None, 'l2', (1,2), 'word',1)
```

```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words='english',
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
Model Score: 0.730769

-------------------------------------------------------------------------------------------------
Label                        alt.atheism       comp.graphics           sci.space  talk.religio
-------------------------------------------------------------------------------------------------
atheism                           0.5494             -0.2549             -0.1978             -0
bobby                             0.4949             -0.1401             -0.2014             -0
atheists                          0.4934             -0.1349             -0.1784             -0
religion                          0.4662             -0.3625             -0.4191              0
islam                             0.4092             -0.1874             -0.1747             -0
graphics                         -0.4461              1.0372             -0.6318             -0
file                             -0.2022              0.6421             -0.4443             -0
image                            -0.2809              0.6346             -0.3821             -0
hi                               -0.2463              0.5866             -0.2724             -0
looking                          -0.3218              0.5552             -0.2740             -0
space                            -0.6818             -0.7212              1.2549             -0
orbit                            -0.2391             -0.3714              0.6171             -0
nasa                             -0.2778             -0.3049              0.5424             -0
launch                           -0.2330             -0.2823              0.5344             -0
moon                             -0.2360             -0.3330              0.4585             -0
christian                        -0.3242             -0.2189             -0.2055              0
christians                       -0.3805             -0.1656             -0.2247              0
koresh                            0.0507             -0.2517             -0.3483              0
order                            -0.3594             -0.0723             -0.1364              0
fbi                              -0.1738             -0.1341             -0.1908              0
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(2, 2), preprocessor=None, stop_words='english',
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
Model Score: 0.525148

-------------------------------------------------------------------------------------------------
Label                        alt.atheism       comp.graphics           sci.space  talk.religio
-------------------------------------------------------------------------------------------------
cheers ken                        0.4111             -0.4690             -0.4460              0
don think                         0.3707             -0.3146             -0.1683             -0
islamic la                        0.3262             -0.1433             -0.1393             -0
natural mo                        0.3177             -0.1297             -0.1298             -0
alt atheis                        0.3072             -0.2202             -0.2126              0
thanks adv                       -0.4119              0.8340             -0.3276             -0
```

```
comp graph                     -0.2162          0.5011          -0.2407         -0
24 bit                         -0.1995          0.4341          -0.1868         -0
greatly ap                     -0.1629          0.4181          -0.2002         -0
does know                      -0.2890          0.3981           0.0533         -0
space stat                     -0.2478         -0.2849           0.5089         -0
sci space                      -0.2027         -0.2496           0.4601         -0
nasa gov                       -0.1999         -0.1341           0.3447         -0
space shut                     -0.1509         -0.1974           0.3259         -0
gamma ray                      -0.1074         -0.1276           0.2637         -0
jesus chri                     -0.1617         -0.2130          -0.2086          0
cheers ken                      0.4111         -0.4690          -0.4460          0
objective                      -0.0474         -0.2034          -0.1969          0
objective                      -0.0542         -0.1356          -0.1310          0
david kore                     -0.0416         -0.1462          -0.1436          0
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 2), preprocessor=None, stop_words='english',
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
Model Score: 0.730769

------------------------------------------------------------------------------------------
Label                       alt.atheism    comp.graphics        sci.space  talk.religior
------------------------------------------------------------------------------------------
atheism                          0.4613          -0.2043          -0.1728         -0
religion                         0.4384          -0.3236          -0.3692         -0
atheists                         0.4206          -0.1261          -0.1536         -0
bobby                            0.4017          -0.1220          -0.1626         -0
islam                            0.3729          -0.1660          -0.1585         -0
graphics                        -0.4071           0.9374          -0.5619         -0
file                            -0.2000           0.5904          -0.3979         -0
image                           -0.2549           0.5710          -0.3392         -0
hi                              -0.2376           0.5344          -0.2551         -0
looking                         -0.2916           0.5154          -0.2544         -0
space                           -0.6222          -0.6629           1.1898         -0
orbit                           -0.2148          -0.3280           0.5496         -0
nasa                            -0.2464          -0.2763           0.4873         -0
launch                          -0.2072          -0.2441           0.4759         -0
moon                            -0.2101          -0.2931           0.4136         -0
christians                      -0.3255          -0.1558          -0.1998          0
christian                       -0.2961          -0.1984          -0.1740          0
koresh                           0.0453          -0.2227          -0.2931          0
fbi                             -0.1417          -0.1176          -0.1601          0
order                           -0.2935          -0.0621          -0.1161          0
```

ANSWER: - We see that the model accuravy has gone down if we look at only bigrams. - It is worth noting that if we use both single words and 2 words, the single word features end up being the important features. - This is very interesting as none of the 2 word features end up in the list. - Also, fbi and order end up as important features within the religion category .

(5) Try to improve the logistic regression classifier by passing a custom preprocessor to CountVectorizer. The preprocessing function runs on the raw text, before it is split into words by the tokenizer. Your preprocessor should try to normalize the input in various ways to improve generalization. For example, try lowercasing everything, replacing sequences of numbers with a single token, removing various other non-letter characters, and shortening long words. If you're not already familiar with regular expressions for manipulating strings, see https://docs.python.org/2/library/re.html, and re.sub() in particular. With your new preprocessor, how much did you reduce the size of the dictionary?

For reference, I was able to improve dev F1 by 2 points.

```
In [211]: def remove_repeated_characters(text):
              regex_pattern = re.compile(r'(.)\1+')
              clean_text = regex_pattern.sub(r'\1\1', text)
              return clean_text



          def remove_two_letter_words(text):
              regex_pattern = re.compile(r'\W*\b\w{1,3}\b')
              regex_pattern1 = re.compile(r'\d+')
              regex_pattern2 = re.compile(r'\W*\b\w{10,18}\b')
              stg_text_1 = regex_pattern1.sub(r'd_token', text)
              stg_text_2 = regex_pattern.sub(r' ', stg_text_1)
              clean_text = regex_pattern2.sub(r' ', stg_text_2)
              return clean_text

          def double_space(text):
              regex_pattern = re.compile(r'\s+')
              clean_text = regex_pattern.sub(r' ', text)
              return clean_text

          #print(remove_punctuations(train_data))
          #P2(train_data, None, 'word', 1, (1,1), 'Y', remove_repeated_characters)
          #P2(train_data, None, 'word', 1, (1,1), 'Y', remove_punctuations)
          Cs = {'C': [1.0,2.0,3.0,4.0,5.0,6.0,7.0,8.0,9.0, 10.0]}
          P3_LogReg('l2', train_data, train_labels, Cs, (1,1), remove_punctuations, 'N', None,
          P3_LogReg('l2', train_data, train_labels, Cs, (1,1), remove_two_letter_words, 'N', '
          P3_LogReg('l2', train_data, train_labels, Cs, (1,1), None, 'N', None, 'word',1, None

CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_punctuations at 0x1a2323aa60>,
        stop_words=None, strip_accents=None,
```

```
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)


/Users/sniggie/Desktop/conda/anaconda2/envs/python3/lib/python3.6/site-packages/sklearn/linear_
  FutureWarning)
/Users/sniggie/Desktop/conda/anaconda2/envs/python3/lib/python3.6/site-packages/sklearn/linear_
  "this warning.", FutureWarning)


*** Model Metrics ***
              precision    recall  f1-score   support

           0       0.64      0.58      0.61       165
           1       0.72      0.88      0.79       185
           2       0.80      0.80      0.80       199
           3       0.59      0.46      0.51       127

   micro avg       0.70      0.70      0.70       676
   macro avg       0.68      0.68      0.68       676
weighted avg       0.70      0.70      0.70       676

Model Score: 0.704142
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
*** Model Metrics ***
              precision    recall  f1-score   support

           0       0.62      0.58      0.60       165
           1       0.83      0.90      0.86       185
           2       0.72      0.87      0.79       199
           3       0.67      0.43      0.53       127

   micro avg       0.73      0.73      0.73       676
   macro avg       0.71      0.70      0.70       676
weighted avg       0.72      0.73      0.72       676

Model Score: 0.726331
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), preprocessor=None, stop_words=None,
        strip_accents=None, token_pattern='(?u)\\b\\w\\w+\\b',
        tokenizer=None, vocabulary=None)
```

```
*** Model Metrics ***
              precision    recall  f1-score   support

           0       0.63      0.56      0.59       165
           1       0.74      0.90      0.81       185
           2       0.78      0.78      0.78       199
           3       0.59      0.49      0.53       127

   micro avg       0.70      0.70      0.70       676
   macro avg       0.68      0.68      0.68       676
weighted avg       0.70      0.70      0.70       676

Model Score: 0.704142
```

** Answer** - There is an improvement of more than 0.2 once we add in the additional conditions for regular expression. - Adding just punctuations didn't impact the accuracy.

(6) The idea of regularization is to avoid learning very large weights (which are likely to fit the training data, but not generalize well) by adding a penalty to the total size of the learned weights. That is, logistic regression seeks the set of weights that minimizes errors in the training data AND has a small size. The default regularization, L2, computes this size as the sum of the squared weights (see P3, above). L1 regularization computes this size as the sum of the absolute values of the weights. The result is that whereas L2 regularization makes all the weights relatively small, L1 regularization drives lots of the weights to 0, effectively removing unimportant features.

Train a logistic regression model using a "l1" penalty. Output the number of learned weights that are not equal to zero. How does this compare to the number of non-zero weights you get with "l2"? Now, reduce the size of the vocabulary by keeping only those features that have at least one non-zero weight and retrain a model using "l2".

Make a plot showing accuracy of the re-trained model vs. the vocabulary size you get when pruning unused features by adjusting the C parameter.

Note: The gradient descent code that trains the logistic regression model sometimes has trouble converging with extreme settings of the C parameter. Relax the convergence criteria by setting tol=.01 (the default is .0001).

```
In [231]: def P6(c_values, stop_words, preprocessor, ngram_range, penalty, analyzer, min_df, to
              np.random.seed(0)
              logreg_model, feat_vect = P3_LogReg_weights(penalty, train_data, train_labels, c_
                                                          stop_words, analyzer, min_df, None, t
              nonzero_features_idx = np.transpose(np.nonzero(logreg_model.coef_))
              #print (nonzero_features_idx[:,1])
              j = 0
              #k=0
              start = time.clock()
              nonzero_features = [feat_vect.get_feature_names()[i] for i in nonzero_features_id
              #print (time.clock() - start)
              return np.unique(nonzero_features)
```

```
def P3_LogReg_score(penalty, data, labels, c_values, ngram_range, preprocessor, stop_
                    min_df, vocab,
                     tolerance):
    feat_vec, dtm_train = P2(data, vocab, analyzer, min_df, ngram_range, 'N', prepro
    dtm_dev = feat_vec.transform(dev_data)
    model = LogisticRegression(penalty = penalty, C = c_values,
                               tol = tolerance, max_iter=1000)
    model.fit(dtm_train, labels)
    print ("Model Score: %3f" % model.score(dtm_dev, dev_labels))
    return c_values, model.score(dtm_dev, dev_labels)

c_values = [ 0.01, 0.05, 0.1,0.3,0.5, 0.7,0.8,0.9, 1.0, 1.5, 2.0,5.0, 10.0, 20.0, 100
c_values_1 = [0 for i in c_values]
scores = [0 for i in c_values]
feature_count = [0 for i in c_values]
#c_values = [1.0]
for i in np.arange(len(c_values)):
    nonzero_features = P6([c_values[i]], 'english', remove_two_letter_words, (1,1),
    print (nonzero_features.shape)
    feature_count[i] = nonzero_features.shape[0]
    c_values_1[i], scores[i] = P3_LogReg_score('l2', train_data, train_labels, c_valu
                                               None, 'word',1, nonzero_features, 0.01)
    print (c_values_1[i], scores[i], feature_count[i])
```

```
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.384615

(8,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['Jesus', 'atheism', 'd_token', 'graphics', 'image', 'pd_token',
       'people', 'space'], dtype='<U8'))
Model Score: 0.392012
0.01 0.39201183431952663 8
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
```

```
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.547337

(74,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['Bible', 'Bobby', ..., 'word', 'year'], dtype='<U9'))
Model Score: 0.622781
0.05 0.6227810650887574 74
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.655325

(161,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['Allen', 'Bible', ..., 'year', 'years'], dtype='<U9'))
Model Score: 0.665680
0.1 0.665680473372781 161
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.680473
```

```
(409,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AMORC', 'Allah', ..., 'young', 'youth'], dtype='<U9'))
Model Score: 0.674556
0.3 0.6745562130177515 409
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.674556

(616,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AMORC', 'Abraham', ..., 'young', 'youth'], dtype='<U9'))
Model Score: 0.674556
0.5 0.6745562130177515 616
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.698225

(816,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
```

```
        vocabulary=array(['AMORC', 'Abraham', ..., 'young', 'youth'], dtype='<U9'))
Model Score: 0.698225
0.7 0.6982248520710059 816
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.693787

(862,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AMORC', 'Abraham', ..., 'youth', 'zone'], dtype='<U52'))
Model Score: 0.692308
0.8 0.6923076923076923 862
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.699704

(937,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AMORC', 'Abraham', ..., 'youth', 'zone'], dtype='<U71'))
Model Score: 0.689349
0.9 0.6893491124260355 937
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
```

```
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.701183

(978,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AMORC', 'Abraham', ..., 'youth', 'zone'], dtype='<U52'))
Model Score: 0.687870
1.0 0.6878698224852071 978
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.698225

(1247,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AIAA', 'AMORC', ..., 'youth', 'zone'], dtype='<U79'))
Model Score: 0.695266
1.5 0.6952662721893491 1247
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.693787

(1547,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
```

```
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AIAA', 'AMORC', ..., 'youth', 'zone'], dtype='<U79'))
Model Score: 0.692308
2.0 0.6923076923076923 1547
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.684911

(2052,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AIAA', 'AMORC', ..., 'zillions', 'zone'], dtype='<U80'))
Model Score: 0.701183
5.0 0.7011834319526628 2052
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.653846

(2942,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AIAA', 'AMORC', ..., 'zillions', 'zone'], dtype='<U79'))
Model Score: 0.690828
10.0 0.6908284023668639 2942
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
```

```
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.658284

(3765,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['ACTUALLY', 'AIAA', ..., 'zillions', 'zone'], dtype='<U80'))
Model Score: 0.689349
20.0 0.6893491124260355 3765
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words='english', strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, vocabulary=None)
Model Score: 0.625740

(7018,)
CountVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.int64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1),
        preprocessor=<function remove_two_letter_words at 0x1a2323a840>,
        stop_words=None, strip_accents=None,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None,
        vocabulary=array(['AAd_token', 'ACCESS', ..., 'zillions', 'zone'], dtype='<U80'))
Model Score: 0.661243
100.0 0.6612426035502958 7018
```

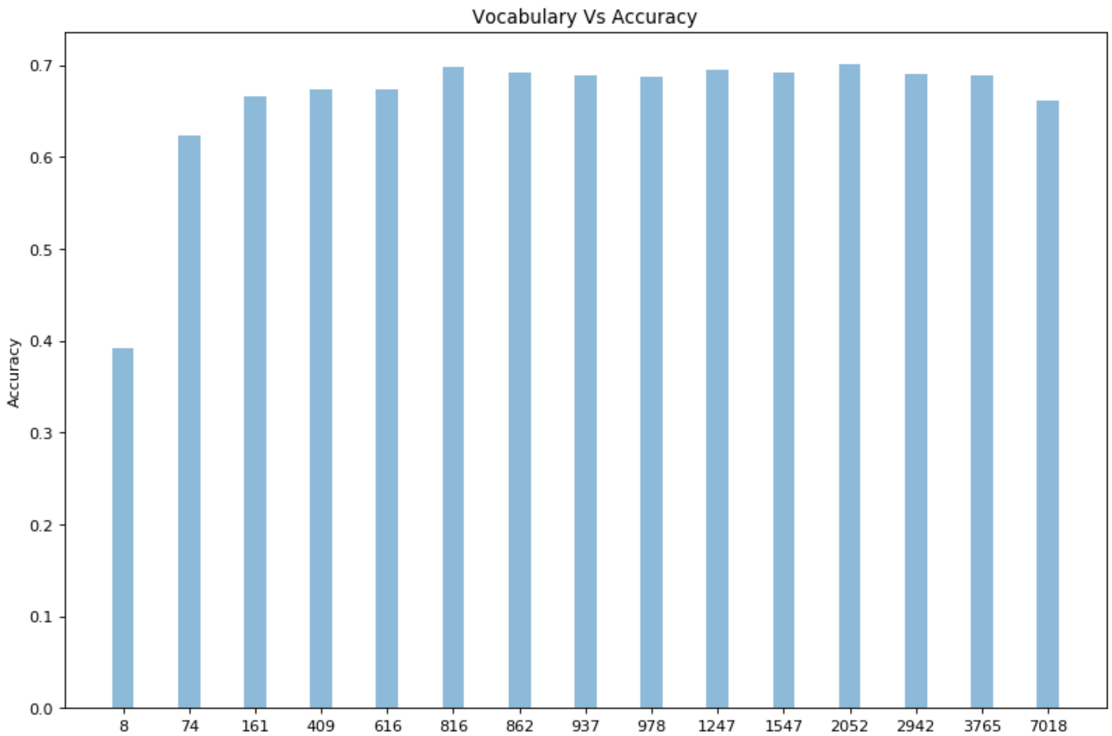
In [232]:
```
plt.figure(num=None, figsize=(12, 8), dpi=80, facecolor='w', edgecolor='k')

y_pos = np.arange(len(feature_count))

plt.bar(3*y_pos, scores,  align='center', alpha=0.5, width = 1.0 )
plt.xticks(3*y_pos, feature_count)
plt.ylabel('Accuracy')
```

```
plt.title('Vocabulary Vs Accuracy')
```

Out[232]: Text(0.5, 1.0, 'Vocabulary Vs Accuracy')



** Answer** - We see that as we increase the Value of C, the number of non-zero features increases. - This can be attributed to the fact that as the regularization strength decrease, the number of non zero coefficient features increase. We See that there isn't a lot of improvement in the performance after a certain value of C. - In fact after a certain value the performance of the model decreases as we add more features.

(7) Use the TfidfVectorizer -- how is this different from the CountVectorizer? Train a logistic regression model with C=100.

Make predictions on the dev data and show the top 3 documents where the ratio R is largest, where R is:

maximum predicted probability / predicted probability of the correct label

What kinds of mistakes is the model making? Suggest a way to address one particular issue that you see.

In [181]:
```
def P7(data, vocab,analyzer, min_df, ngram_range , details, preprocessor, stop_words
    feat_vect = TfidfVectorizer(vocabulary=vocab, analyzer = analyzer, min_df= min_d
                                ngram_range = ngram_range, preprocessor = preprocesso
    print (feat_vect)
    feat_vect.fit(data)
    dtm_train = feat_vect.transform(data)
```

```
        if details == 'Y':
            print (bcolors.BOLD + '\n The size of the vocabulary is:', dtm_train.shape[1]
            print('\n Average length of each example: %.2f' % (dtm_train.nnz /dtm_train.s
            print ('\n Amount of Non-Zero occurences: ', dtm_train.nnz)
            print ('\n sparsity: %.2f%%' % (100.0 * dtm_train.nnz /
                                            (dtm_train.shape[0] * dtm_train.shape[1])))
            print ('\n First Feature string: ', feat_vect.get_feature_names()[0])
            print ('\n Last Feature string: ', feat_vect.get_feature_names()[dtm_train.sh
        return feat_vect, dtm_train

    def P7_LogReg(penalty, data, labels, Cs, ngram_range, preprocessor, validation_ind, s
        feat_vec, dtm_train = P7(data, None, analyzer, min_df, ngram_range, 'N', preproce
        dtm_dev = feat_vec.transform(dev_data)
        model = LogisticRegression(penalty = penalty, multi_class = 'auto', solver = 'lib
        model.fit(dtm_train, labels)
        print("*** Model Metrics ***")
        print(classification_report(dev_labels, model.predict(dtm_dev)))
        print ("\n" + '*** Confusion Matrix ***')
        print(confusion_matrix(dev_labels, model.predict(dtm_dev)))
        print ("Model Score: %3f" % model.score(dtm_dev, dev_labels))
        if validation_ind == 'Y':
            gcv = GridSearchCV(model, param_grid = Cs, n_jobs=-1, cv = 5)
            gcv.fit(dtm_train, labels)
            print(bcolors.BOLD + 'Best score for Logistic Regression Classifier :', gcv.b
            print('Best parameters for Logistic Regression Classifier :', gcv.best_params
        return model, dtm_dev

    # Using the vocabulary from the corpus of words within the text
    P7(train_data, None, 'word', 1, (1,1), 'Y', None, None)

    c_values = [100.0]
    reg_model, dtm_dev = P7_LogReg('l2', train_data, train_labels, Cs, (1,1), None, 'N',
    predicted_probability = (reg_model.predict_proba(dtm_dev))
    label_prob = (predicted_probability[np.arange(len(predicted_probability)), dev_labels
    R = np.max(predicted_probability, axis = 1)/label_prob
    top3_r = (np.argsort(R)[-5:])
    for i in np.nditer(top3_r):
        print (dev_data[i], dev_labels[i], reg_model.predict(dtm_dev[i]), R[i])
        print ('--------------------------------------------')

    dev_predicted = reg_model.predict(dtm_dev)
```

```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), norm='l2', preprocessor=None, smooth_idf=True,
        stop_words=None, strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=True,
```

```
       vocabulary=None)
 The size of the vocabulary is: 26879 Average length of each example: 96.71 Amount of Non-Zero
```

(8) EXTRA CREDIT

Try implementing one of your ideas based on your error analysis. Use logistic regression as your underlying model.

```
In [203]: categories_1 = ['alt.atheism', 'talk.religion.misc']
          newsgroups_train_1 = fetch_20newsgroups(subset='train',
                                                  remove=('headers', 'footers', 'quotes'),
                                                  categories=categories_1)
          newsgroups_test_1 = fetch_20newsgroups(subset='test',
                                                 remove=('headers', 'footers', 'quotes'),
                                                 categories=categories_1)

          # Splitting the data into training, dev and test.
          num_test_1 = len(newsgroups_test_1.target)
          test_data_1, test_labels_1 = newsgroups_test_1.data[int(num_test_1/2):], newsgroups_
          dev_data_1, dev_labels_1 = newsgroups_test_1.data[:int(num_test_1/2)], newsgroups_tes
          train_data_1, train_labels_1 = newsgroups_train_1.data, newsgroups_train_1.target*3

          print('training label shape:', train_labels_1.shape)
          print('test label shape:', test_labels_1.shape)
          print('dev label shape:', dev_labels_1.shape)
          print('labels names:', newsgroups_train_1.target_names)
```

```
training label shape: (857,)
test label shape: (285,)
dev label shape: (285,)
labels names: ['alt.atheism', 'talk.religion.misc']
```

```
In [208]: def P8(data, vocab,analyzer, min_df, ngram_range , details, preprocessor, stop_words
              feat_vect = TfidfVectorizer(vocabulary=vocab, analyzer = analyzer, min_df= min_d
                                          ngram_range = ngram_range, preprocessor = preprocesso
              print (feat_vect)
              feat_vect.fit(data)
              dtm_train = feat_vect.transform(data)
              if details == 'Y':
                  print (bcolors.BOLD + '\n The size of the vocabulary is:', dtm_train.shape[1
```

```
            print('\n Average length of each example: %.2f' % (dtm_train.nnz /dtm_train.s
            print ('\n Amount of Non-Zero occurences: ', dtm_train.nnz)
            print ('\n sparsity: %.2f%%' % (100.0 * dtm_train.nnz /
                                            (dtm_train.shape[0] * dtm_train.shape[1])))
            print ('\n First Feature string: ', feat_vect.get_feature_names()[0])
            print ('\n Last Feature string: ', feat_vect.get_feature_names()[dtm_train.sh
        return feat_vect, dtm_train

    def P8_LogReg(penalty, data, labels, Cs, ngram_range, preprocessor, validation_ind, s
        feat_vec, dtm_train = P8(data, None, analyzer, min_df, ngram_range, 'N', preproce
        dtm_dev = feat_vec.transform(dev_data_1)
        model = LogisticRegression(penalty = penalty, multi_class = 'auto', solver = 'lil
        model.fit(dtm_train, labels)
        print("*** Model Metrics ***")
        print(classification_report(dev_labels_1, model.predict(dtm_dev)))
        print ("\n" + '*** Confusion Matrix ***')
        print(confusion_matrix(dev_labels_1, model.predict(dtm_dev)))
        print ("Model Score: %3f" % model.score(dtm_dev, dev_labels_1))
        if validation_ind == 'Y':
            gcv = GridSearchCV(model, param_grid = Cs, n_jobs=-1, cv = 5)
            gcv.fit(dtm_train, labels)
            print(bcolors.BOLD + 'Best score for Logistic Regression Classifier :', gcv.b
            print('Best parameters for Logistic Regression Classifier :', gcv.best_params
        return model, dtm_dev, feat_vec

    # Using the vocabulary from the corpus of words within the text
    P8(train_data_1, None, 'word', 1, (1,1), 'Y', None, 'english')

    c_values = [100.0]
    reg_model_new, dtm_dev_new, feat_vect_new = P8_LogReg('l2', train_data_1, train_label
```

```
TfidfVectorizer(analyzer='word', binary=False, decode_error='strict',
        dtype=<class 'numpy.float64'>, encoding='utf-8', input='content',
        lowercase=True, max_df=1.0, max_features=None, min_df=1,
        ngram_range=(1, 1), norm='l2', preprocessor=None, smooth_idf=True,
        stop_words='english', strip_accents=None, sublinear_tf=False,
        token_pattern='(?u)\\b\\w\\w+\\b', tokenizer=None, use_idf=True,
        vocabulary=None)
 The size of the vocabulary is: 13389 Average length of each example: 64.91 Amount of Non-Zero
```

In [210]:
```
# Identify the indexes that are predicted Atheism and Religion
dev_indx = np.isin(dev_predicted, [0,3])

dev_data_new = list(np.array(dev_data)[dev_indx])
dev_labels_new = list(np.array(dev_labels)[dev_indx])
#Use the feature vettor we built in the second example for transforming the data
dtm_dev_new = feat_vect_new.transform(dev_data_new)
reg_model_new.predict(dtm_dev_new)
```

```
print("*** Model Metrics ***")
print ("The Accuracy for the Model is :", reg_model_new.score(dtm_dev_new, dev_labels
print(classification_report(dev_labels_new, reg_model_new.predict(dtm_dev_new)))
```

```
*** Model Metrics ***
The Accuracy for the Model is : 0.6753731343283582
              precision    recall  f1-score   support

           0       0.67      0.76      0.72       135
           1       0.00      0.00      0.00         7
           2       0.00      0.00      0.00        14
           3       0.68      0.70      0.69       112

   micro avg       0.68      0.68      0.68       268
   macro avg       0.34      0.36      0.35       268
weighted avg       0.62      0.68      0.65       268
```

** Answer** - We built another model, just using the training data for Atheism and Religion. Once we identify, we fit the data to identify the features. - We use the second model to just classify the data for these categories. When we combine both of them, we see that there is an increase in the performance of classification slightly.