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 (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.

Resources

1. http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html (http://scikit-learn.org/stable/modules/generated/sklearn.feature_extraction.text.TfidfVectorizer.html)
2. http://scikit-learn.org/stable/modules/feature_extraction.html (http://scikit-learn.org/stable/modules/feature_extraction.html)
3. http://scikit-learn.org/stable/tutorial/text_analytics/working_with_text_data.html (http://scikit-learn.org/stable/tutorial/text_analytics/working_with_text_data.html)
4. http://www.markhneedham.com/blog/2015/02/15/pythonscikit-learn-calculating-tfidf-on-how-i-met-your-mother-transcripts/ (http://www.markhneedham.com/blog/2015/02/15/pythonscikit-learn-calculating-tfidf-on-how-i-met-your-mother-transcripts/)
5. http://blog.christianperone.com/2011/09/machine-learning-text-feature-extraction-tf-idf-part-i/ (http://blog.christianperone.com/2011/09/machine-learning-text-feature-extraction-tf-idf-part-i/)
6. http://www.cs.duke.edu/courses/spring14/compsci290/assignments/lab02.html (http://www.cs.duke.edu/courses/spring14/compsci290/assignments/lab02.html)

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

import warnings
warnings.filterwarnings("ignore")

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

# 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.grid_search 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 *
```

```
/Library/Python/2.7/site-packages/sklearn/cross_validation.py:44: Depre
cationWarning: This module was deprecated in version 0.18 in favor of t
he model_selection module into which all the refactored classes and fun
ctions are moved. Also note that the interface of the new CV iterators
 are different from that of this module. This module will be removed in
0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
/Library/Python/2.7/site-packages/sklearn/grid_search.py:43: Deprecatio
nWarning: This module was deprecated in version 0.18 in favor of the mo
del_selection module into which all the refactored classes and function
s are moved. This module will be removed in 0.20.
  DeprecationWarning)
```

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 [2]:
```
categories = ['alt.atheism', 'talk.religion.misc', 'comp.graphics', 'sc
i.space']
newsgroups_train = fetch_20newsgroups(subset='train',
                                      remove=('headers', 'footers', 'quo
tes'),
                                      categories=categories)
newsgroups_test = fetch_20newsgroups(subset='test',
                                     remove=('headers', 'footers', 'quot
es'),
                                     categories=categories)

num_test = len(newsgroups_test.target)
test_data, test_labels = newsgroups_test.data[num_test/2:], newsgroups_t
est.target[num_test/2:]
dev_data, dev_labels = newsgroups_test.data[:num_test/2], newsgroups_tes
t.target[:num_test/2]
train_data, train_labels = newsgroups_train.data, newsgroups_train.targe
t

# Combine training and test data to create a corpus
corpus_data = np.append(newsgroups_train.data,newsgroups_test.data)
corpus_labels =
np.append(newsgroups_train.target,newsgroups_test.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
print 'corpus data shape:',corpus_data.shape
print 'corpus labels shape:',corpus_data.shape

# Initialize the set of all features from the corpus
vectorizer = CountVectorizer(min_df=1)
corpus_x = vectorizer.fit_transform(corpus_data)
all_feature_names = vectorizer.get_feature_names()
```

```
training label shape: (2034,)
test label shape: (677,)
dev label shape: (676,)
labels names: ['alt.atheism', 'comp.graphics', 'sci.space', 'talk.relig
ion.misc']
corpus data shape: (3387,)
corpus labels shape: (3387,)
```

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

[2 pts]

In [3]:
```
#def P1(num_examples=5):
### STUDENT START ###

# Displaying message and label for first five training examples
for i in range(0,5):
    print "Training Label"
    print "**************"
    print train_labels[i]

    print "Training Data"
    print "**************"
    print train_data[i]

### STUDENT END ###
#P1(2)
```

Training Label
****
1
Training Data
****
Hi,

I've noticed that if you only save a model (with all your mapping plane
s
positioned carefully) to a .3DS file that when you reload it after rest
arting
3DS, they are given a default position and orientation. But if you sav
e
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 fi
le.
I'd like to be able to read the texture rule information, does anyone h
ave
the format for the .PRJ file?

Is the .CEL file format available from somewhere?

Rych
Training Label
****
3
Training Data
****

Seems to be, barring evidence to the contrary, that Koresh was simply
another deranged fanatic who thought it neccessary to take a whole bunc
h 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 corrupt
ion
for centuries.
Training Label
****
2
Training Data
****

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

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?

Training Label
****
0
Training Data
****
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 Challenge
s."

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.
Training Label
****
2
Training Data
****
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?

(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 (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.

[6 pts]

In [4]:
```
#def P2():
### STUDENT START ###

from sklearn.feature_extraction.text import CountVectorizer

#(2) Use CountVectorizer to turn the raw training text into feature vect
ors.
#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 t
ext into
#feature vectors using the vocabulary ("transform").

# initialize and fit a CountVectorizer to the training data
vectorizer = CountVectorizer(min_df=1)
train_x = vectorizer.fit_transform(train_data)

# get feature names
feature_names = vectorizer.get_feature_names()

# transform X into a matrix
train_x_ = train_x.toarray()

# set floating point precision and avoid suppressing smaller values
```

```
np.set_printoptions(suppress=False,precision=16)

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

print "The size of the vocabulary is:", len(vectorizer.vocabulary_)
print "The shape of the training data is",train_x.shape
print "The average of non-zero features is:", (train_x.nnz/train_x_.shap
e[0])
print "Fraction of entries in the matrix that are non-zero is:", float(t
rain_x.nnz)/float((train_x.shape[0]*train_x.shape[1]))

#b. What are the 0th and last feature strings (in alphabetical order)?
#Hint: use the vectorizer's get_feature_names function.
print "The first feature string is:", feature_names[0]
print "The last feature string is:", feature_names[len(feature_names)-1]

#c. Specify your own vocabulary with 4 words: ["atheism", "graphics", "s
pace", "religion"].
#Confirm the training vectors are appropriately shaped. Now what's the a
verage number of
#non-zero features per example?
#print len(vectorizer.vocabulary_)
vocab = ["atheism", "graphics", "space", "religion"]

# initialize and fit a CountVectorizer to the training data
vectorizer = CountVectorizer(min_df=1,vocabulary=vocab)
train_x = vectorizer.fit_transform(train_data)

# get feature names
feature_names = vectorizer.get_feature_names()

print "\nDisplaying information using the limited vocabulary\n"
print "The size of the vocabulary is:", len(vectorizer.vocabulary_)
print "The shape of the training data is",train_x.shape
print "The average of non-zero features is:", (train_x.nnz/train_x_.shap
e[0])
print "Fraction of entries in the matrix that are non-zero is:", float(t
rain_x.nnz)/float((train_x.shape[0]*train_x.shape[1]))
print "The first feature string is:", feature_names[0]
print "The last feature string is:", feature_names[len(feature_names)-1]

#d. Instead of extracting unigram word features, use "analyzer" and "ngr
am_range" to extract
#bigram and trigram character features. What size vocabulary does this y
ield?

## Using bigram character features
vectorizer = CountVectorizer(min_df=1,analyzer='char',ngram_range=(2,2))
train_x = vectorizer.fit_transform(train_data)
```

```
print "\nThe size of the vocabulary using bigram character features:", l
en(vectorizer.vocabulary_)

## Using trigram character features
vectorizer = CountVectorizer(min_df=1,analyzer='char',ngram_range=(3,3))
train_x = vectorizer.fit_transform(train_data)

print "\nThe size of the vocabulary using trigram character features:",
len(vectorizer.vocabulary_)

#e. Use the "min_df" argument to prune words that appear in fewer than 1
0 documents.
# What size vocabulary does this yield?
vectorizer = CountVectorizer(min_df=10)
train_x = vectorizer.fit_transform(train_data)

print "\nThe size of the vocabulary using min_df less than 10:", len(vec
torizer.vocabulary_)

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

# Build vectorizer using train data
vectorizer = CountVectorizer(min_df=1)
train_x = vectorizer.fit_transform(train_data)
train_vocab_size = len(vectorizer.vocabulary_)
print "\nDisplaying information using training data\n"
print "The size of the vocabulary is:", len(vectorizer.vocabulary_)
print "The shape of the training data is",train_x.shape
print "The average of non-zero features is:", (train_x.nnz/train_x_.shap
e[0])

# Build vectorizer using dev data
vectorizer = CountVectorizer(min_df=1)
train_x = vectorizer.fit_transform(dev_data)
dev_vocab_size = len(vectorizer.vocabulary_)
print "\nDisplaying information using dev data\n"
print "The size of the vocabulary is:", len(vectorizer.vocabulary_)
print "The shape of the training data is",train_x.shape
print "The average of non-zero features is:", (train_x.nnz/train_x_.shap
e[0])

print "\nThe difference in size between the training data and dev data i
s:", (train_vocab_size-dev_vocab_size)

### STUDENT END ###
#P2()
```

```
The size of the vocabulary is: 26879
The shape of the training data is (2034, 26879)
The average of non-zero features is: 96
Fraction of entries in the matrix that are non-zero is: 0.0035978272269
6
The first feature string is: 00
The last feature string is: zyxel

Displaying information using the limited vocabulary

The size of the vocabulary is: 4
The shape of the training data is (2034, 4)
The average of non-zero features is: 0
Fraction of entries in the matrix that are non-zero is: 0.0671091445428
The first feature string is: atheism
The last feature string is: religion

The size of the vocabulary using bigram character features: 3291

The size of the vocabulary using trigram character features: 32187

The size of the vocabulary using min_df less than 10: 3064

Displaying information using training data

The size of the vocabulary is: 26879
The shape of the training data is (2034, 26879)
The average of non-zero features is: 96

Displaying information using dev data

The size of the vocabulary is: 16246
The shape of the training data is (676, 16246)
The average of non-zero features is: 36

The difference in size between the training data and dev data is: 10633
```

(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.

[4 pts]

In [5]:
```
#def P3():
### STUDENT START ###
```

```
## KNN classifier ##
vectorizer = CountVectorizer(min_df=1)

# build vectorizer on the corpus to ensure that complete vocab is obtain
ed across training and dev data
X = vectorizer.fit_transform(corpus_data)
X_ = X.toarray()

# extract training data and dev data from corpus
knn_train_data = X_[0:len(train_data)]
knn_dev_data = X_[len(train_data):len(train_data)+len(dev_data)]

# create KNN classifier and fit to training data
knn = KNeighborsClassifier(n_neighbors=4)
knn.fit(knn_train_data,train_labels)

# Determine optimal value of K
k_values = {'n_neighbors': [1,2,4,6]}
knn.get_params().keys()
gscv = GridSearchCV(knn,k_values)
gscv.fit(knn_dev_data,dev_labels)
print "Best k value for KNN is ",gscv.best_params_

# Display more information for the best param
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(knn_train_data,train_labels)
prediction = knn.predict(knn_dev_data)
print '\nClasification report for k=1:\n\n', classification_report(dev_l
abels, prediction)
print "\nAccuracy is ", knn.score(knn_dev_data,dev_labels)

## MULTINOMIAL NAIVE BAYES MODEL ###

mnb = MultinomialNB()

alphas = {'alpha': [0.0, 0.0001, 0.001, 0.01, 0.1, 0.5, 1.0, 2.0, 10.0]}

# run a search for the best estimator alpha
gscv = GridSearchCV(mnb,alphas)
gscv.fit(knn_train_data,train_labels)

print "Best alpha value for Multinomial NB is ",gscv.best_params_

# Generating classification report with best value of alpha 0.01
mnb = MultinomialNB(alpha=0.01)
mnb.fit(knn_train_data,train_labels)
prediction = mnb.predict(knn_dev_data)
print '\nClasification report for Multinomial Naive Bayes:\n\n', classif
ication_report(dev_labels, prediction)
print "\nAccuracy is ", mnb.score(knn_dev_data,dev_labels)

## LOGISTIC REGRESSION MODEL ##
param_grid={'C': [0.001, 0.01, 0.1, 1, 10, 100, 1000]}
lr = LogisticRegression(penalty='l2')
gscv = GridSearchCV(lr,param_grid)
gscv.fit(knn_train_data,train_labels)
```

```
print "Best alpha value for Logistic Regression is ",gscv.best_params_

# Generating classification report with best value of C
lr = LogisticRegression(penalty='l2',C=0.1)
lr.fit(knn_train_data,train_labels)
prediction = lr.predict(knn_dev_data)
print '\nClasification report for Logistic Regression:\n\n', classificat
ion_report(dev_labels, prediction)
print "\nAccuracy is ", lr.score(knn_dev_data,dev_labels)

# print coeff for logistic regression
print "\n Weights for Logistic Regression are:", lr.coef_

#c. Logistic regression estimates a weight vector for each class, which
 you
# can access with the coef_ attribute. Output the sum of the squared wei
ght values for
#each class for each setting of the C parameter. Briefly explain the rel
ationship
#between the sum and the value of C.
print "\n Relationship between C and sum of weights\n"
for c_value in param_grid.get('C'):

    lr = LogisticRegression(penalty='l2',C=float(c_value))
    lr.fit(knn_train_data,train_labels)

    print "C-Value:",c_value," and Sum of weight values:", np.sum(lr.coe
f_)


### STUDENT END ###
#P3()
```

```
Best k value for KNN is  {'n_neighbors': 1}

Clasification report for k=1:

             precision    recall  f1-score   support

          0       0.40      0.39      0.40       165
          1       0.51      0.35      0.41       185
          2       0.43      0.45      0.44       199
          3       0.25      0.35      0.30       127

avg / total       0.41      0.39      0.39       676


Accuracy is  0.390532544379
Best alpha value for Multinomial NB is  {'alpha': 0.01}

Clasification report for Multinomial Naive Bayes:

             precision    recall  f1-score   support

          0       0.67      0.72      0.69       165
          1       0.92      0.90      0.91       185
          2       0.81      0.89      0.85       199
          3       0.65      0.50      0.57       127

avg / total       0.78      0.78      0.78       676


Accuracy is  0.779585798817
Best alpha value for Logistic Regression is  {'C': 0.1}

Clasification report for Logistic Regression:

             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

avg / total       0.70      0.70      0.70       676


Accuracy is  0.704142011834

 Weights for Logistic Regression are: [[ -4.9128968293718385e-02   5.18
57913520438795e-02
   -7.6554261439548219e-05 ...,   0.0000000000000000e+00
    0.0000000000000000e+00  -6.7893958159165611e-05]
 [  7.2389755077842260e-02  -3.1100970958436243e-03
   -7.7093929358544987e-03 ...,   0.0000000000000000e+00
    0.0000000000000000e+00   9.2737577838006117e-03]
 [ -2.7249442351296012e-02  -6.2691896679923795e-02
    4.3992448571519085e-03 ...,   0.0000000000000000e+00
    0.0000000000000000e+00  -5.2093569710007235e-03]
 [ -4.6540631795369040e-02  -1.6085872593150835e-02
```

```
  -3.3780270600938011e-03 ...,   0.0000000000000000e+00
   0.0000000000000000e+00  -4.4984399433542179e-05]]

 Relationship between C and sum of weights

C-Value: 0.001  and Sum of weight values: -8.35591486286
C-Value: 0.01  and Sum of weight values: -21.0025071147
C-Value: 0.1  and Sum of weight values: -50.3262946074
C-Value: 1  and Sum of weight values: -124.724549743
C-Value: 10  and Sum of weight values: -266.00636842
C-Value: 100  and Sum of weight values: -456.232172396
C-Value: 1000  and Sum of weight values: -676.455218304
```

ANSWER:

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

Nearest neighbor does not work well for this problem because it tends to overfit the test data since it is looking for exact matches.

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

Naive Bayes is based primarily on joint probabilistic expectation that a given set of words will match a particular class. This model works well for textual data. In the case of logistic regression, we do something similar to KNN by trying to compute the Euclidean distances between words. By modeling words as continuous variables and using the Euclidean distance metric, we lose the ability to quantify the real distance between words. For example, the edit distance (levenshtein distance) or n-gram models may be better able to represent than modeling as continous variables. Logistic regression is however different from KNN in that we are able to introduce regularization in the model to avoid for the implicit overfitting introduced by modeling textual content as continous variables.

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.

C is the regularization parameter. Higher values of C correspond to greater regularization. This causes the weights associated with our features to decrease especially when feature density is high. This is why with increasing C values we find that the sum of weights decreases.

(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?

[5 pts]

```
#def P4():
```

In [6]:

```
#def P4():
### STUDENT START ###

import pandas as pd
from IPython.display import display, HTML
```

```
## KNN classifier ##
vectorizer = CountVectorizer(min_df=1,ngram_range=(1,1))

# build vectorizer on the corpus to ensure that complete vocab is obtain
ed across training and dev data
X = vectorizer.fit_transform(corpus_data)
X_ = X.toarray()

all_feature_names = vectorizer.get_feature_names()

# extract training data and dev data from corpus
knn_train_data = X_[0:len(train_data)]
knn_dev_data = X_[len(train_data):len(train_data)+len(dev_data)]

# Train a logistic regression model
lr = LogisticRegression(penalty='l2',C=0.1)
lr.fit(knn_train_data,train_labels)
prediction = lr.predict(knn_dev_data)
print '\nClasification report for Logistic Regression:\n\n', classificat
ion_report(dev_labels, prediction)
print "\nAccuracy is ", lr.score(knn_dev_data,dev_labels)

# print coeff for logistic regression
print "\n Weights for Logistic Regression are:", lr.coef_

# Determine the features with the top weights
# labels names: ['alt.atheism', 'comp.graphics', 'sci.space', 'talk.reli
gion.misc']
weights = lr.coef_
nzweights = np.nonzero(weights)
print "\n Number of non-zero weights:",np.size(nzweights[0])

atheism_top_idx  = np.argsort(-weights[0])[0:5]
graphics_top_idx = np.argsort(-weights[1])[0:5]
space_top_idx    = np.argsort(-weights[2])[0:5]
religion_top_idx = np.argsort(-weights[3])[0:5]

atheism_top_weights  = weights[0][atheism_top_idx]
graphics_top_weights = weights[1][graphics_top_idx]
space_top_weights    = weights[2][space_top_idx]
religion_top_weights = weights[3][religion_top_idx]

d = {'Atheism Features':np.array(all_feature_names)[atheism_top_idx],
     'Atheism Weights':atheism_top_weights,
     'Graphics Features':np.array(all_feature_names)[graphics_top_idx],
     'Graphics Weights':graphics_top_weights,
     'Space Features':np.array(all_feature_names)[space_top_idx],
     'Space Weights':space_top_weights,
     'Religion Features':np.array(all_feature_names)[religion_top_idx],
    'Religion Weights':religion_top_weights,}

print "\n Displaying top 5 features and weights for unigram features"
df = pd.DataFrame(data=d)
display(df)
HTML(df.to_html())

####################################################
```

```
## Repeating the experiment with bigram features ###
####################################################

vectorizer = CountVectorizer(ngram_range=(2,2),min_df=1)

# build vectorizer on the corpus to ensure that complete vocab is obtain
ed across training and dev data
X = vectorizer.fit_transform(corpus_data)
X_ = X.toarray()

all_feature_names = vectorizer.get_feature_names()

# extract training data and dev data from corpus
knn_train_data = X_[0:len(train_data)]
knn_dev_data = X_[len(train_data):len(train_data)+len(dev_data)]

# Train a logistic regression model
lr = LogisticRegression(penalty='l2',C=0.1)
lr.fit(knn_train_data,train_labels)
prediction = lr.predict(knn_dev_data)
print '\nClasification report for Logistic Regression:\n\n', classificat
ion_report(dev_labels, prediction)
print "\nAccuracy is ", lr.score(knn_dev_data,dev_labels)

# print coeff for logistic regression
print "\n Weights for Logistic Regression are:", lr.coef_

# Determine the features with the top weights
#labels names: ['alt.atheism', 'comp.graphics', 'sci.space', 'talk.relig
ion.misc']
weights = lr.coef_

atheism_top_idx  = np.argsort(-weights[0])[0:5]
graphics_top_idx = np.argsort(-weights[1])[0:5]
space_top_idx    = np.argsort(-weights[2])[0:5]
religion_top_idx = np.argsort(-weights[3])[0:5]

atheism_top_weights  = weights[0][atheism_top_idx]
graphics_top_weights = weights[1][graphics_top_idx]
space_top_weights    = weights[2][space_top_idx]
religion_top_weights = weights[3][religion_top_idx]

d = {'Atheism Features':np.array(all_feature_names)[atheism_top_idx],
     'Atheism Weights':atheism_top_weights,
     'Graphics Features':np.array(all_feature_names)[graphics_top_idx],
     'Graphics Weights':graphics_top_weights,
     'Space Features':np.array(all_feature_names)[space_top_idx],
     'Space Weights':space_top_weights,
     'Religion Features':np.array(all_feature_names)[religion_top_idx],
    'Religion Weights':religion_top_weights,}

print "\n Displaying top 5 features and weights for bigram features"
df = pd.DataFrame(data=d)
HTML(df.to_html())

### STUDENT END ###
#P4()
```

```
Clasification report for Logistic Regression:

             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

avg / total       0.70      0.70      0.70       676


Accuracy is  0.704142011834

 Weights for Logistic Regression are: [[ -4.9128968293718385e-02   5.18
57913520438795e-02
   -7.6554261439548219e-05 ...,   0.0000000000000000e+00
    0.0000000000000000e+00  -6.7893958159165611e-05]
 [  7.2389755077842260e-02  -3.1100970958436243e-03
   -7.7093929358544987e-03 ...,   0.0000000000000000e+00
    0.0000000000000000e+00   9.2737577838006117e-03]
 [ -2.7249442351296012e-02  -6.2691896679923795e-02
    4.3992448571519085e-03 ...,   0.0000000000000000e+00
    0.0000000000000000e+00  -5.2093569710007235e-03]
 [ -4.6540631795369040e-02  -1.6085872593150835e-02
   -3.3780270600938011e-03 ...,   0.0000000000000000e+00
    0.0000000000000000e+00  -4.4984399433542179e-05]]

 Number of non-zero weights: 107516

 Displaying top 5 features and weights for unigram features
```

	Atheism Features	Atheism Weights	Graphics Features	Graphics Weights	Religion Features	Religion Weights	Space Features	Space Weights
0	atheism	0.495559	graphics	1.007475	christian	0.547604	space	1.258785
1	religion	0.493964	image	0.642095	christians	0.499495	orbit	0.597354
2	bobby	0.478096	file	0.641223	blood	0.433870	nasa	0.540887
3	atheists	0.461570	computer	0.558994	order	0.429105	launch	0.478966
4	islam	0.426261	3d	0.546999	fbi	0.422115	moon	0.403120

```
Clasification report for Logistic Regression:

             precision    recall  f1-score   support

          0       0.65      0.53      0.58       165
          1       0.58      0.83      0.68       185
          2       0.62      0.71      0.66       199
          3       0.73      0.28      0.40       127

avg / total       0.64      0.62      0.60       676


Accuracy is  0.616863905325

 Weights for Logistic Regression are: [[  0.0000000000000000e+00  -5.89
89097168497969e-04
    0.0000000000000000e+00 ...,   0.0000000000000000e+00
   -1.6943419923746504e-03   3.6407539446827913e-07]
 [  0.0000000000000000e+00  -2.1996415804253818e-03
    0.0000000000000000e+00 ...,   0.0000000000000000e+00
    8.7342062749455364e-03  -8.8003345276467535e-09]
 [  0.0000000000000000e+00   4.3123545018046109e-03
    0.0000000000000000e+00 ...,   0.0000000000000000e+00
   -3.3529543822680150e-03   3.3181076266162656e-08]
 [  0.0000000000000000e+00  -1.4780772715871893e-03
    0.0000000000000000e+00 ...,   0.0000000000000000e+00
   -1.5071829925553189e-03   2.0221191549270440e-06]]

 Displaying top 5 features and weights for bigram features
```

Out[6]:

	Atheism Features	Atheism Weights	Graphics Features	Graphics Weights	Religion Features	Religion Weights	Space Features	Space Weights
0	cheers kent	0.314805	looking for	0.671226	cheers kent	0.329547	the moon	0.562889
1	in this	0.297924	in advance	0.525636	the fbi	0.320272	the space	0.524644
2	is not	0.296123	out there	0.463000	with you	0.273989	and such	0.370202
3	claim that	0.285118	is there	0.415801	the word	0.255377	sci space	0.367723
4	are you	0.277472	comp graphics	0.382664	jesus christ	0.245855	it was	0.328212

ANSWER:

Using bigrams shows some very interesting word pairs such as "space shuttle", "the bible" and so on. However, it also introduces some constraints to the order in which the text must match, which appears to reduce the overall accuracy of the model.

(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 (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.

[4 pts]

In [7]:
```
#def P5():
### STUDENT START ###

from sklearn.feature_extraction.text import strip_accents_unicode
import nltk
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from nltk.stem import SnowballStemmer

#nltk.download()

cachedStopWords = stopwords.words("english")
stemmer = SnowballStemmer("english")

first_time = True

# DEBUG index = 0

def custom_preprocessor(s):
    global first_time
    global cachedStopWords
    global stemmer

    # DEBUG global index
    # DEBUG index = index+1
    # DEBUG print "custom_preprocessor invocation count:",index

    p = s;

    # remove accents
    p = strip_accents_unicode(s)

    # convert to lower case
    p = p.lower()

    # replace sequences of numbers with a single token
    p = re.sub(r'[\d]+',' N_U_M ',p)

    # remove punctuations
    p = re.sub(r'[^\w\s]','',p)
    std_p = p
```

```
    # Remove stop words
    p = ' '.join([word for word in p.split() if word not in cachedStopWo
rds])
    stop_p = p

    # Perform stemming
    temp = p.split()
    p = ' '.join([stemmer.stem(w) for w in temp])
    stem_p = p

    if first_time == True:
        print "\nOriginal Text:"
        print "----------------"
        print s

        print "\nStd Preprocessing - replacing number sequences, escape
 characters, lower case and punctuations:"
        print "-----------------------------------------------------------
----------------------------------------"
        print std_p

        print "\nProcessing stop words:"
        print "------------------------"
        print stop_p

        print "\nStemming:"
        print "----------"
        print stem_p

        first_time = False

    return p

## Improved Logistic Regression Classifier)
vectorizer = CountVectorizer(min_df=1,preprocessor=custom_preprocessor)

# build vectorizer on the corpus to ensure that complete vocab is obtain
ed across training and dev data
X = vectorizer.fit_transform(corpus_data)
X_ = X.toarray()

# extract training data and dev data from corpus
knn_train_data = X_[0:len(train_data)]
knn_dev_data = X_[len(train_data):len(train_data)+len(dev_data)]

# Train a logistic regression model
lr = LogisticRegression(penalty='l2',C=0.1)
lr.fit(knn_train_data,train_labels)
prediction = lr.predict(knn_dev_data)
print '\nClasification report for Logistic Regression using a customer p
reprocessor:\n\n', classification_report(dev_labels, prediction)
print "\nAccuracy is ", lr.score(knn_dev_data,dev_labels)


### STUDENT END ###
#P5()
```

```
Original Text:
----------------
Hi,

I've noticed that if you only save a model (with all your mapping plane
s
positioned carefully) to a .3DS file that when you reload it after rest
arting
3DS, they are given a default position and orientation.  But if you sav
e
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 fi
le.
I'd like to be able to read the texture rule information, does anyone h
ave
the format for the .PRJ file?

Is the .CEL file format available from somewhere?

Rych

Std Preprocessing - replacing number sequences, escape characters, lowe
r case and punctuations:
-----------------------------------------------------------------------
--------------------------
hi

ive noticed that if you only save a model with all your mapping planes
positioned carefully to a  N_U_M ds file that when you reload it after
 restarting
 N_U_M ds they are given a default position and orientation  but if you
save
to a prj file their positionsorientation are preserved  does anyone
know why this information is not stored in the  N_U_M ds file  nothing
 is
explicitly said in the manual about saving texture rules in the prj fil
e
id like to be able to read the texture rule information does anyone hav
e
the format for the prj file

is the cel file format available from somewhere

rych

Processing stop words:
------------------------
hi ive noticed save model mapping planes positioned carefully N_U_M ds
 file reload restarting N_U_M ds given default position orientation sav
e prj file positionsorientation preserved anyone know information store
d N_U_M ds file nothing explicitly said manual saving texture rules prj
file id like able read texture rule information anyone format prj file
 cel file format available somewhere rych

Stemming:
----------
```

```
hi ive notic save model map plane posit care n_u_m ds file reload resta
rt n_u_m ds given default posit orient save prj file positionsorient pr
eserv anyon know inform store n_u_m ds file noth explicit said manual s
ave textur rule prj file id like abl read textur rule inform anyon form
at prj file cel file format avail somewher rych

Clasification report for Logistic Regression using a customer preproces
sor:

             precision    recall  f1-score   support

          0       0.67      0.58      0.62       165
          1       0.82      0.86      0.84       185
          2       0.74      0.84      0.79       199
          3       0.62      0.54      0.57       127

avg / total       0.72      0.73      0.72       676


Accuracy is  0.727810650888
```

(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).

[4 pts]

In [8]:
```
#def P6():
    ### STUDENT START ###

import numpy as np
import matplotlib.pyplot as plt

L1_features = []
first_time = True

# return only words that have non-zero weights when using L1 penalty
def custom_preprocessor(s):
    global first_time

    p = ' '.join([word for word in s.split() if word in L1_features])
```

```
    if first_time == True:
        print "\nOriginal Text:"
        print "---------------"
        print s

        print "\nKeep L1 non-zero weighted features:"
        print "-----------------------------------"
        print p

        first_time = False

    return p

    # Reduce the size of vocabulary to features that have at least one w
eight

# Keep this random seed here to make comparison easier.
np.random.seed(0)

### STUDENT START ###

# Get non-zero weights
vectorizer = CountVectorizer(min_df=1)
corpus_x = vectorizer.fit_transform(corpus_data)
all_feature_names = vectorizer.get_feature_names()

# build vectorizer on the corpus to ensure that complete vocab is obtain
ed across training and dev data
X = vectorizer.fit_transform(corpus_data)
X_ = X.toarray()

# extract training data and dev data from corpus
knn_train_data = X_[0:len(train_data)]
knn_dev_data = X_[len(train_data):len(train_data)+len(dev_data)]

# Train a logistic regression model
lr = LogisticRegression(penalty='l1',C=0.1)
lr.fit(knn_train_data,train_labels)
prediction = lr.predict(knn_dev_data)
print '\nClasification report for Logistic Regression:\n\n', classificat
ion_report(dev_labels, prediction)
print "\nAccuracy is ", lr.score(knn_dev_data,dev_labels)

# print coeff for logistic regression
print "\n Weights for Logistic Regression are:", lr.coef_

# print number of weights that are not equal to zero
weights = lr.coef_
nzweights = np.nonzero(weights)
print "\n Number of non-zero weights:",np.size(nzweights[0])

# Determine the features with the top weights
# labels names: ['alt.atheism', 'comp.graphics', 'sci.space', 'talk.reli
gion.misc']
weights = lr.coef_
```

```
atheism_nz_idx  = np.array(nzweights[1])[np.where(nzweights[0]==0)]
graphics_nz_idx = np.array(nzweights[1])[np.where(nzweights[0]==1)]
space_nz_idx    = np.array(nzweights[1])[np.where(nzweights[0]==2)]
religion_nz_idx = np.array(nzweights[1])[np.where(nzweights[0]==3)]

atheism_l1_features  =  np.array(all_feature_names)[atheism_nz_idx]
graphics_l1_features =  np.array(all_feature_names)[graphics_nz_idx]
space_l1_features    =  np.array(all_feature_names)[space_nz_idx]
religion_l1_features =  np.array(all_feature_names)[religion_nz_idx]

L1_features = np.append(atheism_l1_features,atheism_l1_features,axis=0)
L1_features = np.append(L1_features,graphics_l1_features,axis=0)
L1_features = np.append(L1_features,space_l1_features,axis=0)
L1_features = np.append(L1_features,religion_l1_features,axis=0)

print "\nAll non-zero L1 features:\n", L1_features

# redo with non-zero L1 weighted features

vectorizer = CountVectorizer(min_df=1,preprocessor=custom_preprocessor)
corpus_x = vectorizer.fit_transform(corpus_data)
all_feature_names = vectorizer.get_feature_names()

# build vectorizer on the corpus to ensure that complete vocab is obtain
ed across training and dev data
X = vectorizer.fit_transform(corpus_data)
X_ = X.toarray()

# extract training data and dev data from corpus
knn_train_data = X_[0:len(train_data)]
knn_dev_data = X_[len(train_data):len(train_data)+len(dev_data)]

# Train a logistic regression model
lr = LogisticRegression(penalty='l2',C=0.1)
lr.fit(knn_train_data,train_labels)
prediction = lr.predict(knn_dev_data)
print '\nClasification report for Logistic Regression:\n\n', classificat
ion_report(dev_labels, prediction)
print "\nAccuracy is ", lr.score(knn_dev_data,dev_labels)

# Plotting accuracy for different values of C (regularization parameter)
## LOGISTIC REGRESSION MODEL ##
c_values = [0.001, 0.01, 0.1, 1, 10, 100, 1000]
accuracy = []
for c_value in c_values:
    # Train a logistic regression model
    lr = LogisticRegression(penalty='l2',C=c_value,tol=0.0001)
    lr.fit(knn_train_data,train_labels)
    accuracy.append(lr.score(knn_dev_data,dev_labels))

# plot accuracy vs C-value
f, (ax1, ax2) = plt.subplots(1, 2, sharey=True)

plt.title('L2 Logistic Regression using l1-reduced feature-set (C & Log-
C) \n',loc='right')

ax1.plot(c_values,accuracy)
```

```python
ax1.set_xlabel('C')
ax1.set_ylabel('Accuracy')

ax2.set_xlabel('Log(C)')
ax2.set_ylabel('Accuracy')
ax2.plot(np.log(c_values),accuracy)

plt.show()

### STUDENT END ###

#P7()
```

```
Clasification report for Logistic Regression:

             precision    recall  f1-score   support

          0       0.58      0.50      0.54       165
          1       0.66      0.85      0.74       185
          2       0.70      0.72      0.71       199
          3       0.56      0.39      0.46       127

avg / total       0.63      0.64      0.63       676


Accuracy is  0.64201183432

 Weights for Logistic Regression are: [[ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]
 [ 0.  0.  0. ...,  0.  0.  0.]]

 Number of non-zero weights: 357

All non-zero L1 features:
[u'10' u'all' u'also' u'am' u'an' u'and' u'argument' u'atheism' u'athei
sts'
 u'be' u'been' u'being' u'bobby' u'but' u'can' u'christ' u'christian'
 u'christians' u'claim' u'could' u'data' u'did' u'does' u'don'
 u'enviroleague' u'evidence' u'exist' u'file' u'files' u'for' u'from'
 u'god' u'graphics' u'have' u'him' u'hudson' u'if' u'image' u'in' u'is'
 u'islam' u'islamic' u'isn' u'it' u'jesus' u'just' u'like' u'makes'
 u'matthew' u'may' u'me' u'moon' u'must' u'my' u'nasa' u'no' u'not'
 u'objective' u'of' u'on' u'one' u'order' u'our' u'out' u'people' u'ple
ase'
 u'program' u'punishment' u'religion' u'religious' u'said' u'satan' u's
ay'
 u'seems' u'she' u'so' u'software' u'some' u'space' u'species' u'syste
m'
 u'tek' u'text' u'thanks' u'that' u'the' u'their' u'there' u'think' u't
his'
 u'time' u'to' u'use' u'using' u'vice' u'want' u'war' u'was' u'we' u'we
ll'
 u'what' u'where' u'with' u'would' u'you' u'your' u'10' u'all' u'also'
 u'am' u'an' u'and' u'argument' u'atheism' u'atheists' u'be' u'been'
 u'being' u'bobby' u'but' u'can' u'christ' u'christian' u'christians'
 u'claim' u'could' u'data' u'did' u'does' u'don' u'enviroleague'
 u'evidence' u'exist' u'file' u'files' u'for' u'from' u'god' u'graphic
s'
 u'have' u'him' u'hudson' u'if' u'image' u'in' u'is' u'islam' u'islami
c'
 u'isn' u'it' u'jesus' u'just' u'like' u'makes' u'matthew' u'may' u'me'
 u'moon' u'must' u'my' u'nasa' u'no' u'not' u'objective' u'of' u'on'
 u'one'
 u'order' u'our' u'out' u'people' u'please' u'program' u'punishment'
 u'religion' u'religious' u'said' u'satan' u'say' u'seems' u'she' u'so'
 u'software' u'some' u'space' u'species' u'system' u'tek' u'text' u'tha
nks'
 u'that' u'the' u'their' u'there' u'think' u'this' u'time' u'to' u'use'
 u'using' u'vice' u'want' u'war' u'was' u'we' u'well' u'what' u'where'
```

u'with' u'would' u'you' u'your' u'256' u'3d' u'am' u'an' u'any' u'anyo
ne'
u'are' u'as' u'atheism' u'be' u'but' u'can' u'card' u'code' u'color'
u'computer' u'does' u'earth' u'edge' u'email' u'file' u'files' u'find'
u'for' u'format' u'ftp' u'god' u'graphics' u'have' u'he' u'hi' u'his'
u'image' u'images' u'in' u'is' u'it' u'line' u'looking' u'need' u'no'
u'not' u'number' u'of' u'on' u'orbit' u'people' u'point' u'points'
u'polygon' u'problem' u'program' u'religion' u'screen' u'software'
u'space' u'sphere' u'thanks' u'that' u'the' u'there' u'they' u'tiff'
u'to'
u'us' u'use' u'using' u've' u'version' u'vga' u'video' u'were' u'who'
u'windows' u'with' u'you' u'your' u'all' u'and' u'any' u'are' u'at'
u'be'
u'by' u'centaur' u'christian' u'color' u'computer' u'cost' u'dc' u'doe
s'
u'down' u'earth' u'file' u'files' u'find' u'flight' u'for' u'get' u'go
d'
u'graphics' u'he' u'high' u'idea' u'image' u'in' u'is' u'it' u'jesus'
u'just' u'know' u'large' u'launch' u'like' u'long' u'me' u'moon' u'mor
e'
u'my' u'nasa' u'nick' u'not' u'objective' u'of' u'off' u'on' u'orbit'
u'out' u'points' u'power' u'prize' u'process' u'project' u'religion'
u'remember' u'rocket' u'rockets' u'said' u'shuttle' u'so' u'software'
u'solar' u'space' u'spacecraft' u'that' u'the' u'they' u'things' u'to'
u'van' u've' u'was' u'what' u'who' u'with' u'would' u'year' u'your'
u'abortion' u'agree' u'and' u'any' u'anyone' u'as' u'at' u'atheism'
u'atheists' u'be' u'blood' u'brian' u'but' u'by' u'can' u'children'
u'christ' u'christian' u'christians' u'computer' u'context' u'could'
u'deleted' u'did' u'does' u'edu' u'evidence' u'fbi' u'file' u'files'
u'fire' u'for' u'god' u'good' u'graphics' u'hare' u'has' u'have' u'he'
u'his' u'homosexuality' u'hudson' u'if' u'image' u'in' u'islam' u'it'
u'jesus' u'jim' u'kent' u'koresh' u'life' u'man' u'matthew' u'may' u'm
e'
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e'
u'of' u'on' u'one' u'or' u'order' u'out' u'problem' u'program' u'softw
are'
u'some' u'space' u'system' u'thanks' u'that' u'the' u'time' u'truth'
u'tyre' u'values' u'was' u'were' u'who' u'will' u'with' u'word' u'woul
d'
u'you' u'your']

Original Text:

Hi,

I've noticed that if you only save a model (with all your mapping plane
s
positioned carefully) to a .3DS file that when you reload it after rest
arting
3DS, they are given a default position and orientation. But if you sav
e
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 fi
le.
I'd like to be able to read the texture rule information, does anyone h

ave
the format for the .PRJ file?

Is the .CEL file format available from somewhere?

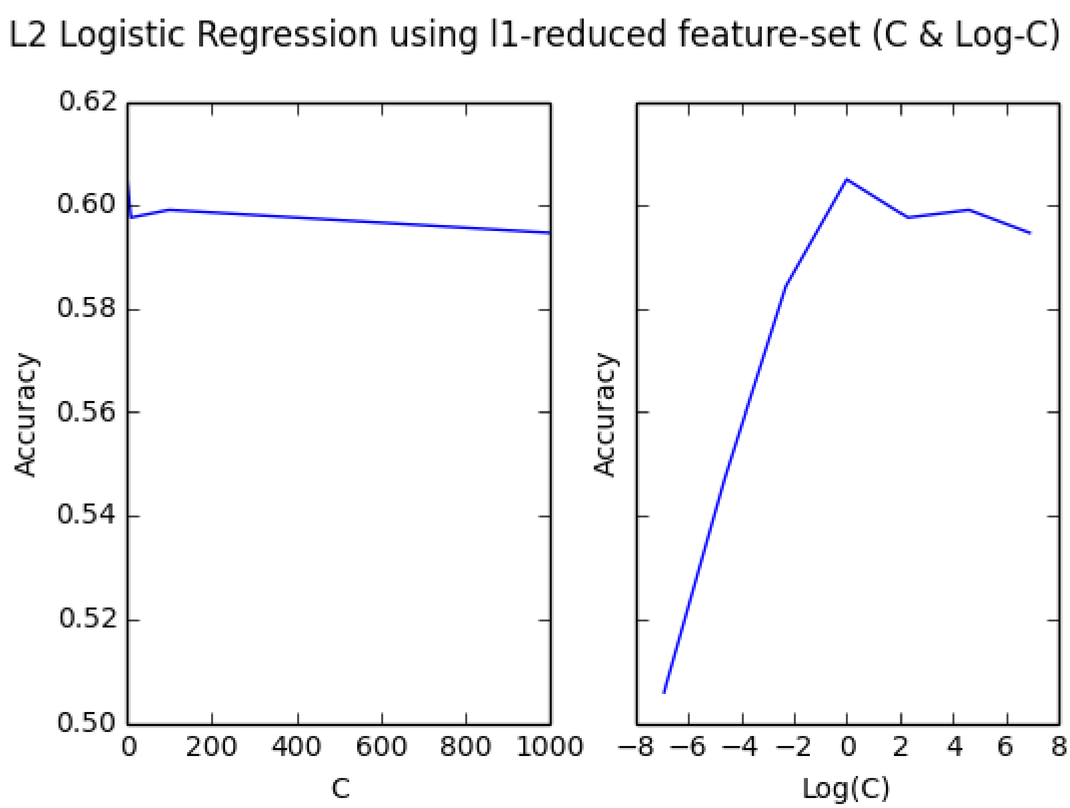
Rych

Keep L1 non-zero weighted features:
----
that if you all your to file that you it they are and if you to file their are anyone know this is not in the is said in the in the like to be to the does anyone have the format for the the file format from

Clasification report for Logistic Regression:

	precision	recall	f1-score	support
0	0.57	0.48	0.52	165
1	0.62	0.76	0.68	185
2	0.60	0.69	0.64	199
3	0.47	0.30	0.37	127
avg / total	0.57	0.58	0.57	676

Accuracy is 0.584319526627



(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.

[4 pts]

In [9]:
```
#def P7():
    ### STUDENT START ###

from sklearn.feature_extraction.text import TfidfVectorizer
import pandas as pd

vectorizer = TfidfVectorizer(min_df=1)

# build vectorizer on the corpus to ensure that complete vocab is obtain
ed across training and dev data
X = vectorizer.fit_transform(corpus_data)
X_ = X.toarray()

# extract training data and dev data from corpus
knn_train_data = X_[0:len(train_data)]
knn_dev_data = X_[len(train_data):len(train_data)+len(dev_data)]

# Train a logistic regression model
lr = LogisticRegression(penalty='l2',C=100)
lr.fit(knn_train_data,train_labels)
prediction = lr.predict(knn_dev_data)
prediction_probs = lr.predict_proba(knn_dev_data)
print '\nClasification report for Logistic Regression:\n\n', classificat
ion_report(dev_labels, prediction)

score =  lr.score(knn_dev_data,dev_labels)
print "\nAccuracy is ", score

# Computing R ratio
r_ratio = np.zeros(shape=(676,4))
for i in range(0,len(dev_labels)):
#for i in range(0,3):
    correct_label_idx   = dev_labels[i]
    predicted_label_idx = np.argmax(prediction_probs[i])

    # set the dev_label index and the ratio
    r_ratio[i,0] = i
    r_ratio[i,1] = correct_label_idx
    r_ratio[i,2] = predicted_label_idx
    r_ratio[i,3] = prediction_probs[i,predicted_label_idx]/prediction_pr
obs[i,correct_label_idx]

# Sort by R ratio
r_ratio_pd = pd.DataFrame(r_ratio).sort_values([3,2,1,0],ascending=[Fals
```

```
e,False,False,False])
r_ratio_pd.columns = ('Test Data Index','Correct Label','Predicted Labe
l','Predicted Probability')
print r_ratio_pd[0:3]

# print the top 3 documents
for  i in range(0,3):
    print "\n"
    label_idx = r_ratio_pd.as_matrix()[i,1]

    #print "Correct Label:", r_ratio_pd.as_matrix()[i,2]
    #print "Predicted Label:", r_ratio_pd.as_matrix()[i,2]
    print "Correct Label Name:", newsgroups_train.target_names[int(r_rat
io_pd.as_matrix()[i,1])]
    print "Predicted Label Name:", newsgroups_train.target_names[int(r_r
atio_pd.as_matrix()[i,2])]
    print "R ratio:", r_ratio_pd.as_matrix()[i,3]
    print "Document:\n",dev_data[int(r_ratio_pd.as_matrix()[i,0])]

    ### STUDENT END ###
#P7()
```

```
Clasification report for Logistic Regression:

             precision    recall  f1-score   support

          0       0.70      0.61      0.65       165
          1       0.80      0.90      0.85       185
          2       0.82      0.83      0.83       199
          3       0.68      0.65      0.66       127

avg / total       0.76      0.76      0.76       676


Accuracy is  0.761834319527
     Test Data Index  Correct Label  Predicted Label  Predicted Probabi
lity
215            215.0            3.0              1.0               545.99
0141
665            665.0            3.0              1.0               333.59
4775
655            655.0            3.0              0.0               180.64
3952


Correct Label Name: talk.religion.misc
Predicted Label Name: comp.graphics
R ratio: 545.990140828
Document:
I am pleased to announce that a *revised version* of _The Easy-to-Read
 Book
of Mormon_ (former title: _Mormon's Book_) by Lynn Matthews Anderson is
now
available through anonymous ftp (see information below). In addition to
the
change in title, the revised ETR BOM has been shortened by several page
s
(eliminating many extraneous "that's" and "of's"), and many (minor) err
ors
have been corrected. This release includes a simplified Joseph Smith St
ory,
testimonies of the three and eight witnesses, and a "Words-to-Know"
glossary.

As with the previous announcement, readers are reminded that this is a
not-for-profit endeavor. This is a copyrighted work, but people are wel
come
to make *verbatim* copies for personal use. People can recuperate the
actual costs of printing (paper, copy center charges), but may not char
ge
anything for their time in making copies, or in any way realize a profi
t
from the use of this book. See the permissions notice in the book itsel
f
for the precise terms.

Negotiations are currently underway with a Mormon publisher vis-a-vis t
he
printing and distribution of bound books. (Sorry, I'm out of the wire-b
```

ound
"first editions.") I will make another announcement about the availabil
ity
of printed copies once everything has been worked out.

FTP information: connect via anonymous ftp to carnot.itc.cmu.edu, then
 "cd
pub" (you won't see anything at all until you do).

"The Easy-to-Read Book of Mormon" is currently available in postscript
 and
RTF (rich text format). (ASCII, LaTeX, and other versions can be made
available; contact dba@andrew.cmu.edu for details.) You should be able
 to
print the postscript file on any postscript printer (such as an Apple
Laserwriter); let dba know if you have any difficulties. (The postscrip
t in
the last release had problems on some printers; this time it should wor
k
better.) RTF is a standard document interchange format that can be read
in
by a number of word processors, including Microsoft Word for both the
Macintosh and Windows. If you don't have a postscript printer, you may
 be
able to use the RTF file to print out a copy of the book.

```
-r--r--r--  1 dba                   1984742 Apr 27 13:12 etrbom.ps
-r--r--r--  1 dba                   1209071 Apr 27 13:13 etrbom.rtf
```

For more information about how this project came about, please refer to
my
article in the current issue of _Sunstone_, entitled "Delighting in
Plainness: Issues Surrounding a Simple Modern English Book of Mormon."

Send all inquiries and comments to:

    Lynn Matthews Anderson
    5806 Hampton Street
    Pittsburgh, PA 15206

Correct Label Name: talk.religion.misc
Predicted Label Name: comp.graphics
R ratio: 333.594774704
Document:
Can anyone provide me a ftp site where I can obtain a online version
of the Book of Mormon. Please email the internet address if possible.

Correct Label Name: talk.religion.misc
Predicted Label Name: alt.atheism
R ratio: 180.643951701
Document:
In <1ren9a$94q@morrow.stanford.edu> salem@pangea.Stanford.EDU (Bruce Sa
lem)