Text Classification Using Naive Bayes

Introduction

In this workbook, we are using Naive Bayes to classify news group documents into one of 20 newsgroups. Data is from the 20 Newsgroups data set, which is downloaded from http://qwone.com/~jason/20Newsgroups/ (http://qwone.com/~jason/20Newsgroups/).

Multinomial Naive Bayes text classification is done initially using scikit-learn, and then by performing calculations manually. The error rate in both cases is similar, at approximately 22% on the test data.

This workbook includes the following sections:

- Introduction
- Download and Read Data
- Create Naive Bayes Classifier (using scikit-learn)
  - Create Word Frequency Matrix
  - Build Classifier from Training Data
  - Evaluate Performance on Test Data
  - Visualizing Error by Plotting Confusion Matrix
- Manual Naive Bayes

Note that code for plotting confusion matrices was modified from example code found at http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html (http://scikit-learn.org/stable/auto_examples/model_selection/plot_confusion_matrix.html).

Download and Read Data

In [1]:
```
!pwd
```

```
/Users/joshwilson/Documents/DSE/jsw037/DSE210/NB
```

In [2]:
```
# create and move to 'data' directory
!mkdir 'data'
%cd data
```

```
/Users/joshwilson/Documents/DSE/jsw037/DSE210/NB/data
```

In [3]:
```
# get the '20news-bydate.tar.gz' data
!curl http://qwone.com/~jason/20Newsgroups/20news-bydate.tar.gz -o '20
news-bydate.tar.gz'
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Ti
me  Current
                                 Dload  Upload   Total   Spent    Le
ft  Speed
100 13.7M  100 13.7M    0     0  1959k      0  0:00:07  0:00:07 --:-
-:-- 2422k
```

In [4]:
```
# uncompress the '20news-bydate.tar.gz' data
!tar zxf 20news-bydate.tar.gz
```

In [5]:
```
# get the '20news-bydate-matlab.tgz' data
!curl http://qwone.com/~jason/20Newsgroups/20news-bydate-matlab.tgz -o
'20news-bydate-matlab.tgz'
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Ti
me  Current
                                 Dload  Upload   Total   Spent    Le
ft  Speed
100 7398k  100 7398k    0     0  1822k      0  0:00:04  0:00:04 --:-
-:-- 1823k
```

In [6]:
```
# uncompress the '20news-bydate-matlab.tgz' data
!tar zxf 20news-bydate-matlab.tgz
```

In [7]:
```
# download vocabulary file
!curl http://qwone.com/~jason/20Newsgroups/vocabulary.txt -o 'vocabula
ry.txt'
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Ti
me  Current
                                 Dload  Upload   Total   Spent    Le
ft  Speed
100  482k  100  482k    0     0   605k      0 --:--:-- --:--:-- --:-
-:--  606k
```

In [8]:
```
# import packages
import pandas as pd
import numpy as np
from sklearn import naive_bayes as nb
```

In [9]:
```
# read in relevant training files
train_data = pd.read_table('20news-bydate/matlab/train.data', sep = '
',
                          header = None, names = ['docIdx', 'wordIdx',
'count'])
train_label = pd.read_table('20news-bydate/matlab/train.label', sep =
' ',
                          header = None, names = ['label_id'])
train_map = pd.read_table('20news-bydate/matlab/train.map', sep = ' ',
                          header = None, names = ['label_name', 'label
_id'])
```

In [10]:
```
train_data.head()
```

Out[10]:

	docIdx	wordIdx	count
0	1	1	4
1	1	2	2
2	1	3	10
3	1	4	4
4	1	5	2

In [11]:
```
# read in relevant test files
test_data = pd.read_table('20news-bydate/matlab/test.data', sep = ' ',
                          header = None, names = ['docIdx', 'wordIdx',
'count'])
test_label = pd.read_table('20news-bydate/matlab/test.label', sep = '
',
                          header = None, names = ['label_id'])
test_map = pd.read_table('20news-bydate/matlab/test.map', sep = ' ',
                          header = None, names = ['label_name', 'label
_id'])
```

In [12]:
```
test_data.head()
```

Out[12]:

	docIdx	wordIdx	count
0	1	3	1
1	1	10	1
2	1	12	8
3	1	17	1
4	1	23	8

In [13]:
```
# read in vocabulary.txt
vocabulary = pd.read_table('vocabulary.txt', header = None, names = ['
word'])
```

In [14]:
```
vocabulary.head()
```

Out[14]:

	word
0	archive
1	name
2	atheism
3	resources
4	alt

Create Naive Bayes Classifier

Create Word Frequency Matrix

In [15]:
```
# create empty train_data_matrix
train_data_matrix = np.zeros((len(train_data['docIdx'].unique()),
                              len(vocabulary['word'])))
print "train_data_matrix shape : ", train_data_matrix.shape
```

```
train_data_matrix shape :  (11269, 61188)
```

In [16]:
```
# from train_data, pull row and column indices, and associated values
from train_data
rows = np.array(train_data['docIdx'])-1
cols = np.array(train_data['wordIdx'])-1
vals = np.array(train_data['count'])
```

In [17]:
```
# populate train_data_matrix
for i in range(len(rows)):
    train_data_matrix[rows[i], cols[i]] = vals[i]
```

In [18]:
```
train_data_matrix
```

Out[18]:
```
array([[  4.,   2.,  10., ...,   0.,   0.,   0.],
       [  0.,   0.,   0., ...,   0.,   0.,   0.],
       [  0.,   0.,   0., ...,   0.,   0.,   0.],
       ...,
       [  0.,   0.,   0., ...,   0.,   0.,   0.],
       [  0.,   0.,   0., ...,   0.,   0.,   0.],
       [  0.,   0.,   0., ...,   0.,   0.,   0.]])
```

In [19]:
```
# set the target values equal to the correct label_ids from train_labe
l
train_data_target = np.array(train_label['label_id'])
print train_data_target.shape
train_data_target
```

```
(11269,)
```

Out[19]:
```
array([ 1,  1,  1, ..., 20, 20, 20])
```

Build Classifier from Training Data

In [20]:
```
mnb = nb.MultinomialNB()
mnb_fit = mnb.fit(train_data_matrix, train_data_target)
mnb_pred = mnb_fit.predict(train_data_matrix)
```

In [21]:
```
mnb_pred
```

Out[21]:
```
array([ 1,  1, 11, ..., 20, 20, 17])
```

In [22]:
```
train_data_target
```

Out[22]:
```
array([ 1,  1,  1, ..., 20, 20, 20])
```

In [23]:
```
print("Number of mislabeled points out of a total %d points : %d"
      % (train_data_matrix.shape[0], (train_data_target != mnb_pred).s
um()))

print("Training data error rate : %.4f"
      % (float((train_data_target != mnb_pred).sum()) / float(train_da
ta_matrix.shape[0])))
```

```
Number of mislabeled points out of a total 11269 points : 664
Training data error rate : 0.0589
```

Evaluate Performance on Test Data

In [24]:
```
# create empty train_data_matrix
test_data_matrix = np.zeros((len(test_data['docIdx'].unique()),
                            len(vocabulary['word'])))
print "test_data_matrix shape : ", test_data_matrix.shape
```

```
test_data_matrix shape :  (7505, 61188)
```

In [25]:
```
# from test_data, pull row and column indices, and associated values f
rom test_data
rows = np.array(test_data['docIdx'])-1
cols = np.array(test_data['wordIdx'])-1
vals = np.array(test_data['count'])
```

In [26]:
```
# populate test_data_matrix
for i in range(len(rows)):
    test_data_matrix[rows[i], cols[i]] = vals[i]
```

In [27]:
```
test_data_matrix
```

Out[27]:
```
array([[ 0.,  0.,  1., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       ...,
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  0.],
       [ 0.,  0.,  0., ...,  0.,  0.,  2.]])
```

In [28]:
```
# set the target values equal to the correct label_ids from test_label
test_data_target = np.array(test_label['label_id'])
print test_data_target.shape
test_data_target
```

```
(7505,)
```

Out[28]:
```
array([ 1,  1,  1, ..., 20, 20, 20])
```

In [29]:
```
# make predictions on test data
mnb_pred_test = mnb_fit.predict(test_data_matrix)
```

In [30]:
```
mnb_pred_test
```

Out[30]:
```
array([ 1,  1,  1, ...,  1, 16,  2])
```

In [31]:
```
print("Number of mislabeled points out of a total %d points : %d"
      % (test_data_matrix.shape[0], (test_data_target != mnb_pred_test
).sum()))

print("Test data error rate : %.4f"
      % (float((test_data_target != mnb_pred_test).sum()) / float(test
_data_matrix.shape[0])))
```

```
Number of mislabeled points out of a total 7505 points : 1643
Test data error rate : 0.2189
```

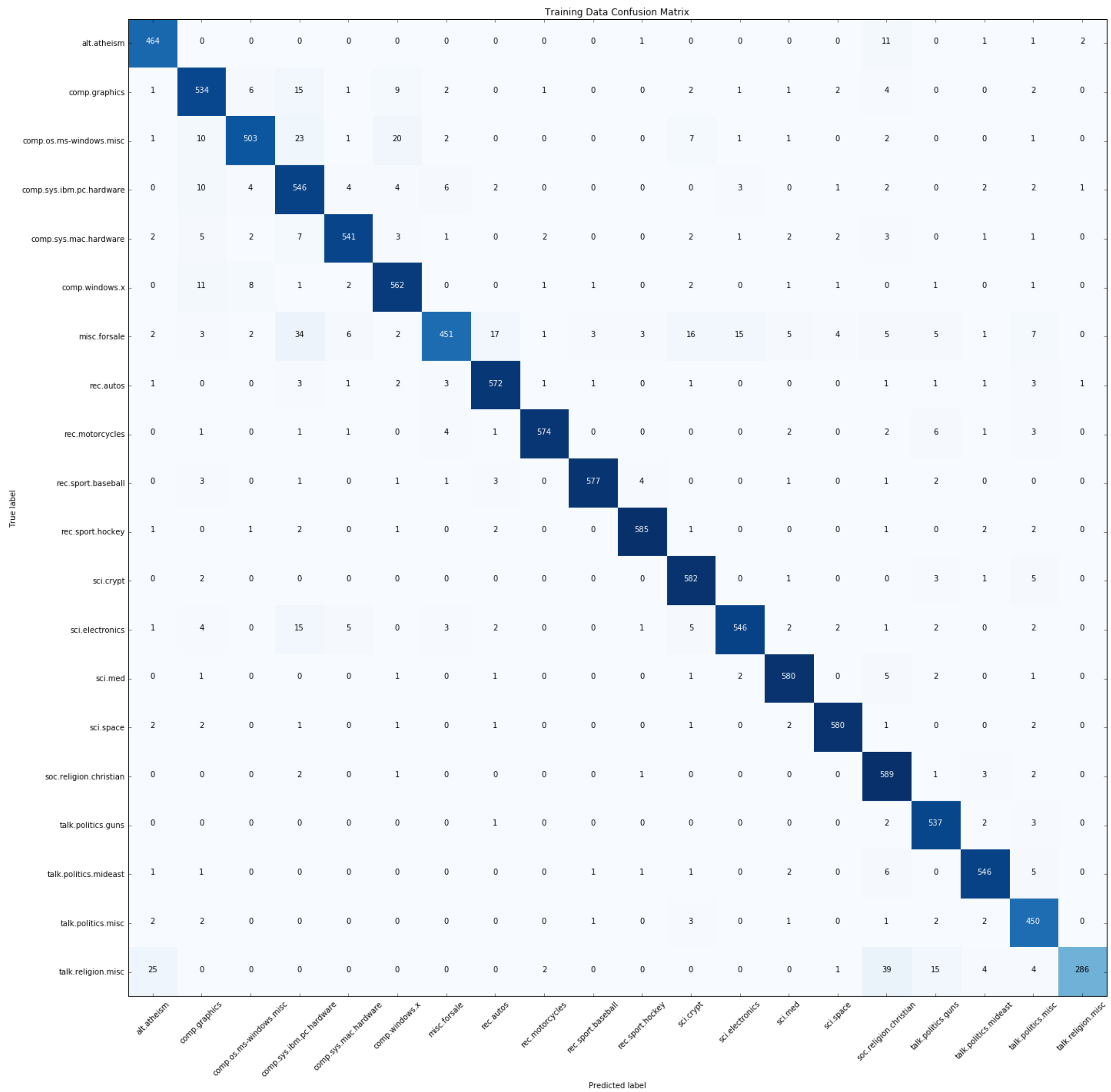
Visualizing Error by Plotting Confusion Matrix

In [32]:
```
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import itertools
```

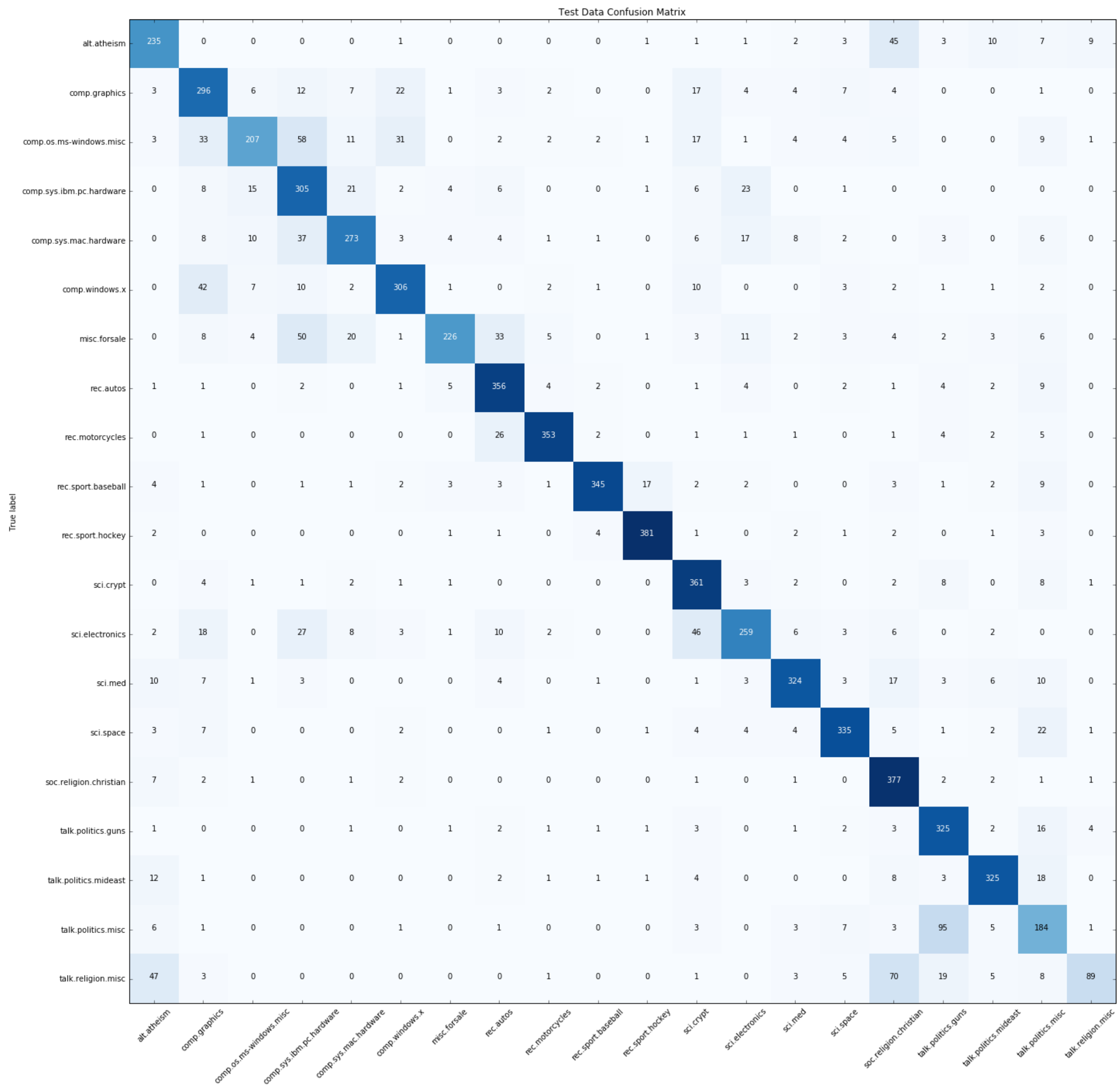
In [33]:
```
%matplotlib inline
```

In [34]:
```
# plot_confusion_matrix code from
# http://scikit-learn.org/stable/auto_examples/model_selection/plot_co
nfusion_matrix.html

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    #plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        #print("Normalized confusion matrix")
    else:
        pass
        #print('Confusion matrix, without normalization')

    #print(cm)

    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1
])):
        plt.text(j, i, cm[i, j],
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [35]:
```
class_names_train = train_map['label_name'].values

# Compute confusion matrix
cnf_matrix_train = confusion_matrix(train_data_target, mnb_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure(figsize = (20,20))
plot_confusion_matrix(cnf_matrix_train, classes=class_names_train,
                      title='Training Data Confusion Matrix')

plt.show();
```



In [36]:
```
class_names_test = test_map['label_name'].values

# Compute confusion matrix
cnf_matrix_test = confusion_matrix(test_data_target, mnb_pred_test)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure(figsize = (20,20))
plot_confusion_matrix(cnf_matrix_test, classes=class_names_test,
                      title='Test Data Confusion Matrix')

plt.show();
```



Manual Naive Bayes

In this section, we perform Multinomial Naive Bayes calculation manually, resulting in accuracy results very similar to those obtained using Multinomial Naive Bayes from scikit-learn.

In [37]:

```
# add label_ids to train_data
label_ids = pd.DataFrame(train_label.iloc[train_data['docIdx']-1]['lab
el_id'])
if 'label_id' not in train_data.columns:
    train_data.insert(len(train_data.columns), 'label_id', label_ids.v
alues)

train_data.head()
```

Out[37]:

	docIdx	wordIdx	count	label_id
0	1	1	4	1
1	1	2	2	1
2	1	3	10	1
3	1	4	4	1
4	1	5	2	1

In [38]:
```
# calculate fraction of documents that belong to each class in the tra
ining data set
classes = train_data['label_id'].unique()

# get label_id values
label_ids = np.array(train_data['label_id'].values)

# determine counts by label_id
values, counts = np.unique(label_ids, return_counts=True)

# calculate fraction of each count
class_probability = 1.0 * counts / sum(counts)

print 'class_probability:\n', class_probability

print '\nCheck that sum of all probabilities add to one:\n', sum(class
_probability)
```

```
class_probability:
[ 0.05  0.04  0.04  0.04  0.04  0.05  0.03  0.05  0.05  0.04  0.05
0.07
  0.04  0.06  0.06  0.07  0.06  0.08  0.06  0.04]

Check that sum of all probabilities add to one:
1.0
```

In [39]:
```
# group training data by label_id and wordIdx to determine total occur
rences of each word by class
train_data_grouped = train_data.groupby(['label_id','wordIdx'], as_ind
ex=False).sum()
del train_data_grouped['docIdx']
train_data_grouped.head()
```

Out[39]:

	label_id	wordIdx	count
0	1	1	13
1	1	2	63
2	1	3	275
3	1	4	9
4	1	5	82

In [40]:
```
# populate train_word_counts matrix
train_word_counts = np.zeros((len(classes), len(vocabulary.index)))

rows = np.array(train_data_grouped['label_id'].values - 1)
cols = np.array(train_data_grouped['wordIdx'].values - 1)
counts = np.array(train_data_grouped['count'].values)

for i in range(len(rows)):
    train_word_counts[rows[i], cols[i]] = counts[i]

# add 1 smoothing
train_word_counts += 1

print 'train_word_counts shape:\n', train_word_counts.shape
print '\ntrain_word_counts:\n', train_word_counts
```

```
train_word_counts shape:
(20, 61188)

train_word_counts:
[[  14.   64.  276. ...,    1.    1.    1.]
 [  61.   60.    1. ...,    1.    1.    1.]
 [  12.   70.    1. ...,    1.    1.    1.]
 ...,
 [  11.  155.    1. ...,    1.    1.    1.]
 [   1.   40.    1. ...,    1.    1.    1.]
 [   1.   46.   10. ...,    1.    1.    1.]]
```

In [41]:

```
# calculate probability distribution of each word for each class
train_word_dist = (train_word_counts.T / train_word_counts.sum(axis=1)
).T

print 'train_word_dist shape:\n', train_word_dist.shape
print '\ntrain_word_dist:\n', train_word_dist
print '\n Check that all row sums are 1:\n', np.apply_along_axis(sum,
1, train_word_dist)
```

```
train_word_dist shape:
(20, 61188)

train_word_dist:
[[  6.67e-05   3.05e-04   1.31e-03 ...,   4.76e-06   4.76e-06   4.76
e-06]
 [  3.56e-04   3.50e-04   5.83e-06 ...,   5.83e-06   5.83e-06   5.83
e-06]
 [  7.90e-05   4.61e-04   6.58e-06 ...,   6.58e-06   6.58e-06   6.58
e-06]
 ...,
 [  3.48e-05   4.91e-04   3.16e-06 ...,   3.16e-06   3.16e-06   3.16
e-06]
 [  4.04e-06   1.62e-04   4.04e-06 ...,   4.04e-06   4.04e-06   4.04
e-06]
 [  5.55e-06   2.55e-04   5.55e-05 ...,   5.55e-06   5.55e-06   5.55
e-06]]

 Check that all row sums are 1:
[ 1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.  1.
1.
  1.  1.]
```

In [42]:
```
# calculate log of posterior probabilities
log_class = np.log(class_probability)
log_probs = np.log(train_word_dist)
scores = log_class + np.dot(test_data_matrix, log_probs.T)
print 'log of posterior probability results shape:\n', scores.shape
print '\nlog of test data posterior probability results for each class
:\n', scores
```

```
log of posterior probability results shape:
(7505, 20)

log of test data posterior probability results for each class:
[[-2004.3  -2229.87 -2252.07 ..., -2146.76 -2116.18 -2078.95]
 [ -512.91  -586.9   -588.46 ...,  -547.43  -555.46  -541.86]
 [-2310.65 -2553.51 -2567.44 ..., -2453.86 -2439.48 -2439.93]
 ...,
 [ -810.16  -867.09  -871.81 ...,  -868.1   -852.14  -846.51]
 [-1204.76 -1277.19 -1287.52 ..., -1217.57 -1214.   -1193.91]
 [-3153.09 -3047.67 -3119.64 ..., -3186.16 -3162.43 -3158.7 ]]
```

In [43]:
```
# make class prediction from scores
predictions = np.argmax(scores, axis=1) + 1
print 'class predictions for test data:\n', predictions
print '\nclass prediction counts:\n', np.unique(predictions, return_co
unts=True)[1]
```

```
class predictions for test data:
[ 1  1  1 ...,  1 16  2]

class prediction counts:
[335 440 248 505 342 382 242 456 377 357 406 494 327 368 381 561 475
376
 326 107]
```

In [44]:
```
print("Number of mislabeled points out of a total %d points : %d"
      % (test_data_matrix.shape[0], (test_data_target != predictions).
sum()))

print("Test data error rate : %.4f"
      % (float((test_data_target != predictions).sum()) / float(test_d
ata_matrix.shape[0])))
```

```
Number of mislabeled points out of a total 7505 points : 1657
Test data error rate : 0.2208
```

In [45]:
```
# Compute confusion matrix
cnf_matrix_test_man = confusion_matrix(test_data_target, predictions)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure(figsize = (20,20))
plot_confusion_matrix(cnf_matrix_test_man, classes=class_names_test,
                      title='Test Data Confusion Matrix')

plt.show();
```