CS 3300 Data Science - Lab 6: Exploratory Data Analysis with Clustering

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Introduction

In this lab we are continuing our exploration of our json emails. As in the last lab, we perform dimensionality reduction using the Truncated SVD method. Then we cluster the data use a clustering approach, I used DBSCAN. We cluster the emails into two distinct clusters using DBSCAN and then perform some analysis on the resulting clusters. Part of this analysis is to determine significantly significant words contained in the clusters.

Importing Libraries

In [1]:
```
import glob
import json
import numpy as np
import pandas as pd
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import TruncatedSVD
from sklearn.cluster import DBSCAN
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import itertools
from scipy.sparse import csc_matrix
from scipy import stats
```

Part I: Loading and Transforming the data

Loading in email json files and putting the data into a pandas dataframe.

In [2]:
```
files = glob.glob('email_json/*', recursive=True)
email_list = []
for file in files:
    with open(file) as file:
        email_list.append(json.load(file))
df = pd.DataFrame.from_records(email_list)
df['category'] = df['category'].astype('category')
```

In [3]:
```python
df.head()
```

Out[3]:

	body	category	from_address	subject	
0	\n\n\n\n\n\n\nDo you feel the pressure to perf...	spam	"Tomas Jacobs" <RickyAmes@aol.com>	Generic Cialis, branded quality@	the00@speed
1	Hi, i've just updated from the gulus and I che...	ham	Yan Morin <yan.morin@savoirfairelinux.com>	Typo in /debian/README	mirrors@
2	authentic viagra\n\nMega authenticV I A G R A...	spam	"Sheila Crenshaw" <7stocknews@tractionmarketin...	authentic viagra	<the00@plg
3	\nHey Billy, \n\nit was really fun going out t...	spam	"Stormy Dempsey" <vqucsmdfgvsg@ruraltek.com>	Nice talking with ya	opt4@speed
4	\n\n\n\n\n\n\nsystem" of the home. It will ha...	spam	"Christi T. Jernigan" <dcube@totalink.net>	or trembling; stomach cramps; trouble in sleep...	ktwarwic@speed

In [4]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 63542 entries, 0 to 63541
Data columns (total 5 columns):
body            63542 non-null object
category        63542 non-null category
from_address    63542 non-null object
subject         63410 non-null object
to_address      63141 non-null object
dtypes: category(1), object(4)
memory usage: 2.0+ MB
```

Using a count vectorizer to put the word counts into a sparse matrix. We us a binary=true option that makes this matrix only keep track of whether or not the word is in an email instead of the actual counts. We also specify min_df=10 to exclude any words that do not appear in at least 10 emails.

In [5]:
```python
vectorizer = CountVectorizer(binary=True, min_df=10)
word_matrix = vectorizer.fit_transform(df['body'])
word_matrix
```

Out[5]:
```
<63542x32144 sparse matrix of type '<class 'numpy.int64'>'
        with 6388795 stored elements in Compressed Sparse Row format>
```

Transforming the feature matrix into a SVD projection matrix with 10 columns.

In [6]:
```
svd = TruncatedSVD(n_components=10)
svd_matrix = svd.fit_transform(word_matrix)
svd_matrix.shape
```

Out[6]: (63542, 10)

Part II: Clustering the Emails

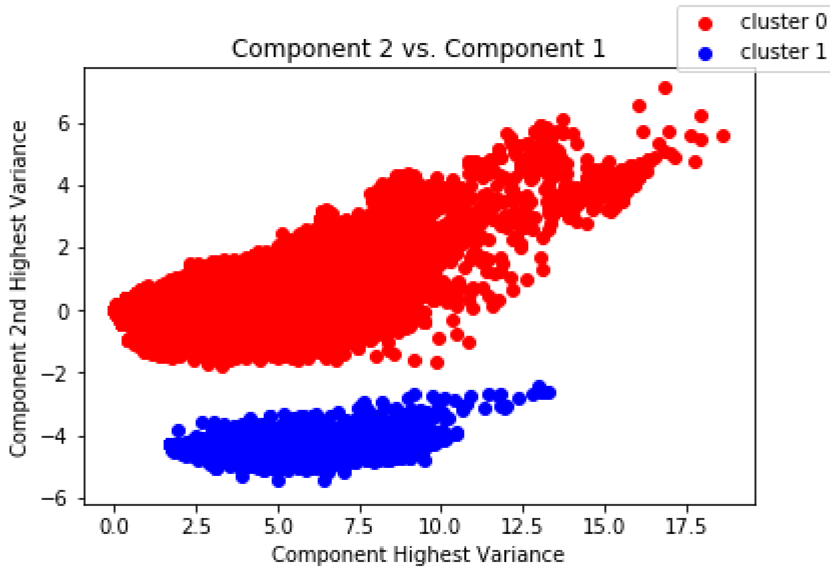
To perform further analysis, we want to cluster the emails. Each message will be assigned a cluster id (0, 1, 2, etc.). I decided to use the DBSCAN algorithm since it works for non-flat geometry and uneven sized clusters. However, I did not want any of the points to be considered as noise so I chose an epsilon value of 1 and a min_samples value of 3 for this to be true. I chose these values by looking at a plot of the data beforehand.

In [7]:
```
clustering = DBSCAN(eps=1, min_samples=3).fit(svd_matrix[:,0:2])
df['clusterID'] = clustering.labels_
np.where(df['clusterID']) == -1 # Represents any points classified as noise
```

Out[7]: False

Plotting the points according to their cluster. The points form 2 distinct clusters which when looking at the plot, makes the most sense.

In [8]:
```
fig, axes = plt.subplots()
cluster0 = np.where(df['clusterID'] == 0)
cluster1 = np.where(df['clusterID'] == 1)
axes.set_xlabel('Component Highest Variance')
axes.set_ylabel('Component 2nd Highest Variance')
axes.set_title('Component 2 vs. Component 1')
plt.scatter(svd_matrix[cluster0,0], svd_matrix[cluster0,1], color='r', label=
'cluster 0')
plt.scatter(svd_matrix[cluster1,0], svd_matrix[cluster1,1], color='b', label=
'cluster 1')
fig.legend();
```

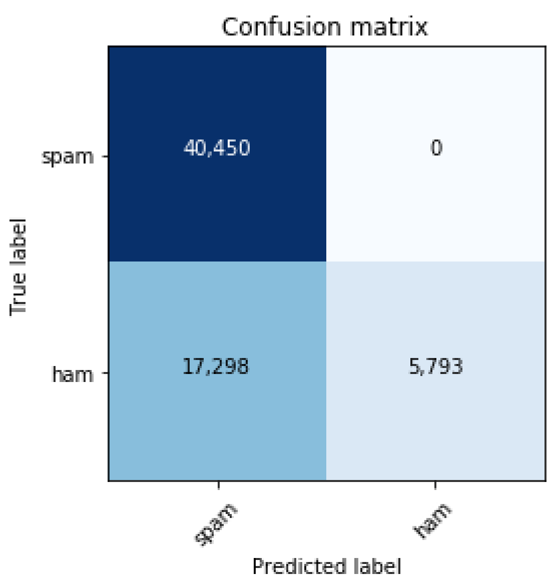


Calculating a confusion matrix for the ham/spam labels versus the cluster labels. I convert the spam/ham labels to a binary classification (0 for spam, 1 for ham) to correspond to the values of the clusters. I chose spam to be 0 because in lab 5 we determined that all of the spam emails were in the upper cluster (cluster 0).

In [9]:
```
df['categoryBinary'] = df['category'].map({'spam': 0, 'ham': 1})
cm = confusion_matrix(df['categoryBinary'], df['clusterID'])
```

In [10]:
```
def plot_confusion_matrix(cm, target_names, title='Confusion matrix'):
    # http://scikit-learn.org/stable/auto_examples/model_selection/
    # plot_confusion_matrix.html
    plt.figure(figsize=(6, 4))
    plt.imshow(cm, interpolation='nearest', cmap=plt.get_cmap('Blues'))
    plt.title(title)
    tick_marks = np.arange(len(target_names))
    plt.xticks(tick_marks, target_names, rotation=45)
    plt.yticks(tick_marks, target_names)
    thresh = cm.max() / 1.5
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, "{:,}".format(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')
    plt.show()
```

In [11]:
```
plot_confusion_matrix(cm[1:3, 1:3], target_names=['spam', 'ham'])
```



Part III: Calculating Document Frequencies of Words

Creating a separate matrix for each cluster containing the rows for the points in that cluster.

In [12]:
```
spam_cluster0 = word_matrix[cluster0]
ham_cluster1 = word_matrix[cluster1]
```

Converting the matrices to CSC format. We will be accessing the data column-wise therefore this will be much faster.

```
In [13]: spam_cluster0_csc = csc_matrix(spam_cluster0)
         ham_cluster1_csc = csc_matrix(ham_cluster1)
         spam_cluster0_csc
```

```
Out[13]: <57748x32144 sparse matrix of type '<class 'numpy.longlong'>'
                 with 5596708 stored elements in Compressed Sparse Column format>
```

```
In [14]: ham_cluster1_csc
```

```
Out[14]: <5793x32144 sparse matrix of type '<class 'numpy.longlong'>'
                 with 790768 stored elements in Compressed Sparse Column format>
```

Calculating the document frequency of each word for each cluster. The document frequemcy is the number of documents that contain each word. Since the feature matrix is binary, we can simply sum along the columns. The resulting matrices have the same shapes with 1 entry (row) for each word in the vocabulary

```
In [15]: doc_freq_spam = spam_cluster0_csc.sum(0)
         doc_freq_ham = ham_cluster1_csc.sum(0)
         doc_freq_spam.shape
```

```
Out[15]: (1, 32144)
```

Finding the column indexes for the words "love", "work", and "different". Then I find the document frequencies for each of these words for each cluster.

```
In [16]: feature_words = vectorizer.get_feature_names()
         print('Column Index of "love": '+ str(feature_words.index('love')))
         print('Column Index of "works": ' + str(feature_words.index('works')))
         print('Column Index of "different": ' + str(feature_words.index('different')))
```

```
Column Index of "love": 18037
Column Index of "works": 31687
Column Index of "different": 10151
```

```
In [17]: print('Document frequency of "love" - spam cluster(0): ' + str(doc_freq_spam[0
         ,18037]))
         print('Document frequency of "works" - spam cluster(0): ' + str(doc_freq_spam[
         0,31687]))
         print('Document frequency of "different" - spam cluster(0): ' + str(doc_freq_s
         pam[0,10151]))
```

```
Document frequency of "love" - spam cluster(0): 2020
Document frequency of "works" - spam cluster(0): 2376
Document frequency of "different" - spam cluster(0): 2100
```

In [18]:
```
print('Document frequency of "love" - ham cluster(1): ' + str(doc_freq_ham[0,1
8037]))
print('Document frequency of "works" - ham cluster(1): ' + str(doc_freq_ham[0,
31687]))
print('Document frequency of "different" - ham cluster(1): ' + str(doc_freq_ha
m[0,10151]))
```

```
Document frequency of "love" - ham cluster(1): 23
Document frequency of "works" - ham cluster(1): 632
Document frequency of "different" - ham cluster(1): 792
```

Part IV: Finding Enriched Words with Statistical Testing

We are using a Binomial test to determine if the number of occurences of a given word in a given cluster is higher than what would be expected from the other cluster.

Our null hypothesis is that the relative document frequencies of the observed clusted are less than or equal to those of the tested. The alternative hypothesis is that the document frequency is higher in cluster 0 (spam) than cluster 1 (ham).

Testing if the words "works" and "love" are enriched in cluster 0.

In [19]:
```
cluster_1_expected_prob = doc_freq_ham[0,31687] / ham_cluster1.shape[0]
works_pvalue = stats.binom_test(doc_freq_spam[0,31687], spam_cluster0.shape[0
],\
                         cluster_1_expected_prob, alternative='greater')
```

In [20]:
```
print('"works" p-value: ' + str(works_pvalue))
```

```
"works" p-value: 0.9999999999999999
```

This p-value indicates that the observed frequency of "works" for cluster 0 (spam) is not greater than the frequency for cluster 1 (ham).

In [21]:
```
cluster_1_expected_prob = doc_freq_ham[0,18037] / ham_cluster1.shape[0]
love_pvalue = stats.binom_test(doc_freq_spam[0,18037], spam_cluster0.shape[0],
\
                         cluster_1_expected_prob, alternative='greater')
```

In [22]:
```
print('"love" p-value: ' + str(love_pvalue))
```

```
"love" p-value: 0.0
```

This p-value indicates that the observed frequency of "love" for cluster 0 (spam) is greater than the frequency for cluster 1 (ham).

Looping through every word to find enriched words for cluster 0 (spam). To do this, we calculate the p-value of every word. If the p-value < .05, we add that word, its p-value, and its cluster 0 document frequency to a list.

In [23]:
```
enriched_words = []
for i in range(doc_freq_ham.size):
    cluster_1_expected_prob = doc_freq_ham[0,i] / ham_cluster1.shape[0]
    word_pvalue = stats.binom_test(doc_freq_spam[0,i], spam_cluster0.shape[0],
\
                                  cluster_1_expected_prob, alternative='greate
r')
    if word_pvalue < .05:
        enriched_words.append((word_pvalue, feature_words[i], doc_freq_spam[0,
i]))
len(enriched_words)
```

Out[23]: 23952

Filtering out any words that contain non-alphabetic characters.

In [24]:
```
enriched_words_alpha = []
for word_tuple in enriched_words:
    if word_tuple[1].isalpha():
        enriched_words_alpha.append(word_tuple)
len(enriched_words_alpha)
```

Out[24]: 20273

Sorting the words in ascending order by their p-values and printing out the first 200 words.

In [25]:
```
enriched_words_alpha_sorted = sorted(enriched_words_alpha, key=lambda x: x[0])
```

In [26]:
```
print(enriched_words_alpha_sorted[0:200])
```

[(0.0, 'aacs', 16), (0.0, 'aback', 10), (0.0, 'abandoning', 14), (0.0, 'abart
let', 166), (0.0, 'abated', 58), (0.0, 'abating', 29), (0.0, 'abba', 18), (0.
0, 'abbas', 30), (0.0, 'abbott', 71), (0.0, 'abducted', 13), (0.0, 'abductio
n', 13), (0.0, 'abdul', 24), (0.0, 'abe', 18), (0.0, 'abecedarian', 23), (0.
0, 'aber', 187), (0.0, 'abfao', 37), (0.0, 'abflauen', 12), (0.0, 'abgeschlos
sen', 21), (0.0, 'abhorred', 123), (0.0, 'abiding', 24), (0.0, 'abilities', 6
5), (0.0, 'abiword', 13), (0.0, 'ablaze', 13), (0.0, 'ableton', 577), (0.0,
'abnormal', 14), (0.0, 'aboard', 60), (0.0, 'abode', 24), (0.0, 'abominable',
13), (0.0, 'abortion', 78), (0.0, 'abortions', 15), (0.0, 'abound', 15), (0.
0, 'abroad', 212), (0.0, 'abrupt', 12), (0.0, 'abruptly', 81), (0.0, 'absentl
y', 11), (0.0, 'absentminded', 11), (0.0, 'absorbs', 12), (0.0, 'absorption',
28), (0.0, 'abstracted', 22), (0.0, 'abstraction', 40), (0.0, 'absurd', 34),
(0.0, 'absurdity', 10), (0.0, 'absurdly', 12), (0.0, 'abundantly', 14), (0.0,
'abused', 23), (0.0, 'abuses', 25), (0.0, 'abusing', 18), (0.0, 'abusive', 1
6), (0.0, 'abwicklung', 22), (0.0, 'academics', 28), (0.0, 'academy', 407),
(0.0, 'acapsite', 51), (0.0, 'accedi', 22), (0.0, 'accelerate', 31), (0.0, 'a
ccelerating', 24), (0.0, 'acceleration', 395), (0.0, 'accelerator', 20), (0.
0, 'acceptances', 12), (0.0, 'accesd', 124), (0.0, 'accessibility', 120), (0.
0, 'accessor', 12), (0.0, 'accessories', 97), (0.0, 'accessors', 11), (0.0,
'accidentes', 12), (0.0, 'accidents', 28), (0.0, 'acclaimed', 16), (0.0, 'acc
ommodations', 22), (0.0, 'accompanied', 50), (0.0, 'accompany', 120), (0.0,
'accomplishment', 34), (0.0, 'accomplishments', 21), (0.0, 'accord', 43), (0.
0, 'account', 2357), (0.0, 'accountability', 21), (0.0, 'accountable', 102),
(0.0, 'accountant', 18), (0.0, 'accra', 53), (0.0, 'accredited', 150), (0.0,
'accueil', 32), (0.0, 'accursed', 14), (0.0, 'accusation', 12), (0.0, 'accusa
tions', 29), (0.0, 'accuse', 40), (0.0, 'accused', 221), (0.0, 'accuses', 2
4), (0.0, 'accusing', 30), (0.0, 'accuweather', 562), (0.0, 'accèsd', 119),
(0.0, 'accèsdmoney', 72), (0.0, 'accéder', 117), (0.0, 'acer', 29), (0.0, 'ac
es', 30), (0.0, 'ache', 14), (0.0, 'achievements', 14), (0.0, 'aci', 14), (0.
0, 'acidity', 11), (0.0, 'ack', 58), (0.0, 'acknowledging', 19), (0.0, 'acl',
73), (0.0, 'acls', 38), (0.0, 'aclu', 12), (0.0, 'acoustic', 11), (0.0, 'ac
p', 27), (0.0, 'acpi', 23), (0.0, 'acquaintance', 56), (0.0, 'acquaintances',
11), (0.0, 'acquainted', 53), (0.0, 'acquaints', 15), (0.0, 'acquire', 191),
(0.0, 'acquired', 179), (0.0, 'acquires', 62), (0.0, 'acquiring', 55), (0.0,
'acquisition', 177), (0.0, 'acquisitions', 29), (0.0, 'acquitted', 13), (0.0,
'acre', 21), (0.0, 'acres', 93), (0.0, 'acrob', 14), (0.0, 'acrobat', 1059),
(0.0, 'actif', 19), (0.0, 'actionable', 27), (0.0, 'actionist', 12), (0.0, 'a
ctivated', 98), (0.0, 'activates', 12), (0.0, 'activatian', 15), (0.0, 'activ
ating', 16), (0.0, 'activism', 10), (0.0, 'activist', 35), (0.0, 'activists',
72), (0.0, 'activities', 708), (0.0, 'activity', 669), (0.0, 'activityfactory
service', 16), (0.0, 'actobat', 32), (0.0, 'actor', 117), (0.0, 'actress', 8
4), (0.0, 'actresses', 11), (0.0, 'acuerdo', 20), (0.0, 'acvertising', 64),
(0.0, 'ada', 20), (0.0, 'adaptation', 12), (0.0, 'adapter', 64), (0.0, 'adapt
ers', 15), (0.0, 'addicted', 80), (0.0, 'addiction', 45), (0.0, 'addictive',
24), (0.0, 'addin', 12), (0.0, 'addison', 10), (0.0, 'additional', 3230), (0.
0, 'additives', 56), (0.0, 'adela', 14), (0.0, 'adelaida', 25), (0.0, 'adelma
n', 14), (0.0, 'adem', 13), (0.0, 'ademas', 13), (0.0, 'además', 10), (0.0,
'adhere', 11), (0.0, 'adid', 12), (0.0, 'adjective', 41), (0.0, 'adm', 12),
(0.0, 'administer', 29), (0.0, 'administrateur', 12), (0.0, 'administrators',
74), (0.0, 'adminpass', 16), (0.0, 'admins', 33), (0.0, 'admiral', 37), (0.0,
'admiration', 42), (0.0, 'admired', 20), (0.0, 'admirrante', 22), (0.0, 'admi
ssible', 61), (0.0, 'admission', 42), (0.0, 'admissions', 12), (0.0, 'admit
s', 87), (0.0, 'admitting', 20), (0.0, 'ado', 21), (0.0, 'adobe', 1119), (0.
0, 'adoption', 60), (0.0, 'adopts', 14), (0.0, 'adorable', 30), (0.0, 'adore
d', 10), (0.0, 'adorned', 22), (0.0, 'adov', 42), (0.0, 'adovcurrent', 70),
(0.0, 'adrenaline', 48), (0.0, 'adresse', 139), (0.0, 'adressierte', 28), (0.
0, 'adriano', 10), (0.0, 'adtj', 11), (0.0, 'adtrevor', 12), (0.0, 'adtrevor

```
s', 10), (0.0, 'adult', 116), (0.0, 'adultery', 14), (0.0, 'advancement', 21
2), (0.0, 'advancements', 11), (0.0, 'advancing', 52), (0.0, 'advantageous',
18), (0.0, 'advent', 27), (0.0, 'adventage', 100), (0.0, 'adventure', 76),
(0.0, 'adventures', 57), (0.0, 'adverb', 12)]
```

Repeating with the clusters reversed to find the enriched words in cluster 1 (ham).

In [27]:
```
enriched_words_1 = []
for i in range(doc_freq_ham.size):
    cluster_0_expected_prob = doc_freq_spam[0,i] / spam_cluster0.shape[0]
    word_pvalue = stats.binom_test(doc_freq_ham[0,i], ham_cluster1.shape[0],\
                                  cluster_0_expected_prob, alternative='greate
r')
    if word_pvalue < .05:
        enriched_words_1.append((word_pvalue, feature_words[i], doc_freq_ham[0
,i]))
len(enriched_words_1)
```

Out[27]:
```
5387
```

Filtering out any words that contain non-alphabetic characters.

In [28]:
```
enriched_words_1_alpha = []
for word_tuple in enriched_words_1:
    if word_tuple[1].isalpha():
        enriched_words_1_alpha.append(word_tuple)
len(enriched_words_1_alpha)
```

Out[28]:
```
4550
```

Sorting the words in ascending order by their p-values and printing out the first 200 words.

In [29]:
```
enriched_words_alpha_1_sorted = sorted(enriched_words_1_alpha, key=lambda x: x
[0])
```

In [30]:

```
print(enriched_words_alpha_1_sorted[0:200])
```

[(0.0, 'abline', 66), (0.0, 'ac', 566), (0.0, 'acafs', 36), (0.0, 'adai', 2
1), (0.0, 'adaikalavan', 11), (0.0, 'adschai', 65), (0.0, 'advance', 618),
(0.0, 'affymetrix', 11), (0.0, 'agingandhealth', 50), (0.0, 'alin', 40), (0.
0, 'alternative', 1511), (0.0, 'am', 2224), (0.0, 'amicogodzilla', 10), (0.0,
'and', 5781), (0.0, 'andrewpr', 11), (0.0, 'annis', 11), (0.0, 'anova', 131),
(0.0, 'anup', 28), (0.0, 'any', 2093), (0.0, 'anyone', 763), (0.0, 'aov', 4
6), (0.0, 'archive', 481), (0.0, 'arima', 16), (0.0, 'autocorrelation', 17),
(0.0, 'autoregressive', 10), (0.0, 'axis', 241), (0.0, 'banyu', 10), (0.0, 'b
arata', 11), (0.0, 'barplot', 40), (0.0, 'barplots', 13), (0.0, 'batchfiles',
23), (0.0, 'bayesianfilter', 18), (0.0, 'bendix', 10), (0.0, 'bengtsson', 1
3), (0.0, 'benilton', 24), (0.0, 'bfgs', 48), (0.0, 'bhagavad', 12), (0.0, 'b
ic', 42), (0.0, 'biddle', 10), (0.0, 'biglm', 10), (0.0, 'biobase', 18), (0.
0, 'biocomputing', 10), (0.0, 'bioconductor', 64), (0.0, 'bioinformation', 1
1), (0.0, 'biometrie', 22), (0.0, 'biostat', 146), (0.0, 'biostatistical', 4
4), (0.0, 'biostatistician', 27), (0.0, 'biostatistics', 178), (0.0, 'biplo
t', 25), (0.0, 'biplots', 12), (0.0, 'bivand', 24), (0.0, 'bivariate', 34),
(0.0, 'blas', 11), (0.0, 'blomberg', 29), (0.0, 'bolker', 26), (0.0, 'bosonde
rzoek', 19), (0.0, 'bothell', 14), (0.0, 'bounces', 535), (0.0, 'boxplot', 5
5), (0.0, 'boxplots', 27), (0.0, 'brian', 438), (0.0, 'brutschy', 10), (0.0,
'bty', 14), (0.0, 'but', 3412), (0.0, 'byrow', 44), (0.0, 'calboli', 11), (0.
0, 'can', 3023), (0.0, 'carstensen', 10), (0.0, 'causas', 35), (0.0, 'cberr
y', 41), (0.0, 'cbind', 223), (0.0, 'ccil', 14), (0.0, 'ccilindia', 16), (0.
0, 'cedex', 10), (0.0, 'cex', 60), (0.0, 'cezar', 13), (0.0, 'ch', 5793), (0.
0, 'charilaos', 17), (0.0, 'chiruka', 23), (0.0, 'chisq', 24), (0.0, 'chm', 2
5), (0.0, 'cholesky', 12), (0.0, 'christos', 17), (0.0, 'clipplot', 10), (0.
0, 'cmdscale', 11), (0.0, 'cmis', 12), (0.0, 'cnio', 10), (0.0, 'code', 579
3), (0.0, 'codifies', 16), (0.0, 'coef', 72), (0.0, 'coefficients', 143), (0.
0, 'col', 276), (0.0, 'colclasses', 38), (0.0, 'colnames', 129), (0.0, 'colsu
ms', 17), (0.0, 'column', 450), (0.0, 'columns', 430), (0.0, 'commented', 579
3), (0.0, 'computerstuff', 21), (0.0, 'concatentate', 11), (0.0, 'confidenti
a', 13), (0.0, 'confuced', 10), (0.0, 'constroptim', 13), (0.0, 'contained',
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```
y', 21), (0.0, 'fwf', 24), (0.0, 'gabor', 199), (0.0, 'garch', 11), (0.0, 'ga
temaze', 23), (0.0, 'gaverstraat', 19), (0.0, 'gcv', 12), (0.0, 'gdata', 18)]
```

Reflection Questions

a. The emails might form 2 distinct clusters because of the two main types of emails (spam and ham). The words in a typical spam email are different than the words in a typically work/normal email therefore they are sorted into 2 distinct clusters.

b. Spam emails are only contained in cluster 0. Ham messages are in both cluster 1 and 0. Therefore, cluster 1 is only made up of ham emails, but cluster 0 contains both spam and ham emails.

c. When examining the first 200 significant words in cluster 1 (ham), there seem to be a lot of words relating to data science. Cluster 0 (spam) contains words more common to spam emails, like "abortions".

d. Printing the first 25 rows from the DataFrame for each cluster.

In [31]:
```
df[df['clusterID'] == 0].head(25)
```

Out[31]:

	body	category	from_address	subject	
0	\n\n\n\n\n\n\nDo you feel the pressure to perf...	spam	"Tomas Jacobs" <RickyAmes@aol.com>	Generic Cialis, branded quality@	
1	Hi, i've just updated from the gulus and I che...	ham	Yan Morin <yan.morin@savoirfairelinux.com>	Typo in /debian/README	c
2	authentic viagra\n\nMega authenticV I A G R A...	spam	"Sheila Crenshaw" <7stocknews@tractionmarketin...	authentic viagra	
3	\nHey Billy, \n\nit was really fun going out t...	spam	"Stormy Dempsey" <vqucsmdfgvsg@ruraltek.com>	Nice talking with ya	
4	\n\n\n\n\n\n\nsystem" of the home. It will ha...	spam	"Christi T. Jernigan" <dcube@totalink.net>	or trembling; stomach cramps; trouble in sleep...	
5	\n\n\n\n\n\n\nthe program and the creative abi...	spam	"Bobby L. Fleming" <zvyrepeated@liselebel.com>	Which is duty	ı
6	\n\n\n\t\t\t\t\t\t\t\t\t\t\t\t\t\t\t\t\t\t\t...	spam	"Esteban Everett" <dbmagyrln@dbmag.com>	Theorize get inside for local esc0rts who do i...	
7	\n\n\n\n\n\n HoodiaLife - Start Losing Weight ...	spam	Real Loss <fibond@terra.com.do>	Losing Weight Quickly	
9	\n\n\n\n\n\n\nGood day!\nVisit our new online ...	spam	"Billy Chin" <boxer@0733.com>	For Smile	
10	\nCheck out the wonders of pound melting\n\n\n...	spam	"Josie Abernathy" <cebcalhounrennerhog@calhoun...	Less weight - more pleasure and joy	
11	\n\n\n\n\n\n\nmovement on the tablet. I could...	spam	wing as <mstep@mavorama.com>	problems in animal studies using rats or rabbi...	
12	\n\n\n\n\n\n\n\n	spam	"Geoffrey" <reginald@funeasy.biz>	We cure any desease!	<m
13	\n\n\n\n\n\nWhat is HGH Life™? \n HGH Life™ is ...	spam	4ever Young <ualicia@netscape.net>	Human Growth Hormone	
14	Hey Billy, \n\nit was really fun going out the...	spam	"Caroyln Herbert" <slqwil@planetonline.com>	hi man	
15	\n\n\n\n\n\n\ncan assist advertising and marke...	spam	Domingo Bolden <lfriend@dryden.com>	when taken for a long time or in large doses, ...	
17	\n\n\n\n\n\n\n\n	spam	"Henry" <gilbert@garageservices.biz>	We cure any desease!	
18	\n\n\n\n\n\n\n\n	spam	"Simon" <walter@griffield.biz>	Need medicine? All here!	
19	\n\n\n\n\n\n\n\n	spam	"Philip" <richard@expomedica.biz>	Need medicine? All here!	
20	\n\n\n\n\n\n\nBecome Fit For Life!\n\nHGH is a...	spam	Young Future <kdemetrius@publicist.com>	Become Fit For Life!	
21		spam	"Gena Blanco" <nytwdn@incamail.com>	Please Read This C	<ç

	body	category	from_address	subject
22	\nMake your fat friends envy you\n\n\n\n\n\n\n...	spam	"Carlene Campos" <cebcaligularhog@caligular.com>	Be leaner and slimmer by next week
23	\n\n\n\n\nRemember HANS and FIZ\nFire Mountain...	spam	"Chadwick Milesc" <ctuballerina@bb-autom.nl>	But serpentine
25	\n\n\n\n\n\n\n\n	spam	"Henry" <richard@expomedica.biz>	All products for your health!
26	\n\n\n\n\n\n\n\nSunday, 08 April, 2007, 18:00 ...	ham	"BBC daily email" <dailyemail@bbc.co.uk>	Your daily e-mail from the BBC
27	\n\n\n\n\n\nWhat is HGH Life™?\n HGH Life™ is ...	spam	4ever Young <doaraceli@altavista.nl>	HGH really helps!

In [32]:
```
df[df['clusterID'] == 1].head(25)
```

Out[32]:

	body	category	from_address	subject	
8	\nHi...\n\nI have to use R to find out the 90%...	ham	"Jochen.F" <jjfahr@ucalgary.ca>	[R] Confidence-Intervals.... help...	r-help@s
16	Hm... sounds like a homework problem to me...\...	ham	"Sarah Goslee" <sarah.goslee@gmail.com>	Re: [R] Confidence-Intervals.... help...	<jjfal
24	Daer r-helpers,\n\nCan anyone help with the fo...	ham	Michael Kubovy <kubovy@virginia.edu>	[R] Failure of mcsamp() but not mcmcsamp()	r-help@s
68	On 4/6/07, Wilfred Zegwaard wrote:\n\n> I'm n...	ham	"Johann Hibschman" <johannh@gmail.com>	Re: [R] Reasons to Use R	"W <wilfred.zegwaa
75	On 4/8/07, Johann Hibschman wrote:\n> R's pas...	ham	"Gabor Grothendieck" <ggrothendieck@gmail.com>	Re: [R] Reasons to Use R	"Joh <johan
112	I have a question to everybody.\n\nAfter log10...	ham	"Zia Uddin Ahmed" <zua3@cornell.edu>	[R] How do I back transforme ordinary log-krig...	r-help@s
149	\nI am writing some code to obtain publication...	ham	"Cressoni, Massimo $NIH/NHLBI$ [F]" <cresson...	[R] Plot symbols dimensions	<r-help@sta
278	Dear Johann and Gabor,\n\nIt's what amounts to...	ham	Wilfred Zegwaard <wilfred.zegwaard@gmail.com>	Re: [R] Reasons to Use R	r-help@s
307	Dear R-users,\n\nI would like to use "bruto" f...	ham	=?ISO-2022-JP?B?GyRCQG44fRsoQiAbJEI9JDwjGyhC?=...	[R] Could not fit correct values in discrimina...	r-help@s
318	Dear R users,\n\nI am new to R. I would like t...	ham	"joey repice" <fireseedmusic@gmail.com>	[R] R:Maximum likelihood estimation using BHHH...	r-help@s
323	Hi,\n\nI am using tsls function from sem packa...	ham	adschai@optonline.net	[R] Dealing with large nominal predictor in se...	r-help@s
408	On Sun, 8 Apr 2007, hadley wickham wrote:\n\n>...	ham	Prof Brian Ripley <ripley@stats.ox.ac.uk>	Re: [R] data encapsulation with classes	<h.wickha
472	Hello,\n\nI want to know if there are some fun...	ham	Shao <xshining@gmail.com>	[R] How to solve differential and integral equ...	help@sta

	body	category	from_address	subject	
501	Joey,\n\nFirst of all, it is bad habit to call...	ham	chao gai <chaogai@duineveld.demon.nl>	Re: [R] R:Maximum likelihood estimation using ...	r-help@s
534	Thanks,\nI have much to learn~~~\n\nShao chunx...	ham	Shao <xshining@gmail.com>	Re: [R] How to solve differential and integral...	help@sta
578	Dear adschai,\n\nIt's not possible to know fro...	ham	"John Fox" <jfox@mcmaster.ca>	Re: [R] Dealing with large nominal predictor i...	<adschai
582	Thanks anhnmncb\nI think the problem comes fro...	ham	fsando <fsando@fs-analyse.dk>	Re: [R] R 'could not find any X11 fonts'	r-help@s
594	I am trying to install the gnomeGUI package\nI...	ham	fsando <fsando@fs-analyse.dk>	[R] Problem installing gnomeGUI in Ubuntu: "HA...	r-help@s
622	Shuji,\n\nI suspect that bruto blows up becaus...	ham	"Kuhn, Max" <Max.Kuhn@pfizer.com>	Re: [R] Could not fit correct values in discri...	<kawaguch
629	>>>>> "BDR" == Prof Brian Ripley \n>>>>> o...	ham	Martin Maechler <maechler@stat.math.ethz.ch>	Re: [R] data encapsulation with classes	P <ripley(
630	Does anyone know of a package that includes th...	ham	"Chris Elsaesser" <chris.elsaesser@spadac.com>	[R] Modified Sims test	<r-help@sta
668	Gabor has already showed you one way to make y...	ham	"Greg Snow" <Greg.Snow@intermountainmail.org>	Re: [R] lm() intercept at the end, rather than...	"I <dimitrijoe@
694	tha s9ze of db is an issue with R. We are stil...	ham	"Jorge Cornejo-Donoso" <jorgecornejo@uach.cl>	Re: [R] Reasons to Use R	"'Wi <wilfred.zegw
706	Have you tried 64 bit machines with larger mem...	ham	"Gabor Grothendieck" <ggrothendieck@gmail.com>	Re: [R] Reasons to Use R	"Jorge C <jorgeco
715	I have a Dell with 2 Intel XEON 3.0 procesors ...	ham	"Jorge Cornejo-Donoso" <jorgecornejo@uach.cl>	Re: [R] Reasons to Use R	"'Gabo <ggrothendie

Looking at the first 25 rows of each cluster, some patterns also emerge in the addresses and subject lines. The to_address of the cluster 0 (mostly spam) emails are all to uwaterloo.ca accounts, while the to_address of the cluster 1 (ham) emails are to a variety of different providers including waterloo.ca but also others such as develooper.com.

For the from_addresses, the cluster 0 (mostly spam) emails are all from different addresses while the cluster 1 (ham) emails have several repeated senders.

For the subject line, all of the cluster 1 (ham) emails have [R] included. For the cluster 0 (mostly spam) emails, the subject lines are much more varied.

e. The clusters represent email from two separate mailing lists. One mailing list is for the R programming language (cluster 1 - ham), while the other mailing list is for a university (cluster 0 - spam). The university mailing list contained all of the spam emails.

Conclusion

From this clustering analysis we were able to determine the significant words of each cluster that may have been combined to create the componenets of the clusters we created when using SVD. Many of these words that could have been combined to create cluster 1 (ham) were related to programming, such as bayesianfilter, which made sense since many of them came from a R programming language email list. Cluster 0 (mostly spam with some ham) had more random words, like abortion or adultery, that are less likely to be in professional emails and more likely to be from spam.