Yelp_Dataset_-_Clustering_and_PCA_new

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1 Yelp Data Challenge - Clustering and PCA

BitTiger DS501
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```
In [19]: import pandas as pd
         import numpy as np
         import matplotlib.pyplot as plt
         % matplotlib inline
         plt.style.use("ggplot")

In [20]: df = pd.read_csv('data/last_2_years_restaurant_reviews.csv')

In [21]: df.head(2)

Out[21]:               business_id                  name  \
         0  --9e1ONYQuAa-CB_Rrw7Tw  Delmonico Steakhouse
         1  --9e1ONYQuAa-CB_Rrw7Tw  Delmonico Steakhouse

                                      categories  avg_stars  cool        date  \
         0  [Steakhouses, Restaurants, Cajun/Creole]        4.0     0  2015-06-26
         1  [Steakhouses, Restaurants, Cajun/Creole]        4.0     0  2015-06-29

            funny               review_id  stars  \
         0      0  nCqdz-NW64KazpxqnDr0sQ      1
         1      0  iwx6s6yQxc7yjS7NFANZig      4

                                                        text    type  useful  \
         0  I mainly went for the ceasar salad prepared ta...  review       0
         1  Nice atmosphere and wonderful service. I had t...  review       0

                           user_id  count
         0  0XVzm4kVIAaH4eQAxWbhvw    318
         1  2aeNFntqY2QDZLADNo8iQQ    318
```

1.1 1. Cluster the review text data for all the restaurants

1.1.1 Define your feature variables, here is the text of the review

```
In [22]: # Take the values of the column that contains review text data, save to a variable na
         documents = df['text'].values
         documents.shape

Out[22]: (348016,)
```

1.1.2 Define your target variable (any categorical variable that may be meaningful)

For example, I am interested in perfect (5 stars) and imperfect (1-4 stars) rating

```
In [23]: # Make a column and take the values, save to a variable named "target"
         target = (df['stars'] == 5).astype(int).values
         target.shape

Out[23]: (348016,)
```

You may want to look at the statistic of the target variable

```
In [24]: # To be implemented
         print('statistics of the target variable')
         print('median value: %f' % (np.median(target)))
         print('mean value: %f' % (np.mean(target)))
         print('standard deviation value: %f' % (np.std(target)))

statistics of the target variable
median value: 0.000000
mean value: 0.460668
standard deviation value: 0.498451
```

1.1.3 Create training dataset and test dataset

```
In [25]: from sklearn.model_selection import train_test_split

In [26]: # documents is your X, target is your y
         # Now split the data to training set and test set
         # You may want to start with a big "test_size", since large training set can easily c
         x_train, x_test, y_train, y_test = train_test_split(documents, target, test_size = 0.
```

1.1.4 Get NLP representation of the documents

Fit TfidfVectorizer with training data only, then tranform all the data to tf-idf

```
In [27]: from sklearn.feature_extraction.text import TfidfVectorizer
         import nltk
         from nltk.tokenize import word_tokenize
         from nltk.corpus import stopwords
```

```
In [28]: # Create TfidfVectorizer, and name it vectorizer, choose a reasonable max_features, e
         vectorizer = TfidfVectorizer(stop_words = 'english', max_features = 2000)
```

```
In [29]: # Train the model with your training data
         train_vector = vectorizer.fit_transform(x_train).toarray()
```

```
In [30]: # Get the vocab of your tfidf
         vocab = vectorizer.get_feature_names()
```

```
In [31]: # Use the trained model to transform all the reviews
         # transformed trained model => train_vector
         # transformed test model => test_vector
         test_vector = vectorizer.transform(x_test)
```

```
In [32]: print 'shape of trainsformed training data:', train_vector.shape
         print 'shape of trainsformed testing data:', test_vector.shape
```

```
shape of trainsformed training data: (69603, 2000)
shape of trainsformed testing data: (278413, 2000)
```

1.1.5 Cluster reviews with KMeans

Fit k-means clustering with the training vectors and apply it on all the data

```
In [33]: from sklearn.cluster import KMeans
         from sklearn.metrics import silhouette_score
         from scipy.spatial.distance import euclidean
```

```
In [34]: # choose the best K
         """
         SSE_List = []
         Silhouette_List = []
         cluster_choices = [5,10,20,40]
         for i in cluster_choices:
             print('%d center cluster is complete' % (i))
             kmeans = KMeans(n_clusters=i, random_state=0).fit(train_vector)
             SSE_List.append(kmeans.inertia_)
             Silhouette_List.append(silhouette_score(train_vector, kmeans.labels_))
         """
```

```
Out[34]: "\nSSE_List = []\nSilhouette_List = []\ncluster_choices = [5,10,20,40]\nfor i in clus
```

```
In [35]: # plot the SSE and Silhouette metric results
         """
         plt.subplot(211)
         plt.plot(cluster_choices, SSE_List)
         plt.ylabel('SSE')
         plt.subplot(212)
         plt.plot(cluster_choices, Silhouette_List)
```

```
    plt.ylabel('Silhouette')
    plt.show()
    """
```

```
Out[35]: "\nplt.subplot(211)\nplt.plot(cluster_choices, SSE_List)\nplt.ylabel('SSE')\nplt.subpl
```

Make predictions on all your data

```
In [36]: kmeans = KMeans(n_clusters = 20, random_state=42)
         kmeans.fit(train_vector)
```

```
Out[36]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=20, n_init=10, n_jobs=1, precompute_distances='auto',
             random_state=42, tol=0.0001, verbose=0)
```

```
In [37]: # To be implemented
         doc_vector = vectorizer.fit_transform(documents).toarray()
         target_pred = kmeans.predict(doc_vector)
```

Inspect the centroids To find out what "topics" Kmeans has discovered we must inspect the centroids. Print out the centroids of the Kmeans clustering.

These centroids are simply a bunch of vectors. To make any sense of them we need to map these vectors back into our 'word space'. Think of each feature/dimension of the centroid vector as representing the "average" review or the average occurances of words for that cluster.

```
In [38]: # To be implemented
         def get_top_values(lst, n, labels):
             '''
             INPUT: LIST, INTEGER, LIST
             OUTPUT: LIST

             Given a list of values, find the indices with the highest n values.
             Return the labels for each of these indices.

             e.g.
             lst = [7, 3, 2, 4, 1]
             n = 2
             labels = ["cat", "dog", "mouse", "pig", "rabbit"]
             output: ["cat", "pig"]
             '''
             return [labels[i] for i in np.argsort(lst)[::-1][:n]]  # np.argsort by default so
```

Find the top 10 features for each cluster. For topics we are only really interested in the most present words, i.e. features/dimensions with the greatest representation in the centroid. Print out the top ten words for each centroid.

- Sort each centroid vector to find the top 10 features
- Go back to your vectorizer object to find out what words each of these features corresponds to.

```
In [39]: # To be implemented
         n = 10
         for index, point in enumerate(kmeans.cluster_centers_):
             print('%d center has the top prominent words:' % (index))
             print(get_top_values(point, n, vocab))
```

```
0 center has the top prominent words:
[u'ordered', u'like', u'good', u'sauce', u'just', u'food', u'place', u'got', u'cheese', u'meat
1 center has the top prominent words:
[u'steak', u'good', u'great', u'ordered', u'service', u'food', u'place', u'cooked', u'best', u
2 center has the top prominent words:
[u'great', u'food', u'service', u'place', u'amazing', u'awesome', u'atmosphere', u'staff', u'f
3 center has the top prominent words:
[u'good', u'food', u'service', u'really', u'place', u'nice', u'pretty', u'great', u'time', u'l
4 center has the top prominent words:
[u'vegas', u'best', u'las', u'food', u'place', u've', u'amazing', u'service', u'great', u'time
5 center has the top prominent words:
[u'pho', u'broth', u'good', u'place', u'rolls', u'vietnamese', u'spring', u'service', u'food',
6 center has the top prominent words:
[u'sushi', u'rolls', u'place', u'roll', u'ayce', u'great', u'fresh', u'fish', u'good', u'eat']
7 center has the top prominent words:
[u'food', u'place', u'service', u'amazing', u'just', u'time', u'like', u'delicious', u'staff',
8 center has the top prominent words:
[u'prices', u'reasonable', u'food', u'great', u'good', u'place', u'service', u'friendly', u'hi
9 center has the top prominent words:
[u'buffet', u'food', u'good', u'buffets', u'crab', u'selection', u'vegas', u'legs', u'price',
10 center has the top prominent words:
[u'love', u'place', u'food', u'great', u'service', u'amazing', u'friendly', u'good', u'staff',
11 center has the top prominent words:
[u'thai', u'pad', u'food', u'curry', u'place', u'good', u'chicken', u'rice', u'restaurant', u'
12 center has the top prominent words:
[u'tacos', u'taco', u'asada', u'good', u'mexican', u'food', u'salsa', u'carne', u'fish', u'gre
13 center has the top prominent words:
[u'breakfast', u'eggs', u'great', u'place', u'good', u'food', u'pancakes', u'coffee', u'servic
14 center has the top prominent words:
[u'burger', u'fries', u'burgers', u'good', u'cheese', u'shake', u'place', u'food', u'great', u
15 center has the top prominent words:
[u'ramen', u'broth', u'noodles', u'place', u'good', u'miso', u'spicy', u'great', u'pork', u'bo
16 center has the top prominent words:
[u'lobster', u'roll', u'good', u'great', u'bisque', u'food', u'crab', u'shrimp', u'service', u
17 center has the top prominent words:
[u'pizza', u'crust', u'good', u'place', u'great', u'cheese', u'pepperoni', u'just', u'best', u
18 center has the top prominent words:
[u'chicken', u'fried', u'food', u'good', u'place', u'ordered', u'rice', u'great', u'salad', u'
19 center has the top prominent words:
[u'order', u'minutes', u'food', u'service', u'time', u'asked', u'said', u'came', u'table', u'j
```

Try different k If you set k == to a different number, how does the top features change?

```
In [40]: # To be implemented
         kmeans = KMeans(n_clusters = 10, random_state=42)
         kmeans.fit(train_vector)
         target_pred = kmeans.predict(doc_vector)
         for index, point in enumerate(kmeans.cluster_centers_):
             print('%d center has the top n prominent words:' % (index))
             print(get_top_values(point, n, vocab))
```

```
0 center has the top n prominent words:
[u'sushi', u'rolls', u'roll', u'place', u'ayce', u'great', u'fresh', u'good', u'fish', u'servic
1 center has the top n prominent words:
[u'chicken', u'fried', u'good', u'rice', u'food', u'thai', u'ordered', u'place', u'sauce', u'gr
2 center has the top n prominent words:
[u'burger', u'fries', u'burgers', u'good', u'cheese', u'shake', u'place', u'food', u'great', u
3 center has the top n prominent words:
[u'pizza', u'crust', u'good', u'place', u'great', u'cheese', u'best', u'just', u'pepperoni', u
4 center has the top n prominent words:
[u'food', u'order', u'minutes', u'time', u'service', u'just', u'came', u'table', u'asked', u'sa
5 center has the top n prominent words:
[u'great', u'food', u'service', u'place', u'good', u'friendly', u'awesome', u'atmosphere', u's
6 center has the top n prominent words:
[u'love', u'place', u'food', u'great', u'service', u'good', u'amazing', u'friendly', u'deliciou
7 center has the top n prominent words:
[u'best', u'vegas', u'amazing', u'food', u'place', u'las', u'service', u've', u'time', u'defin
8 center has the top n prominent words:
[u'buffet', u'food', u'good', u'buffets', u'vegas', u'crab', u'selection', u'legs', u'price', u
9 center has the top n prominent words:
[u'good', u'food', u'place', u'like', u'service', u'really', u'just', u'nice', u'delicious', u
```

The words are quite similar to each other

Print out the rating and review of a random sample of the reviews assigned to each cluster to get a sense of the cluster.

```
In [41]: # To be implemented
         rand_index = 42
         print('chosen review:')
         print(documents[rand_index])
         print('chosen rating:')
         print(target[rand_index])
         print('top n prominent words:')
         print(get_top_values(kmeans.cluster_centers_[target_pred[rand_index]], n, vocab))
```

```
chosen review:
The strip steak was to die for! The banana desert was absolutely genius. Our server (forgot he
chosen rating:
```

```
0
top n prominent words:
[u'good', u'food', u'place', u'like', u'service', u'really', u'just', u'nice', u'delicious', u
```

1.2 2. Cluster all the reviews of the most reviewed restaurant

Let's find the most reviewed restaurant and analyze its reviews

```
In [42]: # Find the business who got most reviews, get your filtered df, name it df_top_restau
         max_count = np.max(df['count'])
         max_count

Out[42]: 4015

In [43]: business_id = df[df['count'] == max_count]['business_id'].unique()
         business_id

Out[43]: array(['hihud--QRriCYZw1zZvW4g'], dtype=object)

In [44]: df_top_restaurant = df[df['business_id'] == business_id[0]]
```

We can also load restaurant profile information from the business dataset (optional)

```
In [45]: # Load business dataset (optional)
         # Take a look at the most reviewed restaurant's profile (optional)
         pass
```

1.2.1 Vectorize the text feature

```
In [46]: # Take the values of the column that contains review text data, save to a variable na
         documents_top_restaurant = df_top_restaurant['text'].values
         documents_top_restaurant.shape

Out[46]: (4015,)
```

1.2.2 Define your target variable (for later classification use)

Again, we look at perfect (5 stars) and imperfect (1-4 stars) rating

```
In [47]: # To be implemented
         target_top_restaurant = (df_top_restaurant['stars'] == 5).astype(int).values
         target_top_restaurant.shape

Out[47]: (4015,)
```

Check the statistic of the target variable

```
In [48]: # To be implemented
         print('statistics of the target variable')
         print('median value: %f' % (np.median(target_top_restaurant)))
         print('mean value: %f' % (np.mean(target_top_restaurant)))
         print('standard deviation value: %f' % (np.std(target_top_restaurant)))
```

```
statistics of the target variable
median value: 1.000000
mean value: 0.764633
standard deviation value: 0.424228
```

1.2.3 Create training dataset and test dataset

```
In [49]: from sklearn.model_selection import train_test_split
```

```
In [50]: # documents_top_restaurant is your X, target_top_restaurant is your y
         # Now split the data to training set and test set
         # Now your data is smaller, you can use a typical "test_size", e.g. 0.3-0.7
         x_train, x_test, y_train, y_test = train_test_split(documents_top_restaurant, target_
```

1.2.4 Get NLP representation of the documents

```
In [51]: from sklearn.feature_extraction.text import TfidfVectorizer
```

```
In [52]: # Create TfidfVectorizer, and name it vectorizer
         vectorizer_top = TfidfVectorizer(stop_words = 'english', max_features = 2000)
```

```
In [53]: # Train the model with your training data
         train_vector_top = vectorizer_top.fit_transform(x_train).toarray()
```

```
In [54]: # Get the vocab of your tfidf
         vocab_top = vectorizer_top.get_feature_names()
```

```
In [55]: # Use the trained model to transform the test data
         test_vector_top = vectorizer_top.transform(x_test).toarray()
```

```
In [56]: # Use the trained model to transform all the data
         doc_vector_top = vectorizer_top.transform(documents_top_restaurant).toarray()
```

1.2.5 Cluster reviews with KMeans

Fit k-means clustering on the training vectors and make predictions on all data

```
In [57]: # To be implemented
         kmeans = KMeans(n_clusters = 20, random_state=42)
         kmeans.fit(train_vector_top)
```

```
Out[57]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=20, n_init=10, n_jobs=1, precompute_distances='auto',
             random_state=42, tol=0.0001, verbose=0)
```

Make predictions on all your data

In [58]:
```python
# To be implemented
target_labels = kmeans.predict(doc_vector_top)
```

Inspect the centroids

In [59]:
```python
# To be implemented
for index, center in enumerate(kmeans.cluster_centers_):
    print('%d center: ' % (index))
    print(center)
```

```
0 center:
[  1.40946282e-18   1.56125113e-17   4.99801825e-03 ...,   1.30104261e-18
   0.00000000e+00   8.67361738e-19]
1 center:
[  2.16840434e-19   5.00937231e-03  -1.95156391e-18 ...,   1.45187767e-03
   0.00000000e+00   9.75781955e-19]
2 center:
[  8.61280755e-04   1.14603344e-02   8.81826599e-04 ...,   1.62630326e-18
   0.00000000e+00   9.75781955e-19]
3 center:
[ -4.01154804e-18   1.15319126e-03  -1.95156391e-18 ...,   1.77108012e-03
   1.78893358e-18   1.90187997e-03]
4 center:
[  2.35020877e-03   1.40436555e-02   1.62503074e-03 ...,   2.61653260e-03
   1.14663367e-03  -3.25260652e-18]
5 center:
[  1.51788304e-18   2.87079580e-03   1.94707403e-03 ...,   9.71807657e-04
   0.00000000e+00   4.78826105e-03]
6 center:
[  1.40946282e-18   5.13578845e-03  -1.73472348e-18 ...,   1.40946282e-18
   0.00000000e+00   8.67361738e-19]
7 center:
[  2.72178900e-03   1.01285846e-03   2.12413755e-03 ...,   6.50521303e-19
   0.00000000e+00   7.58941521e-19]
8 center:
[  4.14350916e-03   8.23117335e-03   2.16967488e-03 ...,   7.58941521e-19
   0.00000000e+00   2.42693649e-03]
9 center:
[  1.19262239e-18   3.28736429e-03  -1.51788304e-18 ...,   9.75781955e-19
   0.00000000e+00   8.67361738e-19]
10 center:
[  1.30104261e-18   3.83946108e-03  -1.73472348e-18 ...,   1.08420217e-18
   0.00000000e+00   8.67361738e-19]
11 center:
[ -1.40946282e-18   3.08122800e-03  -1.73472348e-18 ...,   1.73472348e-18
   5.42101086e-20   9.75781955e-19]
12 center:
```

```
[  8.67361738e-19   7.35162010e-03   6.12071818e-03 ...,   5.42101086e-19
   0.00000000e+00   6.50521303e-19]
13 center:
[ -3.25260652e-19  -1.73472348e-18   1.49360200e-02 ...,  -4.33680869e-19
   0.00000000e+00  -3.25260652e-19]
14 center:
[  1.19262239e-18   2.85642789e-03  -1.95156391e-18 ...,   1.51788304e-18
   0.00000000e+00   9.75781955e-19]
15 center:
[  2.86154762e-03   5.70486937e-03   4.09193793e-03 ...,   1.73472348e-18
   1.88589477e-03   9.75781955e-19]
16 center:
[  2.84467956e-03   1.38777878e-17  -1.73472348e-18 ...,   1.08420217e-18
   0.00000000e+00   7.58941521e-19]
17 center:
[  1.30104261e-18   3.78247889e-03  -1.73472348e-18 ...,   1.08420217e-18
   1.74293595e-03   8.67361738e-19]
18 center:
[  1.19262239e-18   1.27780805e-02  -1.51788304e-18 ...,   9.75781955e-19
   0.00000000e+00   8.67361738e-19]
19 center:
[  1.40946282e-18   7.27050642e-03   1.31131146e-03 ...,   1.30104261e-18
   0.00000000e+00   1.75555679e-03]
```

Find the top 10 features for each cluster.

In [60]:
```python
# To be implemented
n = 10
for index, point in enumerate(kmeans.cluster_centers_):
    print('%d center has the top prominent words:' % (index))
    print(get_top_values(point, n, vocab_top))
```

```
0 center has the top prominent words:
[u'meat', u'lovers', u'lover', u'ordered', u'great', u'food', u'delicious', u'service', u'defi
1 center has the top prominent words:
[u'definitely', u'recommend', u'time', u'food', u'friends', u'come', u'amazing', u'service', u
2 center has the top prominent words:
[u'happy', u'hour', u'great', u'food', u'good', u'place', u'service', u'came', u'awesome', u'c
3 center has the top prominent words:
[u'great', u'meats', u'korean', u'food', u'dishes', u'service', u'meat', u'bbq', u'good', u'ma
4 center has the top prominent words:
[u'place', u'food', u'just', u'good', u'like', u'service', u'came', u'pretty', u'kbbq', u'time
5 center has the top prominent words:
[u'spicy', u'chicken', u'tuna', u'kimbap', u'good', u'pork', u'food', u'great', u'korean', u'l
6 center has the top prominent words:
[u'really', u'good', u'food', u'enjoyed', u'great', u'service', u'come', u'place', u'definitel
7 center has the top prominent words:
```

```
[u'better', u'bbq', u'korean', u'places', u'great', u'quality', u'service', u'food', u'la', u'p
8 center has the top prominent words:
[u'pork', u'belly', u'beef', u'toro', u'good', u'korean', u'place', u'ordered', u'kalbi', u'bbq
9 center has the top prominent words:
[u'wait', u'long', u'food', u'time', u'worth', u'good', u'service', u'amazing', u'place', u'gre
10 center has the top prominent words:
[u'las', u'vegas', u'bbq', u'korean', u'great', u'good', u'food', u'best', u'place', u'service
11 center has the top prominent words:
[u'great', u'food', u'service', u'place', u'atmosphere', u'awesome', u'amazing', u'vegas', u'co
12 center has the top prominent words:
[u'kobe', u'beef', u'good', u'style', u'great', u'place', u'bbq', u'service', u'meat', u'delici
13 center has the top prominent words:
[u'trip', u'vegas', u'food', u'great', u'service', u'time', u'meal', u'meat', u'definitely', u
14 center has the top prominent words:
[u'good', u'food', u'service', u'bbq', u'korean', u'meat', u'quality', u'place', u'pretty', u'p
15 center has the top prominent words:
[u'best', u'korean', u'bbq', u've', u'vegas', u'food', u'place', u'service', u'town', u'great']
16 center has the top prominent words:
[u'love', u'place', u'great', u'food', u'service', u'come', u'awesome', u'good', u'staff', u'bb
17 center has the top prominent words:
[u'gangnam', u'people', u'combo', u'food', u'got', u'set', u'great', u'come', u'delicious', u'c
18 center has the top prominent words:
[u'nice', u'good', u'place', u'food', u'atmosphere', u'restaurant', u'really', u'bbq', u'frienc
19 center has the top prominent words:
[u'free', u'review', u'dessert', u'yelp', u'good', u'great', u'food', u'ice', u'cream', u'meat
```

Print out the rating and review of a random sample of the reviews assigned to each cluster to get a sense of the cluster.

In [61]:
```python
# To be implemented
rand_index = 42
print('chosen review:')
print(documents_top_restaurant[rand_index])
print('chosen rating:')
print(target_top_restaurant[rand_index])
print('top n prominent words:')
print(get_top_values(kmeans.cluster_centers_[target_labels[rand_index]], n, vocab_top
```

```
chosen review:
Authentic Korean BBQ with a grill in the table. The wait staff was friendly. They were helpful
chosen rating:
1
top n prominent words:
[u'great', u'meats', u'korean', u'food', u'dishes', u'service', u'meat', u'bbq', u'good', u'ma
```

1.3 3. Use PCA to reduce dimensionality

1.3.1 Stardardize features

Your X_train and X_test

```
In [62]: from sklearn.preprocessing import StandardScaler
         # To be implemented

         scaler = StandardScaler()
         doc_scale = scaler.fit_transform(doc_vector_top)
         x_train_scale, x_test_scale, y_train, y_test = train_test_split(doc_scale, target_top
```

1.3.2 Use PCA to transform data (train and test) and get princial components

```
In [63]: from sklearn.decomposition import PCA

         # Let's pick a n_components
         n_components = 2000
         pca = PCA(n_components=n_components)
         train_components = pca.fit_transform(x_train_scale)
         test_components = pca.transform(x_test_scale)
         print(train_components.T.dot(train_components).shape)
         total_variance = np.sum(train_components.T.dot(train_components))

         n_components = 50

         pca = PCA(n_components=n_components)
         train_components = pca.fit_transform(x_train_scale)
         test_components = pca.transform(x_test_scale)
         explained_variance = np.sum(train_components.T.dot(train_components))
         print(train_components.T.dot(train_components).shape)
```

```
(2000, 2000)
(50, 50)
```

```
In [64]: print(total_variance)
         print(explained_variance)
```

```
5974785.68905
586620.119405
```

1.3.3 See how much (and how much percentage of) variance the principal components explain

```
In [65]: percent = explained_variance / total_variance * 100
         print("explained variance with 50 principal components: %f percent" % percent)
```

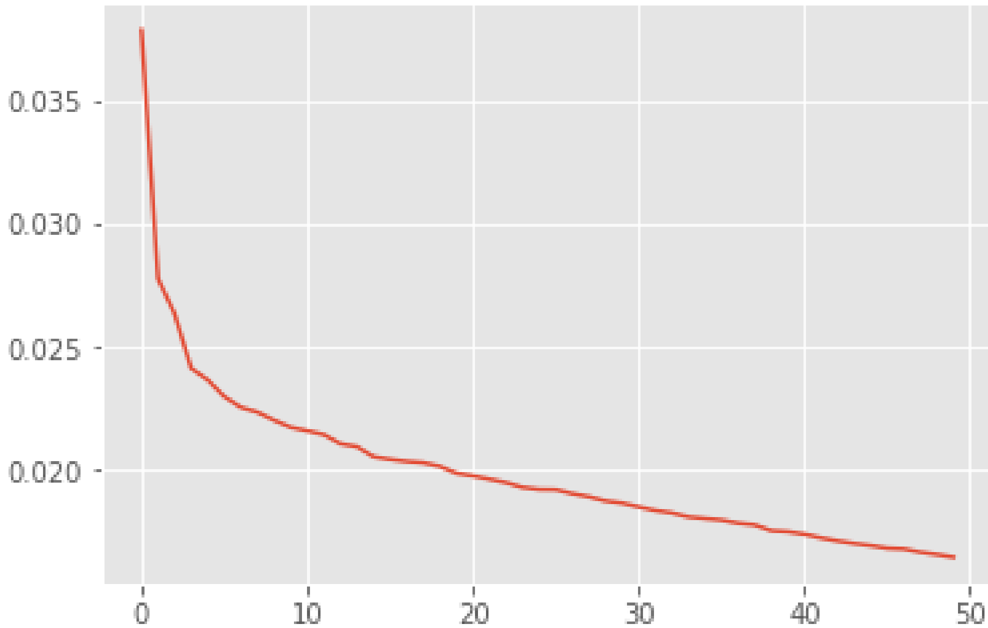
```
explained variance with 50 principal components: 9.818262 percent
```

1.3.4 Viz: plot proportion of variance explained with top principal components

For clear display, you may start with plotting <=20 principal components

In [66]:
```
# To be implemented
variance = train_components.T.dot(train_components).sum(axis = 0) / explained_varianc
plt.plot(variance)
```

Out[66]:
```
[<matplotlib.lines.Line2D at 0x11b20ec50>]
```



1.4 Classifying positive/negative review with PCA preprocessing

1.4.1 Logistic Regression Classifier

Use standardized tf-idf vectors as features

In [67]:
```
# Build a Logistic Regression Classifier, train with standardized tf-idf vectors

from sklearn.linear_model import LogisticRegression
LogisticModel = LogisticRegression(C = 0.01)
LogisticModel.fit(x_train_scale, y_train)
```

Out[67]:
```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)
```

```
In [68]: # Get score for training set
         LogisticModel.score(x_train_scale, y_train)

Out[68]: 0.96903914590747331

In [69]: # Get score for test set
         LogisticModel.score(x_test_scale, y_test)

Out[69]: 0.74854771784232366
```

Use (Stardardized + PCA) tf-idf vectors as features

```
In [70]: # Build a Logistic Regression Classifier, train with PCA tranformed X

         from sklearn.linear_model import LogisticRegression

         # To be implemented
         LogisticModel = LogisticRegression(C = 0.01)
         LogisticModel.fit(train_components, y_train)

Out[70]: LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False)

In [71]: # Get score for training set
         LogisticModel.score(train_components, y_train)

Out[71]: 0.79893238434163705

In [72]: # Get score for test set, REMEMBER to use PCA-transformed X!
         LogisticModel.score(test_components, y_test)

Out[72]: 0.78921161825726138
```

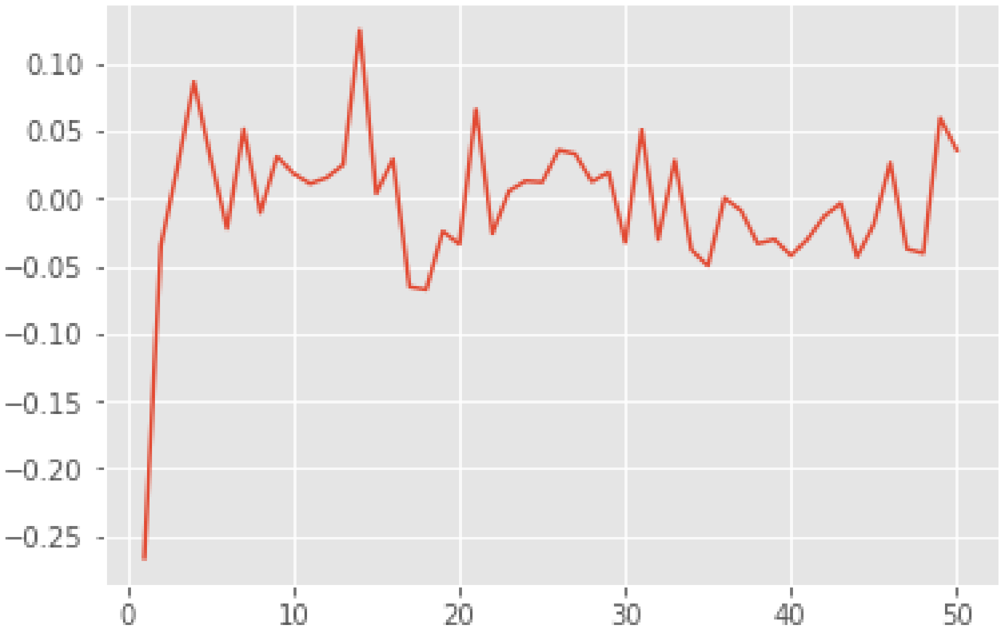
Q: What do you see from the training score and the test score? How do you compare the results from PCA and non-PCA preprocessing? A: (insert your comments here)

1. It is less likely to overfit, because it reduces the dimensionality and ease the curse of dimensionality
2. The test score is higher than that without PCA

You can plot the coefficients against principal components

```
In [73]: # To be implemented
         PCA_Name = range(1, 51)
         plt.plot(PCA_Name, LogisticModel.coef_[0])

Out[73]: [<matplotlib.lines.Line2D at 0x12a712d90>]
```



1.4.2 Random Forest Classifier

Use standardized tf-idf vectors as features

```
In [74]: # Build a Random Forest Classifier

         from sklearn.ensemble import RandomForestClassifier

         RandomForestModel = RandomForestClassifier(criterion = 'entropy', min_samples_split=2(
         RandomForestModel.fit(x_train_scale, y_train)

Out[74]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_split=1e-07, min_samples_leaf=1,
                     min_samples_split=20, min_weight_fraction_leaf=0.0,
                     n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
                     verbose=0, warm_start=False)

In [75]: # Get score for training set
         RandomForestModel.score(x_train_scale, y_train)

Out[75]: 0.946975088967971 56

In [76]: # Get score for test set
         RandomForestModel.score(x_test_scale, y_test)

Out[76]: 0.7585062240663900 1
```

Use (Stardardized + PCA) tf-idf vectors as features

```
In [77]: # Build a Random Forest Classifier

         from sklearn.ensemble import RandomForestClassifier

         RandomForestModel = RandomForestClassifier(criterion = 'entropy', min_samples_split=2(
         RandomForestModel.fit(train_components, y_train)
```

```
Out[77]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='entropy',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_impurity_split=1e-07, min_samples_leaf=1,
                     min_samples_split=20, min_weight_fraction_leaf=0.0,
                     n_estimators=10, n_jobs=1, oob_score=False, random_state=None,
                     verbose=0, warm_start=False)
```

```
In [78]: # Get score for training set
         RandomForestModel.score(train_components, y_train)
```

```
Out[78]: 0.905693950177935 97
```

```
In [79]: # Get score for test set, REMEMBER to use PCA-transformed X!
         RandomForestModel.score(test_components, y_test)
```

```
Out[79]: 0.7643153526970953 8
```

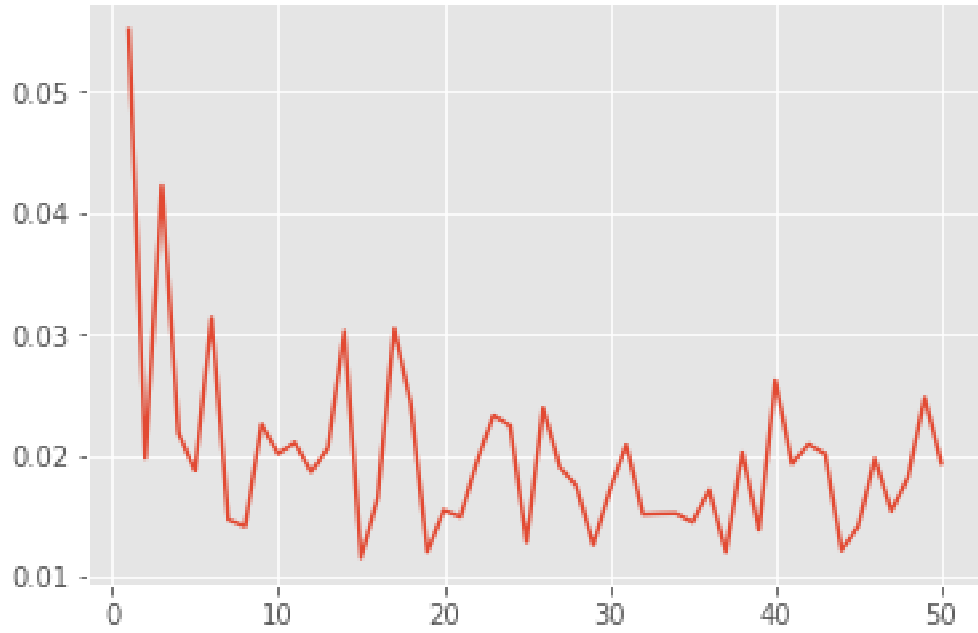
Q: What do you see from the training result and the test result? A: (insert your comments here)

1. It did not have much effect since it does not use the distance to train. Therefore, it will not help much to avoid overfit
2. The model performs a little bit worse than the un-PCA-ed model because it loses information when PCA is applied and causes some information to be thrown away because of their low-importance

You can plot the feature importances against principal components

```
In [80]: # To be implemented
         plt.plot(PCA_Name, RandomForestModel.feature_importances_)
```

```
Out[80]: [<matplotlib.lines.Line2D at 0x129b32910>]
```



1.5 Extra Credit #1: Can you cluster restaurants from their category information?

Hint: a business may have mutiple categories, e.g. a restaurant can have both "Restaurants" and "Korean"

```
In [81]: # preprocessing the categories data
         docs = df['categories'].values
         target = (df['stars'] == 5).astype(int).values
         doc = [doc[1:-1] for doc in docs]
```

```
In [82]: # vectorizer
         from sklearn.feature_extraction.text import TfidfVectorizer
         import nltk
         from nltk.tokenize import word_tokenize
         from nltk.corpus import stopwords

         from sklearn.model_selection import train_test_split
         x_train, x_test, y_train, y_test = train_test_split(doc, target, test_size = 0.8, ranc

         vectorizer_categories = TfidfVectorizer(stop_words = 'english', max_features = 2000)
         train_vector_categories = vectorizer_categories.fit_transform(x_train).toarray()
         vocab_categories = vectorizer_categories.get_feature_names()
         test_vector_categories = vectorizer_categories.transform(x_test).toarray()
```

```
In [83]: # cluster restaurants
         kmeans = KMeans(n_clusters = 20, random_state=42)
         kmeans.fit(train_vector_categories)
```

```
Out[83]: KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
             n_clusters=20, n_init=10, n_jobs=1, precompute_distances='auto',
             random_state=42, tol=0.0001, verbose=0)
```

```
In [84]: doc_vector_categories = vectorizer_categories.transform(doc).toarray()
         labels = kmeans.predict(doc_vector_categories)
```

```
In [85]: for index, point in enumerate(kmeans.cluster_centers_):
             print('%d center has the top prominent words:' % (index))
             print(get_top_values(point, n, vocab_categories))
```

```
0 center has the top prominent words:
[u'barbeque', u'korean', u'plates', u'small', u'tapas', u'restaurants', u'japanese', u'fusion'
1 center has the top prominent words:
[u'bars', u'nightlife', u'mexican', u'sports', u'restaurants', u'lounges', u'pubs', u'american
2 center has the top prominent words:
[u'burgers', u'tapas', u'restaurants', u'small', u'plates', u'spanish', u'salad', u'gastropubs
3 center has the top prominent words:
[u'breakfast', u'brunch', u'american', u'traditional', u'restaurants', u'new', u'sandwiches', u
4 center has the top prominent words:
[u'italian', u'restaurants', u'seafood', u'american', u'delis', u'traditional', u'nightlife', u
5 center has the top prominent words:
[u'asian', u'fusion', u'restaurants', u'chinese', u'japanese', u'bars', u'hawaiian', u'food', u
6 center has the top prominent words:
[u'sushi', u'japanese', u'bars', u'restaurants', u'fusion', u'asian', u'seafood', u'nightlife'
7 center has the top prominent words:
[u'seafood', u'steakhouses', u'american', u'restaurants', u'traditional', u'new', u'cajun', u'
8 center has the top prominent words:
[u'fast', u'food', u'burgers', u'restaurants', u'mexican', u'chicken', u'wings', u'sandwiches'
9 center has the top prominent words:
[u'american', u'new', u'traditional', u'restaurants', u'burgers', u'nightlife', u'bars', u'sou
10 center has the top prominent words:
[u'pizza', u'italian', u'restaurants', u'wings', u'chicken', u'sandwiches', u'salad', u'food',
11 center has the top prominent words:
[u'mexican', u'restaurants', u'seafood', u'food', u'vegetarian', u'cuisine', u'new', u'latin',
12 center has the top prominent words:
[u'food', u'restaurants', u'services', u'event', u'planning', u'sandwiches', u'specialty', u'i
13 center has the top prominent words:
[u'buffets', u'breakfast', u'brunch', u'restaurants', u'sandwiches', u'food', u'american', u'b
14 center has the top prominent words:
[u'chinese', u'thai', u'restaurants', u'noodles', u'ramen', u'japanese', u'sum', u'dim', u'tai
15 center has the top prominent words:
[u'vietnamese', u'restaurants', u'soup', u'chinese', u'noodles', u'barbeque', u'sandwiches', u
16 center has the top prominent words:
[u'bars', u'wine', u'nightlife', u'cocktail', u'beer', u'american', u'spirits', u'restaurants'
17 center has the top prominent words:
[u'tea', u'coffee', u'food', u'cafes', u'desserts', u'restaurants', u'bubble', u'breakfast', u
18 center has the top prominent words:
```

```
[u'steakhouses', u'restaurants', u'french', u'american', u'new', u'breakfast', u'brunch', u'che
19 center has the top prominent words:
[u'mediterranean', u'middle', u'eastern', u'greek', u'restaurants', u'lebanese', u'vegetarian'
```

1.6 Extra Credit #2: Can you try different distance/similarity metrics for clusterings, e.g. Pearson correlation, Jaccard distance, etc.

Hint: You can take a look at scipy documentations to use other distances

Q: How do you compare with Cosine distance or Euclidean distance? Cosine Distance is less influenced by the curse of dimensionality than the Euclidean Distance.

In [86]:
```
train_vector_categories.shape
```

Out[86]:
```
(69603, 406)
```

In [87]:
```
from scipy.spatial.distance import pdist
from scipy.spatial.distance import euclidean
from scipy.spatial.distance import cosine
from scipy.spatial.distance import jaccard
from scipy.spatial.distance import correlation
from collections import defaultdict

import random

'''
class Customized_KMeans():
    def __init__(self, k, iterations = 300, distFunc = euclidean):
        self.k = k
        self.distFunc = distFunc
        self.iterations = iterations
        self.cluster_centers = []
        self.inertia = 0

    def initial(self, X):
        index = random.randint(0, X.shape[0] - 1) # find the first one
        centers = [tuple(X[index])]
        while len(centers) < self.k:
            default_dist = 0
            default_center = []
            for pt in X:
                min_dist = np.min([self.distFunc(center, pt) for center in centers])
                if min_dist > default_dist:
                    default_dist = min_dist
                    default_center = tuple(pt)
            centers.append(default_center)
        return centers
```

```
    def fit(self, X):
        self.cluster_centers = self.initial(X)
        print('initialization complete')
        for it in xrange(self.iterations):
            clusters = defaultdict(list)
            labels = self.predict(X)
            new_centers = []
            for i in xrange(X.shape[0]):
                clusters[labels[i]].append(X[i])
            for i in range(self.k):
                new_centers.append(np.mean(clusters[i], axis = 0))
            new_centers = [tuple(center) for center in new_centers]
            if set(self.cluster_centers) == set(new_centers):
                break
            self.cluster_centers = new_centers


    def predict(self, X):
        label = []
        for pt in X:
            dist_list = [self.distFunc(pt, center) for center in self.cluster_centers
            label.append(np.argmin(dist_list))
        return label
'''
def initial(X, distFunc, k):
    index = random.randint(0, X.shape[0] - 1) # find the first one
    centers = [tuple(X[index])]
    while len(centers) < k:
        default_dist = 0
        default_center = []
        for pt in X:
            min_dist = np.min([distFunc(center, pt) for center in centers])
            if min_dist > default_dist:
                default_dist = min_dist
                default_center = tuple(pt)
        centers.append(default_center)
    return centers
def k_means(X, distFunc, k=5, max_iter=300):
    """Performs k means

    Args:
    - X - feature matrix
    - k - number of clusters
    - max_iter - maximum iteratations

    Returns:
    - clusters - dict mapping cluster centers to observations
```

```
    """
    centers = [tuple(pt) for pt in initial(X, distFunc, k)]
    for i in xrange(max_iter):
        clusters = defaultdict(list)

        for datapoint in X:
            distances = [distFunc(datapoint, center) for center in centers]
            center = centers[np.argmin(distances)]
            clusters[center].append(datapoint)

        new_centers = []
        for center, pts in clusters.iteritems():
            new_center = np.mean(pts, axis=0)
            new_centers.append(tuple(new_center))

        if set(new_centers) == set(centers):
            break

        centers = new_centers

    return clusters, centers
```

In [88]:
```
def printFeatures(cluster, vocab):
    for index, point in enumerate(cluster):
        print('%d center has the top prominent words:' % (index))
        print(get_top_values(point, n, vocab))
```

In [89]:
```
euclidean_clusters, euclidean_centers = k_means(train_vector_categories, euclidean)
print('Euclidean Prediction Complete')
printFeatures(euclidean_clusters, vocab_categories)
```

```
Euclidean Prediction Complete
0 center has the top prominent words:
[u'food', u'brunch', u'breakfast', u'restaurants', u'fast', u'sandwiches', u'tea', u'burgers',
1 center has the top prominent words:
[u'american', u'new', u'traditional', u'restaurants', u'bars', u'breakfast', u'brunch', u'nigh
2 center has the top prominent words:
[u'pizza', u'italian', u'restaurants', u'wings', u'chicken', u'sandwiches', u'food', u'bars', u
3 center has the top prominent words:
[u'japanese', u'sushi', u'bars', u'restaurants', u'fusion', u'asian', u'ramen', u'tapas', u'pla
4 center has the top prominent words:
[u'restaurants', u'mexican', u'bars', u'nightlife', u'italian', u'chinese', u'steakhouses', u's
```

In [90]:
```
cosine_clusters, cosine_centers = k_means(train_vector_categories, cosine)
print('Cosine Prediction')
printFeatures(cosine_clusters, vocab_categories)
```

```
Cosine Prediction
0 center has the top prominent words:
```

```
[u'food', u'fast', u'sandwiches', u'restaurants', u'brunch', u'breakfast', u'tea', u'cafes', u
1 center has the top prominent words:
[u'italian', u'pizza', u'restaurants', u'bars', u'food', u'nightlife', u'wine', u'salad', u'am
2 center has the top prominent words:
[u'american', u'restaurants', u'new', u'bars', u'traditional', u'mexican', u'nightlife', u'ste
3 center has the top prominent words:
[u'japanese', u'sushi', u'bars', u'restaurants', u'chinese', u'asian', u'fusion', u'barbeque',
4 center has the top prominent words:
[u'thai', u'restaurants', u'vegetarian', u'mediterranean', u'indian', u'event', u'services', u
```

```
In [91]: correlation_clusters, correlation_centers = k_means(train_vector_categories, correlat
         print('Correlation Prediction')
         printFeatures(correlation_clusters, vocab_categories)
```

```
Correlation Prediction
0 center has the top prominent words:
[u'food', u'burgers', u'restaurants', u'fast', u'tea', u'cafes', u'coffee', u'sandwiches', u'v
1 center has the top prominent words:
[u'chinese', u'restaurants', u'asian', u'fusion', u'japanese', u'korean', u'barbeque', u'thai'
2 center has the top prominent words:
[u'american', u'breakfast', u'brunch', u'traditional', u'restaurants', u'new', u'steakhouses',
3 center has the top prominent words:
[u'bars', u'nightlife', u'mexican', u'restaurants', u'sushi', u'japanese', u'american', u'wine
4 center has the top prominent words:
[u'pizza', u'italian', u'restaurants', u'food', u'american', u'bars', u'sandwiches', u'wings',
```

```
In [92]: jaccard_clusters, jaccard_centers = k_means(train_vector_categories, jaccard)
         print('Jaccard Prediction')
         printFeatures(jaccard_clusters, vocab_categories)
```

```
Jaccard Prediction
0 center has the top prominent words:
[u'restaurants', u'bars', u'american', u'food', u'new', u'nightlife', u'traditional', u'mexica
1 center has the top prominent words:
[u'soup', u'salad', u'mexican', u'nightlife', u'bars', u'restaurants', u'eastern', u'education
```

1.7 Extra Credit #3: Can you cluster categories from business entities? What does it mean by a cluster?

Hint: Think the example where words can be clustered from the transposed tf-idf matrix.

Clustering categories from business entities is to categorize each "business entity"/"business id". That is to classify each entity into similar categories

```
In [93]: entities = df[['business_id', 'categories']]
         entities = entities.drop_duplicates()
         category = entities['categories'].values
```

```
category_name = np.array([name[1:-1] for name in category])
target = np.zeros(category_name.shape)
x_train, x_test, y_train, y_test = train_test_split(category_name, target, test_size =
```

In [94]:
```
category_name[0]
```

Out[94]:
```
'Steakhouses, Restaurants, Cajun/Creole'
```

In [95]:
```
from sklearn.feature_extraction.text import TfidfVectorizer
import nltk
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from sklearn.cluster import KMeans

vectorizer = TfidfVectorizer(stop_words = 'english', max_features = 2000)
train_vector = vectorizer.fit_transform(x_train).toarray()
vocab = vectorizer.get_feature_names()
test_vector = vectorizer.transform(x_test).toarray()
category_vector = vectorizer.transform(category_name).toarray()
```

In [96]:
```
kmeans_cluster = KMeans(n_clusters = 5, random_state = 42)
kmeans_cluster.fit(train_vector)
```

Out[96]:
```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
    n_clusters=5, n_init=10, n_jobs=1, precompute_distances='auto',
    random_state=42, tol=0.0001, verbose=0)
```

In [97]:
```
category_label = kmeans_cluster.predict(category_vector)
data_col = {'categories': category, 'label': category_label}
df_label = pd.DataFrame(data = data_col)
df_label.head(5)
```

Out[97]:

	categories	label
0	[Steakhouses, Restaurants, Cajun/Creole]	1
1	[Restaurants, Korean, Sushi Bars]	0
2	[Restaurants, Bars, Nightlife, Seafood, Americ...	0
3	[Restaurants, Thai]	1
4	[Buffets, Restaurants]	1

In [98]:
```
df_merge = pd.merge(entities, df_label, how='outer', left_on='categories', right_on='
df_merge.head(5)
```

Out[98]:

	business_id	categories \
0	--9e1ONYQuAa-CB_Rrw7Tw	[Steakhouses, Restaurants, Cajun/Creole]
1	-1vfRrlnNnNJ5boOVghMPA	[Restaurants, Korean, Sushi Bars]
2	-3zffZUHoY8bQjGfPSoBKQ	[Restaurants, Bars, Nightlife, Seafood, Americ...
3	-8R_-EkGpUhBk55K9Dd4mg	[Restaurants, Thai]
4	-8R_-EkGpUhBk55K9Dd4mg	[Restaurants, Thai]

```
   label
0      1
1      0
2      0
3      1
4      1
```

```
In [99]: df_merge.shape
         df_merge['label'].value_counts()
```

```
Out[99]: 1    35813
         2    10706
         3     9672
         4     1961
         0     1308
         Name: label, dtype: int64
```

```
In [100]: for index, point in enumerate(kmeans_cluster.cluster_centers_):
              print('%d center has the top prominent words:' % (index))
              print(get_top_values(point, n, vocab))
```

```
0 center has the top prominent words:
[u'bars', u'nightlife', u'sushi', u'american', u'restaurants', u'sports', u'japanese', u'tradi
1 center has the top prominent words:
[u'restaurants', u'mexican', u'food', u'chinese', u'sandwiches', u'thai', u'seafood', u'italia
2 center has the top prominent words:
[u'pizza', u'restaurants', u'italian', u'wings', u'chicken', u'sandwiches', u'food', u'salad',
3 center has the top prominent words:
[u'fast', u'food', u'restaurants', u'burgers', u'sandwiches', u'mexican', u'chinese', u'chicke
4 center has the top prominent words:
[u'american', u'traditional', u'new', u'breakfast', u'brunch', u'restaurants', u'burgers', u'd
```

1.8 Extra Credit #4: What are the characteristics of each of the clustered ? For each cluster, which restaurant can best represent ("define") its cluster?

Hint: how to interpret "best"?

How to define 'best represent'? In my opinion, the restaurant is considered to be best representative to the cluster when the distance or similarity is the smallest. Therefore, find the best representative one by comparing the metrics.

```
In [101]: from scipy.spatial.distance import euclidean

          cluster_center = {}
          shape = category_vector.shape
          for i in xrange(shape[0]):
              distance = euclidean(category_vector[i], kmeans_cluster.cluster_centers_[categor
              if category_label[i] in cluster_center:
                  if cluster_center[category_label[i]][1] >= distance:
```

```
                cluster_center[category_label[i]] = [i, distance]
        else:
            cluster_center[category_label[i]] = [i, distance]
```

```
In [102]: for key, value in cluster_center.items():
              print('cluster Number: %d' % key)
              print('best represent: %s' % category_name[value[0]])
```

```
cluster Number: 0
best represent: Japanese, Bars, Nightlife, American (New), Restaurants, Sushi Bars
cluster Number: 1
best represent: Mexican, Restaurants, Food
cluster Number: 2
best represent: Restaurants, Pizza
cluster Number: 3
best represent: Restaurants, Fast Food
cluster Number: 4
best represent: American (New), Restaurants, American (Traditional), Breakfast & Brunch
```

1.9 Extra Credit #5: Can you think of other use cases that clustering can be used?

Hint: of course you can make use of other yelp dataset. You can try anything you want as long as you can explain it.

```
In [103]: # To be implemented
```