Homework 3: PCA on digit recognition data
Total: 5 pts

The goal of this assignment is to better understand how PCA can be used for data compression, visualization, and improved classification. Your tasks will be to make appropriate modifications to the provided Jupyter notebook which uses PCA on the digit recognition task from the course.

Deliverable for submission: A PDF and original Jupyter notebook sheet containing your code and results.

Hint/Help: Code for the following problems is provided below.

1. PCA on digits for visualization
2. PCA on digits for compression
3. PCA on digits improve classification
4. K-means clustering on digits

Steps:

1. **Information in the first two components:** Print the percent variance explained for each PCA component, from the first to the last. This should be a decreasing number. Note how little information is in the first two used for plotting. **Hint**: use the **sklearn.Decomposition.PCA.explained_variance_ratio_** attribute.

2. **Understanding a PCA component:** Indicate in writing in the notebook which of the plotted PCA components is most useful for discriminating a 0 from a 1 (the first, second, third…?), and how you can observe that in both the samples in the reduced dimensionality plot and the picture of the component itself.

3. **Observing compression:** Make a table with the following columns in order

a) The number of PCA components used in a compression
b) The percent an image is compressed with that many components, from 100% to 0%. That is, the 1 - (number_of_components / 64) expressed as a percentage
c) The percent variance explained in the original data by those components. This would be the cumulative sum of what was shown in step 1.

4. **PCA affecting recognition accuracy:** Make a plot of the accuracy of **K nearest neighbors with k = 1** as the number of PCA dimensions is increased. Note: Unlike Gaussian Naive Bayes in the example, it is possible that the maximum accuracy is at 64 dimensions.

```
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# 1. PCA on digits for visualization
# 2. PCA on digits for compression
# 3. PCA on digits improve classification
# 4. K-means clustering on digits

import numpy as np
import pylab as py

%matplotlib inline
```
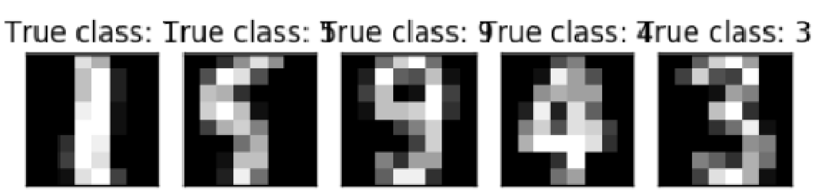

```
# digit recognition setup...

from sklearn.datasets import load_digits
digits = load_digits()

X, y = digits.data, digits.target
print("data shape: %r, target shape: %r" % (X.shape, y.shape))
print("classes: %r" % list(np.unique(y)))

n_samples, n_features = X.shape
print("n_samples=%d" % n_samples)
print("n_features=%d" % n_features)
```

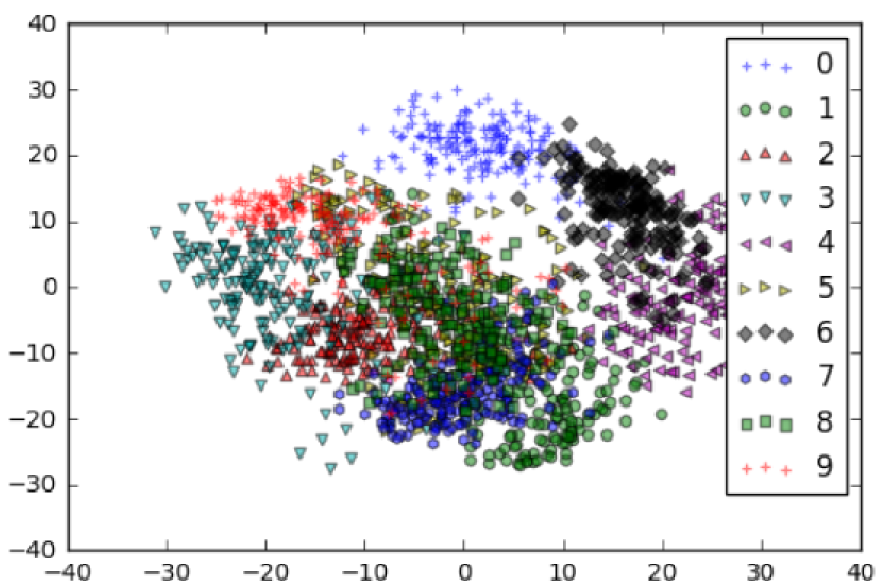
```
data shape: (1797, 64), target shape: (1797,)
classes: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
n_samples=1797
n_features=64
```

```
def plot_gallery(data, labels, shape, interpolation='nearest'):
    for i in range(data.shape[0]):
        py.subplot(1, data.shape[0], (i + 1))
        py.imshow(data[i].reshape(shape), interpolation=interpolation)
        py.title(labels[i])
        py.xticks(()), py.yticks(())
        py.gray()

subsample = np.random.permutation(X.shape[0])[:5]
images = X[subsample]
labels = ['True class: %d' % l for l in y[subsample]]
plot_gallery(images, labels, shape=(8, 8))
```

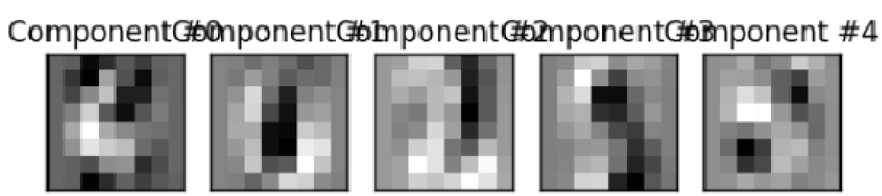



```
# 1. PCA on digits for visualization
```

```
from sklearn.decomposition import RandomizedPCA

pca = RandomizedPCA(n_components=5)
X_pca = pca.fit_transform(X)

X_pca.shape

from itertools import cycle

colors = ['b', 'g', 'r', 'c', 'm', 'y', 'k']
markers = ['+', 'o', '^', 'v', '<', '>', 'D', 'h', 's']
for i, c, m in zip(np.unique(y), cycle(colors), cycle(markers)):
    py.scatter(X_pca[y == i, 0], X_pca[y == i, 1],
        c=c, marker=m, label=i, alpha=0.5)

_ = py.legend(loc='best')
```




```
labels = ['Component #%d' % i for i in range(len(pca.components_))]
plot_gallery(pca.components_, labels, shape=(8, 8))
```




```
# 2. PCA on digits for compression

n = 8 # number of digits for demonstration
dims = [1,2,3,5,10,20,40,64]
```

```
print('compressed images of first',n,'digits')
print('with this many PCA components:',dims)
for d in dims:  # dimensionality for compressed signal
    pca = RandomizedPCA(n_components=d)
    pca.fit_transform(X)
    reduced_X = pca.transform(X[0:n]) # the reduced dimensionality
    recovered_X = pca.inverse_transform(reduced_X)
    py.figure()
    plot_gallery(recovered_X, y[0:n], shape=(8, 8))
```

```
compressed images of first 8 digits
with this many PCA components: [1, 2, 3, 5, 10, 20, 40, 64]
```


```
# 3. PCA on digits improve classification
```

```
from sklearn.cross_validation import train_test_split

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.5, random_state=0)

print("train data shape: %r, train target shape: %r"
      % (X_train.shape, y_train.shape))
print("test data shape: %r, test target shape: %r"
      % (X_test.shape, y_test.shape))

from sklearn.naive_bayes import GaussianNB
model = GaussianNB().fit(X_train, y_train)
train_score = model.score(X_train, y_train)
print('training score (overfitting!):',train_score)

test_score = model.score(X_test, y_test)
print('test score:',test_score)
```

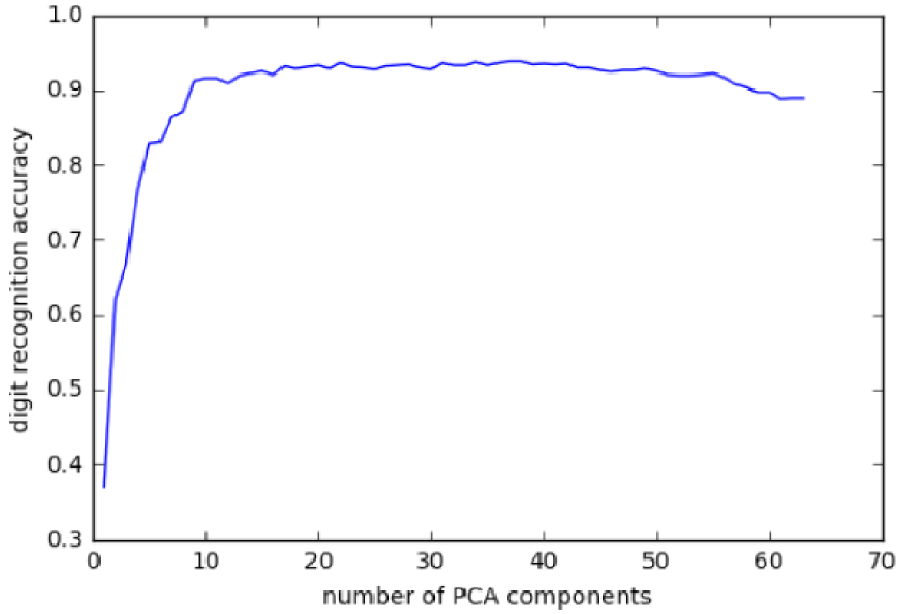
```
train data shape: (898, 64), train target shape: (898,)
test data shape: (899, 64), test target shape: (899,)
training score (overfitting!): 0.875278396437
test score: 0.83426028921
```

```
# but now using PCA features instead of pixels directly!

pca = RandomizedPCA(n_components=10)
pca.fit(X_train)

tX_train = pca.transform(X_train)
tX_test = pca.transform(X_test)

model = GaussianNB().fit(tX_train, y_train)
train_score = model.score(tX_train, y_train)
print('training score (overfitting!):',train_score)

test_score = model.score(tX_test, y_test)
print('test score:',test_score)

from sklearn import metrics
y_test_pred = model.predict(tX_test)
expected = y_test
predicted = model.predict(tX_test)
print("Confusion matrix:\n%s" % metrics.confusion_matrix(expected, predicted))
```

```
training score (overfitting!): 0.916481069042
test score: 0.916573971079
Confusion matrix:
[[89  0  0  0  0  0  0  0  0  0]
 [ 0 85  2  0  0  0  0  0  2  1]
 [ 0  7 83  1  0  0  0  1  0  0]
 [ 0  0  2 79  0  4  0  2  2  4]
 [ 0  1  0  0 71  0  0  4  0  0]
 [ 0  0  0  0  1 98  0  0  0  9]
 [ 0  2  0  0  0  0 84  0  2  1]
 [ 0  1  0  0  0  0  0 77  0  0]
 [ 0 12  0  1  0  1  0  1 73  4]
 [ 0  1  0  1  0  3  0  2  0 85]]
```

```
# let's plot accuracy vs number of components!

accuracy = []
n_comp = range(1,64)
for i in n_comp:
    pca = RandomizedPCA(n_components=i)
    pca.fit(X_train)

    tX_train = pca.transform(X_train)
    tX_test = pca.transform(X_test)

    model = GaussianNB().fit(tX_train, y_train)
    test_score = model.score(tX_test, y_test)
    accuracy.append(test_score)

py.plot(n_comp, accuracy)
py.xlabel('number of PCA components')
py.ylabel('digit recognition accuracy')
```

```
<matplotlib.text.Text at 0x11526c048>
```




```
# 4. K-means clustering on digits

# identify 10 clusters (which should correspond to digits)
from sklearn import cluster

k_means = cluster.KMeans(n_clusters=10)
k_means.fit(digits.data)

print('true  :',digits.target[::50])
print('kmeans:',k_means.labels_[::50])

metrics.adjusted_rand_score(digits.target, k_means.labels_)
```

```
true  : [0 2 4 0 1 4 7 7 4 4 8 6 2 4 2 6 4 5 4 3 1 1 9 8 7 1 3 3 2 5 1 5 2 5 5 3]
kmeans: [2 1 6 2 8 6 3 3 6 6 9 4 7 6 1 4 6 5 6 0 7 1 9 0 3 1 0 0 9 9 8 5 7 5 5 0]
0.6591633948326813
```

```
dbscan = cluster.DBSCAN(eps = 24, min_samples = 20)
dbscan.fit(digits.data)

print('true  :',digits.target[::50])
print('dbscan:',dbscan.labels_[::50])

metrics.adjusted_rand_score(digits.target, dbscan.labels_)
```

```
true  : [0 2 4 0 1 4 7 7 4 4 8 6 2 4 2 6 4 5 4 3 1 1 9 8 7 1 3 3 2 5 1 5 2 5 5 3]
dbscan: [ 0 -1  4  0  3  4  5  5  4  4 -1  2  8  4 -1  2  4  7  4  1 -1  6 -1 -1
  6  1  1 -1  7 -1  7  8  7  7  1]
0.5100021253245306
```