hw7-writeup-25912237

December 10, 2015

In [61]:
```
%matplotlib inline
%load_ext autoreload
import numpy as np
import pandas as pd
import scipy as sp
import scipy.io
import datetime
from math import ceil

import matplotlib.pyplot as plt
import matplotlib
```

```
The autoreload extension is already loaded. To reload it, use:
  %reload_ext autoreload
```

In [62]:
```
from scipy.spatial.distance import cdist
```

In [63]:
```
images = scipy.io.loadmat("mnist_data/images.mat")['images'].T.reshape((60000,784)) / 255
np.random.shuffle(images)
images.shape
```

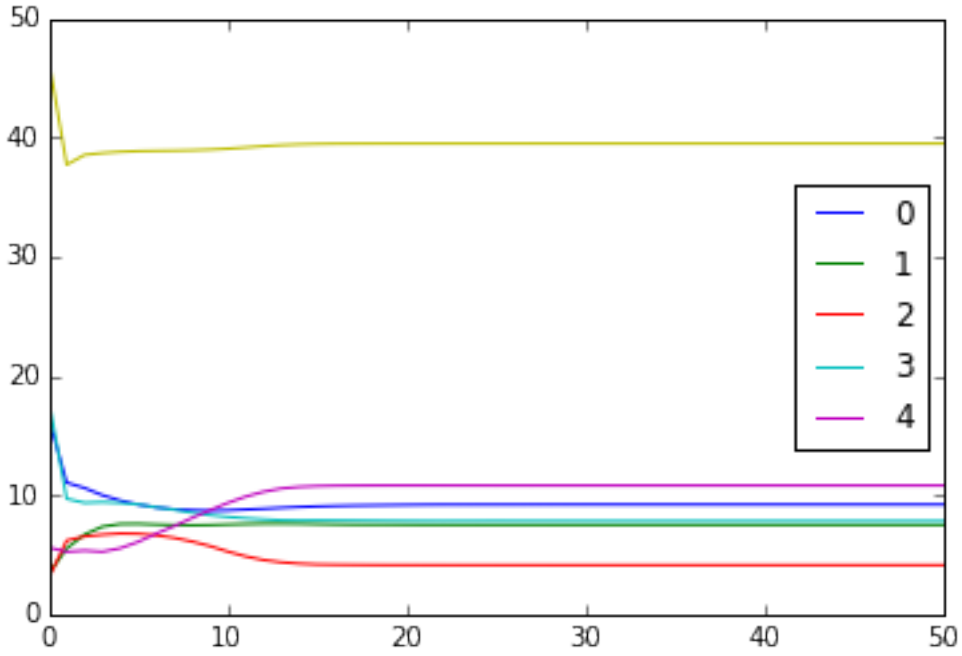
Out[63]:
```
(60000, 784)
```

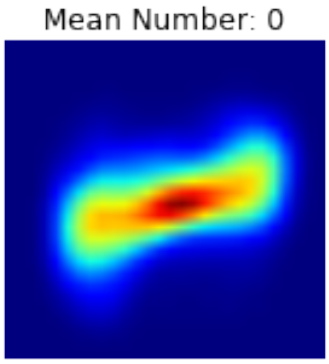
In [64]:
```
class KMeans:
    def __init__(self, k=5, num_iters=10, seed=10):
        self.k = k
        self.num_iters = num_iters
        self.losses = []
        self.seed = seed
        self.means = None
        self.start = None # keep track of where we started

    def fit(self, X, y=None):
        n_examples, n_features = X.shape
        np.random.seed(self.seed)
        start = X[np.random.choice(len(X), self.k, False)]
        start = np.abs(np.random.normal(X.mean(axis=0).mean(), X.mean(axis=0).std(), size=(sel
        self.start = start
        self.means = start
        for it in range(self.num_iters):
            assignments = self.predict(X)
            for mean in range(self.k):
                self.means[mean] = X[assignments == mean].mean(axis=0)
        self.mean_stats(X)
```

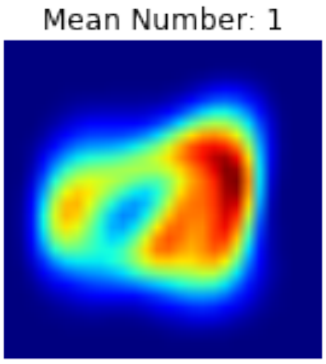
```
            return self

        def loss(self, pred_values):
            loss = []
            assignments = pred_values.argmin(axis=1)
            for mean in range(self.k):
                n_assign = pred_values[assignments == mean].sum()
                loss.append(n_assign/len(assignments))
            self.losses.append(loss)

        def mean_stats(self, X):
            preds = self.predict(X)
            pd.DataFrame(self.losses).plot()
            pd.DataFrame(self.losses).sum(axis=1).plot()
            for mean in range(self.k):
                print("Number in Mean Number %i %i" % (mean, len(X[preds == mean])))

        def plot_means(self, figsize=(10,8)):
            fig = plt.figure(figsize=figsize)
            gs = matplotlib.gridspec.GridSpec(ceil(self.k/2), 2, width_ratios=[1,1])
            for mean, ax in zip(range(self.k),gs):
                sp = plt.subplot(ax)
                sp.imshow(self.means[mean].reshape((28,28)))
                sp.set_title("Mean Number: %i" % mean)
                sp.set_axis_off()

        def predict(self, X, y=None):
            pred_values = cdist(X, self.means, 'euclidean')
            self.loss(pred_values)
            return pred_values.argmin(axis=1)
```

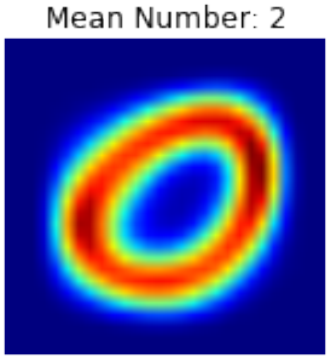
In [65]:
```
%autoreload
s = np.random.randint(0, 1000)
print(s)
k = 5
it = 50
km = KMeans(k, it, s).fit(images).plot_means()
```

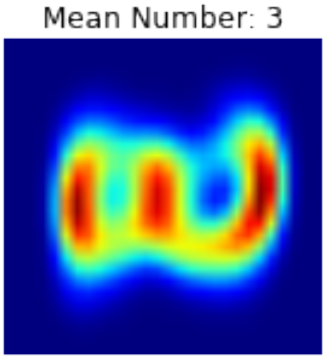
```
379
Number in Mean Number 0 15254
Number in Mean Number 1 10912
Number in Mean Number 2 5570
Number in Mean Number 3 11646
Number in Mean Number 4 16618
```

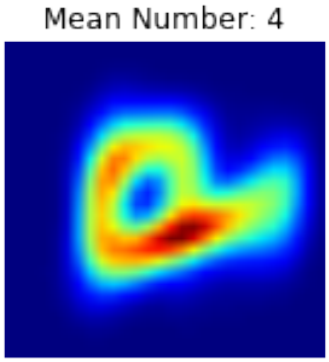

50
40
30
20
10
0
0
10
20
30
40
50
0
1
2
3
4







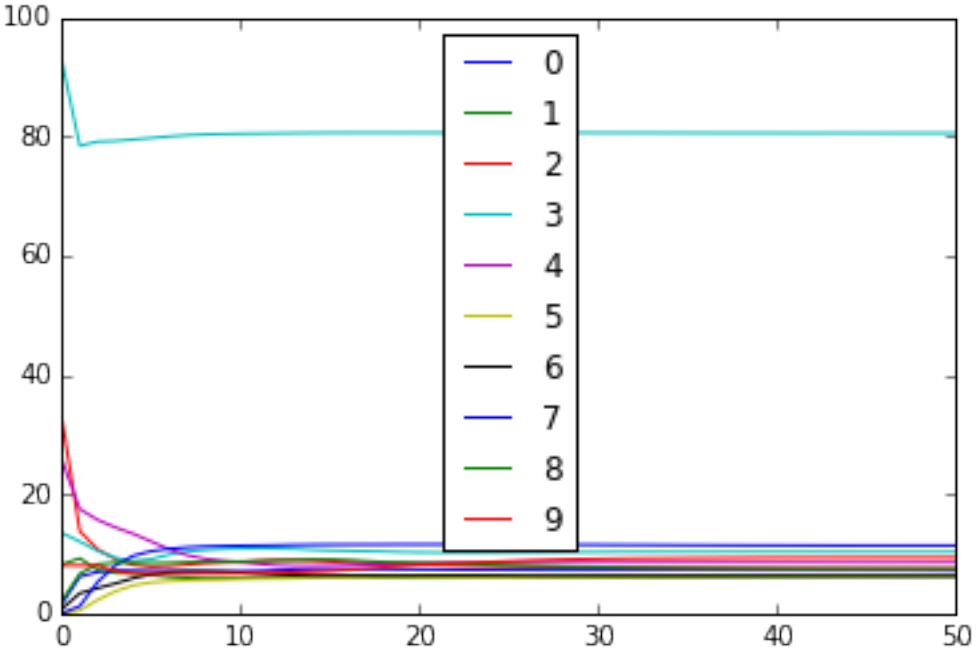


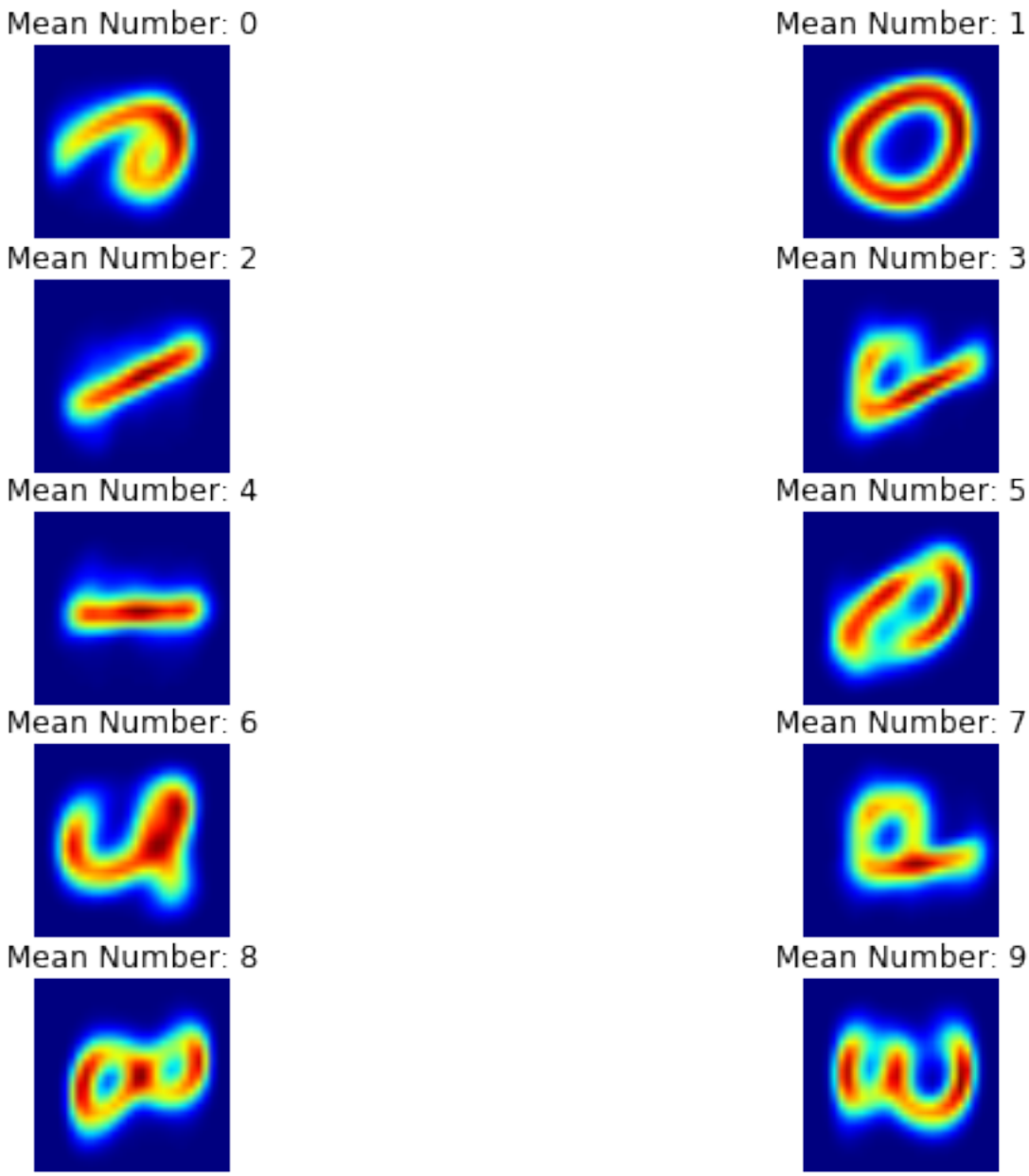



```
In [66]: %autoreload
         s = np.random.randint(0, 1000)
         print(s)
         k = 10
         km = KMeans(k, it, s).fit(images).plot_means()
```

```
509
Number in Mean Number 0 5222
Number in Mean Number 1 4002
Number in Mean Number 2 6065
Number in Mean Number 3 7970
Number in Mean Number 4 7155
Number in Mean Number 5 4549
Number in Mean Number 6 4354
```

```
Number in Mean Number 7 8417
Number in Mean Number 8 5544
Number in Mean Number 9 6722
```

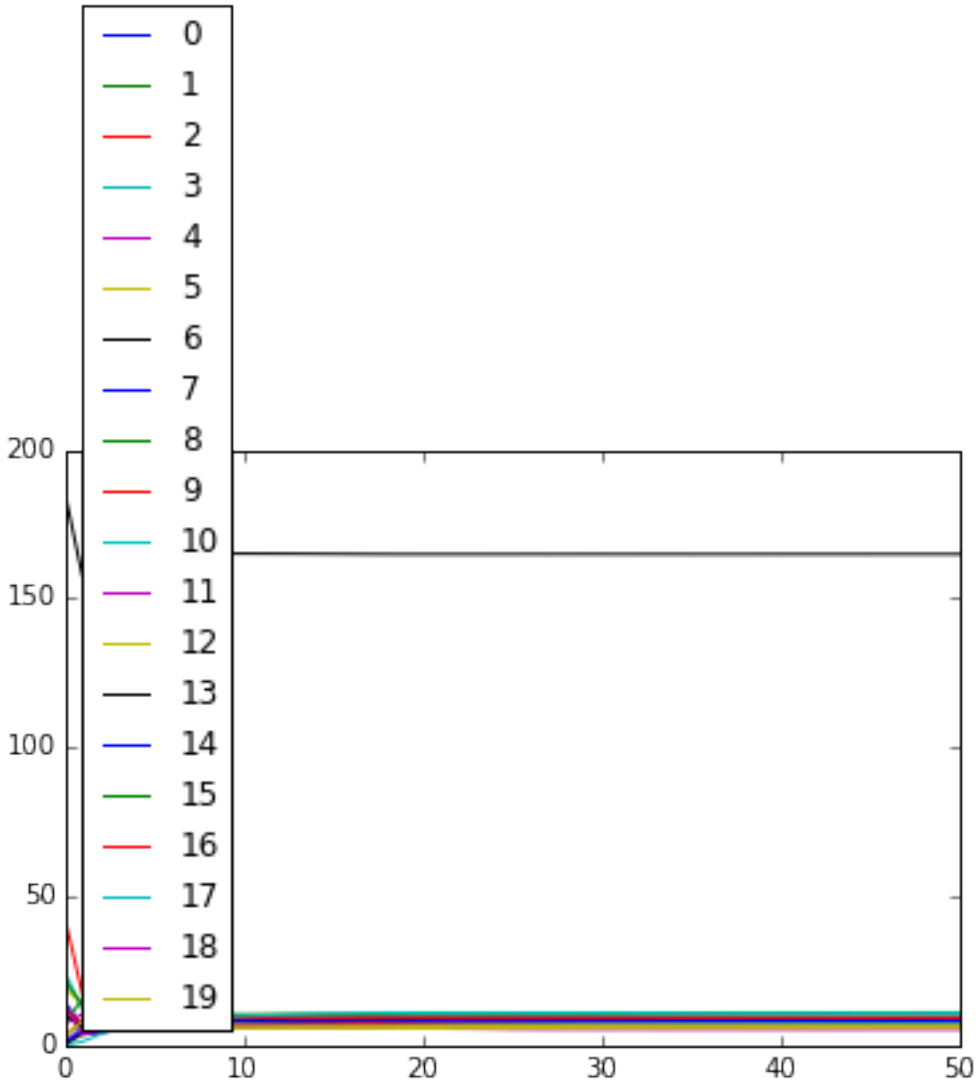


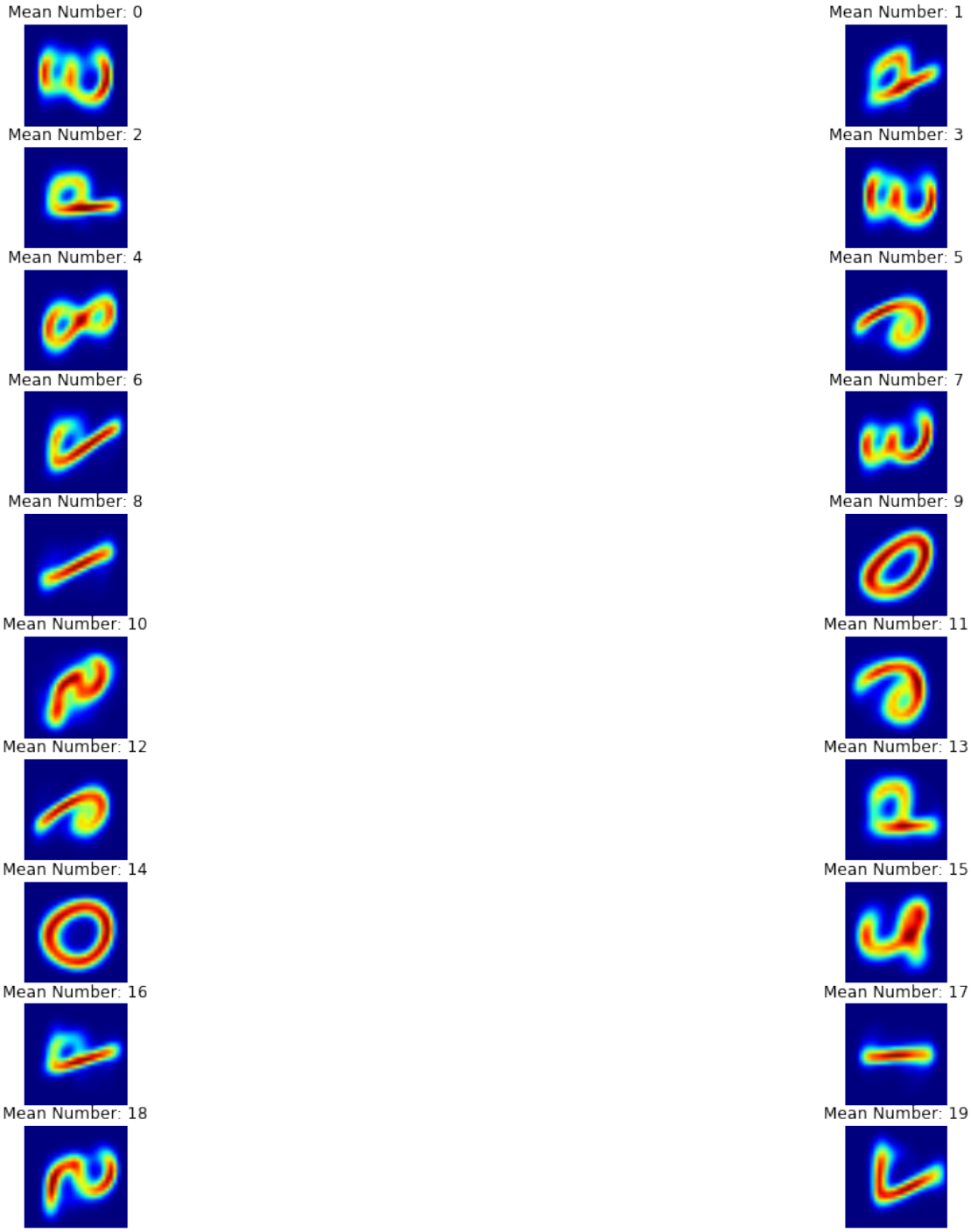



```
In [67]: %autoreload
         s = np.random.randint(0, 1000)
         print(s)
         k = 20
         km = KMeans(k, it, s).fit(images).plot_means((20,16))
```

```
28
Number in Mean Number 0 2681
Number in Mean Number 1 2893
Number in Mean Number 2 3629
```

```
Number in Mean Number 3 3338
Number in Mean Number 4 3367
Number in Mean Number 5 2576
Number in Mean Number 6 3010
Number in Mean Number 7 3107
Number in Mean Number 8 3763
Number in Mean Number 9 2490
Number in Mean Number 10 2872
Number in Mean Number 11 1760
Number in Mean Number 12 2224
Number in Mean Number 13 2908
Number in Mean Number 14 2624
Number in Mean Number 15 3731
Number in Mean Number 16 3737
Number in Mean Number 17 4444
Number in Mean Number 18 2430
Number in Mean Number 19 2416
```





The loss definitely varies with the random initializations. We can see that it can sometimes get it right, while some shapes are just random masses. The more centers we have, the more we can see that we get specific letters. However there are still overlaps.

1 Problem 2

```
In [68]: train = scipy.io.loadmat("joke_data/joke_train.mat")['train']
         validation = pd.read_csv("joke_data/validation.txt", header=None)
         validation.columns = ['User_Index','Joke_Index', 'Truth']
         query = pd.read_csv("joke_data/query.txt", header=None)
         query.columns = ['KaggleId', 'User_Index', 'Joke_Index']
```

1.1 2.2

```
In [69]: recs = pd.DataFrame(train).mean(axis=0).values
         avg_preds = validation.Joke_Index.map(lambda x: 1 if recs[x - 1] > 0 else 0)
         print("Accuracy via Averages:", sum(validation.Truth == avg_preds) / len(validation))
```

```
Accuracy via Averages: 0.620325203252
```

knn version

```
In [70]: class KNN:
             def __init__(self, k):
                 self.k = k
                 self.X = None

             def fit(self, X):
                 self.X = X
                 return self

             def inner_predict(self, X):
                 for chunk in np.vsplit(X, 43):
                     preds = cdist(self.X, chunk, 'euclidean')
                     for x_neighbors in preds.T.argsort(axis=1)[:,:self.k]:
                         yield self.X[x_neighbors].mean(axis=0)

             def predict(self, X):
                 temp = pd.DataFrame(self.inner_predict(X_train), columns=np.arange(1,101)) \
                     .applymap(lambda x: 1 if x > 0 else 0)
                 temp.index = temp.index + 1
                 return temp
```

```
In [71]: X_train = pd.DataFrame(train).fillna(0).values
         k = 10
         knn = KNN(k)
         preds = knn.fit(X_train).predict(X_train)
         scores = []
         for ((user, joke), rating) in validation.groupby(['User_Index', 'Joke_Index']):
             truth = rating['Truth'].values[0]
             guess = preds.ix[user, joke]
             scores.append(truth == guess)
         print("k=%i Accuracy: %.3f" % (k, sum(scores)/len(scores)))
```

```
k=10 Accuracy: 0.642
```

```
In [72]: X_train = pd.DataFrame(train).fillna(0).values
         k = 100
         knn = KNN(k)
         preds = knn.fit(X_train).predict(X_train)
```

```
        scores = []
        for ((user, joke), rating) in validation.groupby(['User_Index', 'Joke_Index']):
            truth = rating['Truth'].values[0]
            guess = preds.ix[user, joke]
            scores.append(truth == guess)
        print("k=%i Accuracy: %.3f" % (k, sum(scores)/len(scores)))
```

```
k=100 Accuracy: 0.689
```

```
In [73]: X_train = pd.DataFrame(train).fillna(0).values
         k = 1000
         knn = KNN(k)
         preds = knn.fit(X_train).predict(X_train)
         scores = []
         for ((user, joke), rating) in validation.groupby(['User_Index', 'Joke_Index']):
             truth = rating['Truth'].values[0]
             guess = preds.ix[user, joke]
             scores.append(truth == guess)
         print("k=%i Accuracy: %.3f" % (k, sum(scores)/len(scores)))
```

```
k=1000 Accuracy: 0.694
```

KNN definitely seems to have better results. They consistently have better accuracies.

1.2 2.3

1.2.1 2.3.1 & 2.3.2

```
In [74]: import scipy as sp
         import scipy.sparse.linalg
         mse = lambda y, y_hat: (y_hat - y) ** 2
```

```
In [75]: X_train = pd.DataFrame(train).fillna(0).values
```

```
In [76]: class LFM:
             def __init__(self, k):
                 self.u = None
                 self.s = None
                 self.v = None
                 self.k = k
             def fit(self, X):
                 u, s, v = sp.sparse.linalg.svds(X, k=self.k)
                 self.u = u
                 self.s = s
                 self.v = v
                 temp = pd.DataFrame((self.u * self.s).dot(self.v), columns=np.arange(1,101)) \
                             .applymap(lambda x: 1 if x > 0 else 0)
                 temp.index = temp.index + 1
                 self.rebuilt = temp
                 return self
             def evaluate(self, validation):
                 y = []
                 y_hat = []
                 for ((user, joke), rating) in validation.groupby(['User_Index', 'Joke_Index']):
                     truth = rating['Truth'].values[0]
                     guess = self.rebuilt.ix[user, joke]
```

```
                    y.append(truth)
                    y_hat.append(guess)

                y = pd.Series(y)
                y_hat = pd.Series(y_hat)

                error = mse(y, y_hat).sum()
                scores = y == y_hat
                print("k=%i Accuracy: %.3f" % (self.k, sum(scores)/len(scores)))
                return(self.k, sum(scores)/len(scores), error)
            def predict(self, query):
                y_hat = []
                for ((user, joke), identifier) in query.groupby(['User_Index', 'Joke_Index']):
                    guess = self.rebuilt.ix[user, joke]
                    kId = identifier['KaggleId'].values[0]
                    y_hat.append((kId, guess))

                y_hat = pd.DataFrame(y_hat)
                y_hat.columns = ["Id", "Category"]
                return y_hat
```

```
In [77]: all_k = []
```

```
In [78]: k=2
         lfm = LFM(k=k)
         all_k.append(lfm.fit(X_train).evaluate(validation))
```

```
k=2 Accuracy: 0.705
```

```
In [79]: k=5
         lfm = LFM(k=k)
         all_k.append(lfm.fit(X_train).evaluate(validation))
```

```
k=5 Accuracy: 0.715
```

```
In [80]: k=10
         lfm = LFM(k=k)
         all_k.append(lfm.fit(X_train).evaluate(validation))
```

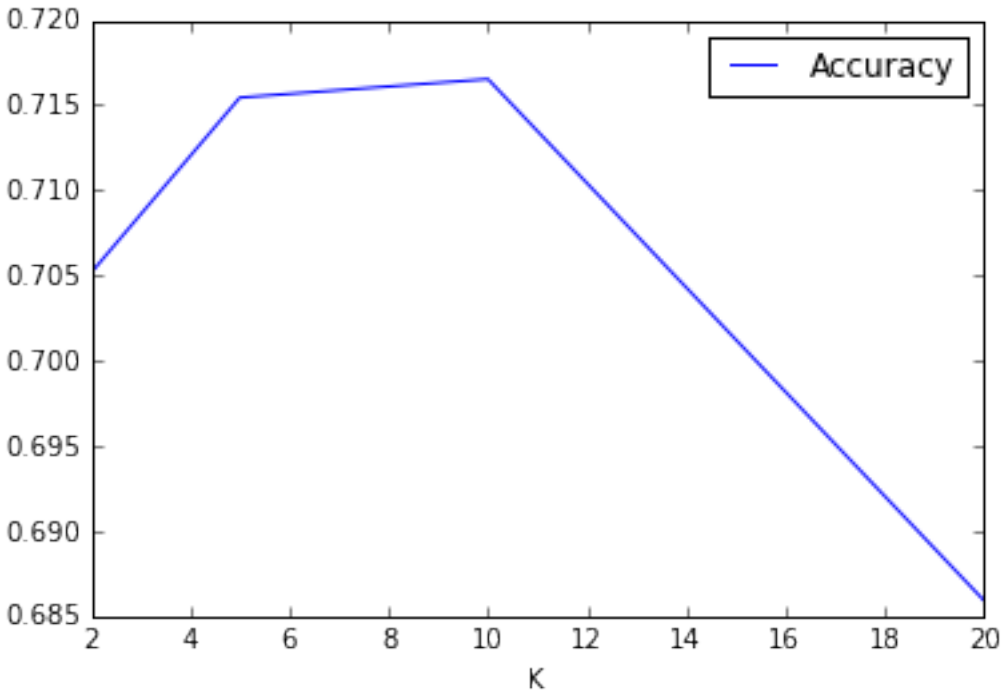
```
k=10 Accuracy: 0.717
```

```
In [81]: k=20
         lfm = LFM(k=k)
         all_k.append(lfm.fit(X_train).evaluate(validation))
```

```
k=20 Accuracy: 0.686
```

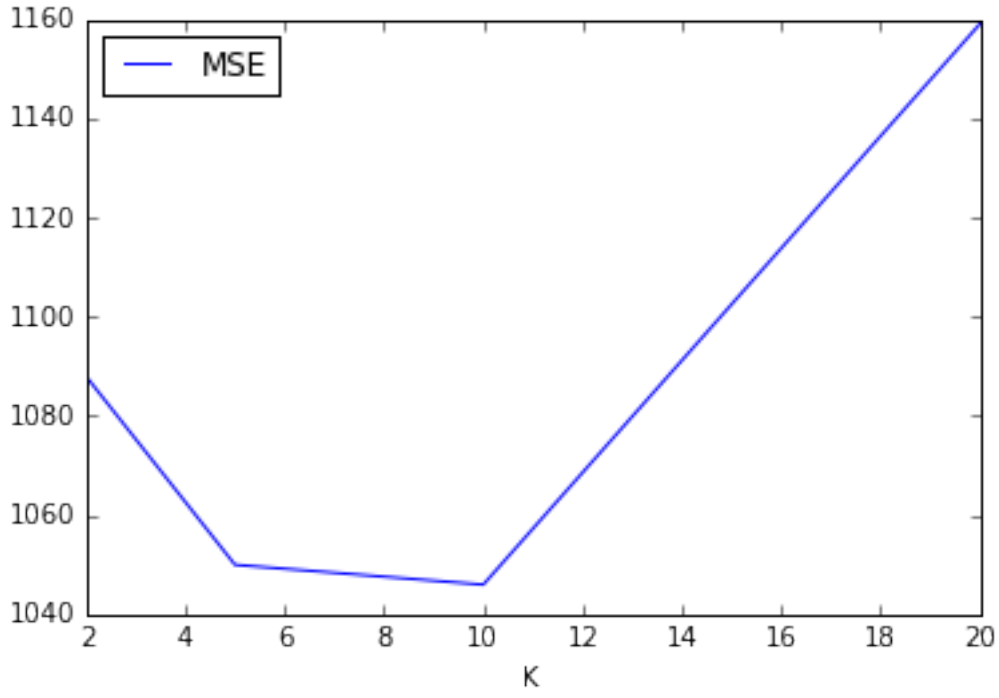
```
In [82]: pd.DataFrame(all_k, columns=['K', 'Accuracy', 'MSE']).plot(x='K', y='Accuracy')
```

```
Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x1085b7f98>
```



In [83]: `pd.DataFrame(all_k, columns=['K', 'Accuracy', 'MSE']).plot(x='K', y='MSE')`

Out[83]: `<matplotlib.axes._subplots.AxesSubplot at 0x108293be0>`



1.2.2 2.3.3

In [84]:
```
regualarized_mse = lambda U, V, truth, weights: np.sum((weights * (truth - U.dot(V))**2))
```

In [85]:
```
X_train.shape
```

Out[85]:
```
(24983, 100)
```

In [87]:
```
class RegularizedLFM:
    def __init__(self, k, lamb, n_iters):
        self.U = None
        self.V = None
        self.k = k
        self.n_iters = n_iters
        self.lamb = lamb
        self.errors = []

    def fit(self, X_):
        W = pd.DataFrame(X_).notnull().astype(np.float64).values
        X_ = pd.DataFrame(X_).fillna(0).values

        U = np.random.normal(size=(len(X_), self.k))
        V = np.random.normal(size=(self.k, len(X_[0])))

        for _ in range(self.n_iters):
            U = np.linalg.solve(V.dot(V.T) + self.lamb * np.eye(self.k), V.dot(X_.T)).T
            V = np.linalg.solve(U.T.dot(U) + self.lamb * np.eye(self.k), U.T.dot(X_))
            self.errors.append((_, regualarized_mse(U, V, X_, W)))

        self.U = U
        self.V = V
        self.rebuilt = pd.DataFrame(U.dot(V), columns=np.arange(1,101)) \
                            .applymap(lambda x: 1 if x > 0 else 0)
        self.rebuilt.index = self.rebuilt.index + 1
        assert self.rebuilt.shape == X_.shape
        return self

    def evaluate(self, validation):
        y = []
        y_hat = []
        for ((user, joke), rating) in validation.groupby(['User_Index', 'Joke_Index']):
            truth = rating['Truth'].values[0]
            guess = self.rebuilt.ix[user, joke]
            y.append(truth)
            y_hat.append(guess)

        y = pd.Series(y)
        y_hat = pd.Series(y_hat)

        error = mse(y, y_hat).sum()
        scores = y == y_hat
        print("k=%i Accuracy: %.3f" % (self.k, sum(scores)/len(scores)))
        return(self.k, sum(scores)/len(scores), error)
    def predict(self, query):
        y_hat = []
```

```
                for ((user, joke), identifier) in query.groupby(['User_Index', 'Joke_Index']):
                    guess = self.rebuilt.ix[user, joke]
                    kId = identifier['KaggleId'].values[0]
                    y_hat.append((kId, guess))

                y_hat = pd.DataFrame(y_hat)
                y_hat.columns = ["Id", "Category"]
                return y_hat
```

```
In [88]: all_k = []
```

```
In [89]: k=2
         rlfm = RegularizedLFM(k, 1e-3, 15)
         all_k.append(rlfm.fit(X_train).evaluate(validation))
```

```
k=2 Accuracy: 0.705
```

```
In [90]: k=5
         rlfm = RegularizedLFM(k, 1e-3, 15)
         all_k.append(rlfm.fit(X_train).evaluate(validation))
```

```
k=5 Accuracy: 0.712
```

```
In [91]: k=10
         rlfm = RegularizedLFM(k, 1e-3, 15)
         all_k.append(rlfm.fit(X_train).evaluate(validation))
```

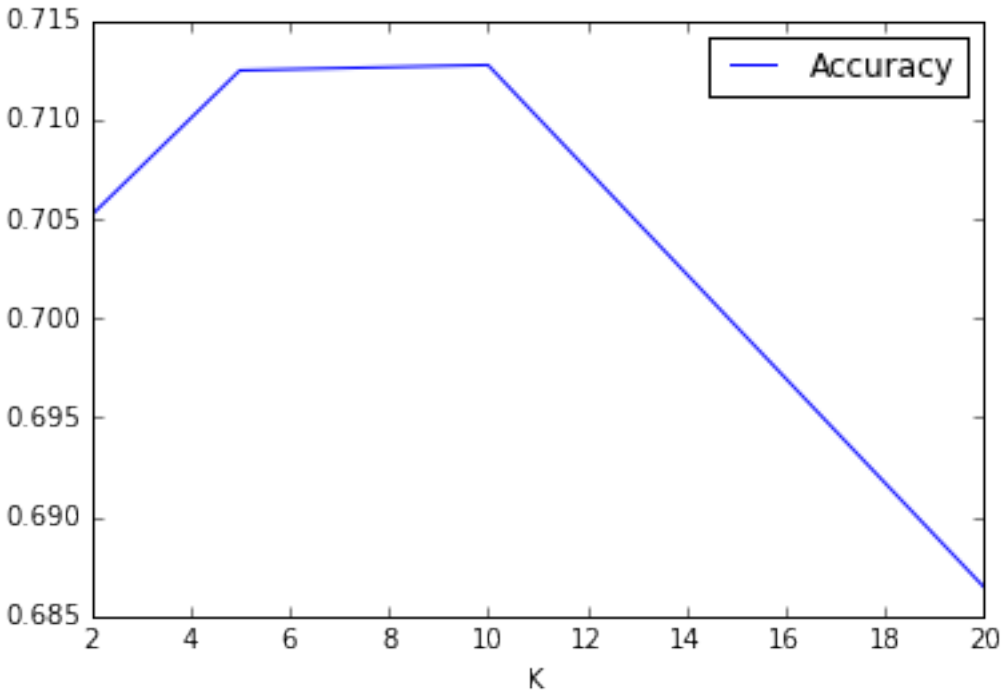
```
k=10 Accuracy: 0.713
```

```
In [92]: k=20
         rlfm = RegularizedLFM(k, 1e-6, 15)
         all_k.append(rlfm.fit(X_train).evaluate(validation))
```

```
k=20 Accuracy: 0.686
```

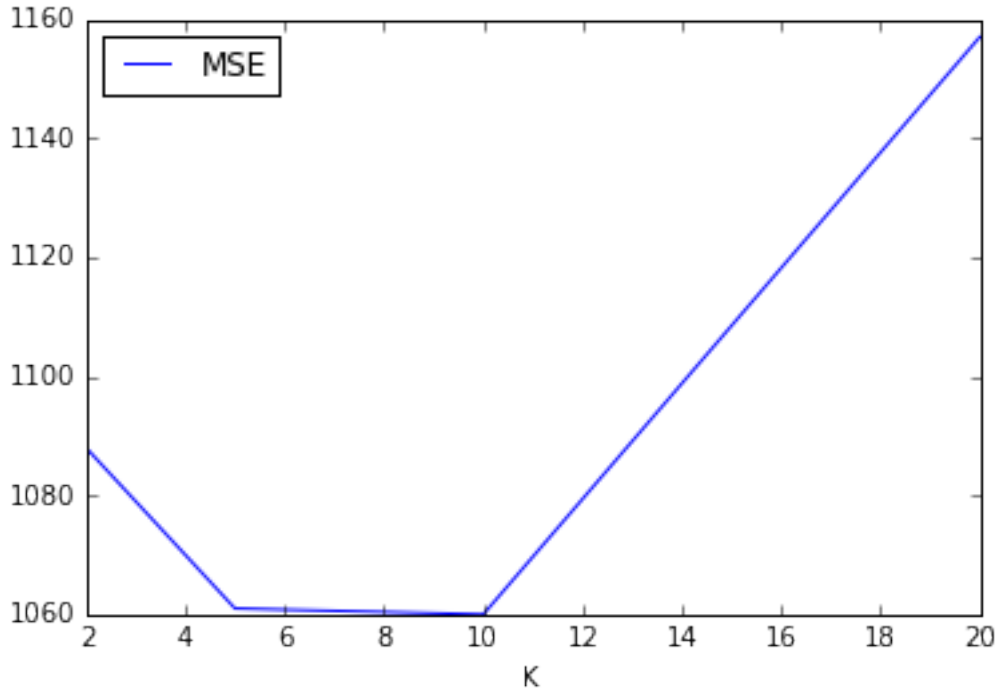
```
In [93]: pd.DataFrame(all_k, columns=['K', 'Accuracy', 'MSE']).plot(x='K', y='Accuracy')
```

```
Out[93]: <matplotlib.axes._subplots.AxesSubplot at 0x108454400>
```



In [94]: pd.DataFrame(all_k, columns=['K', 'Accuracy', 'MSE']).plot(x='K', y='MSE')

Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x109aa87f0>



1.2.3 2.4.1

```
In [95]: k=10
         rlfm = RegularizedLFM(k, 1e-6, 15)
         all_k.append(rlfm.fit(X_train).evaluate(validation))

k=10 Accuracy: 0.714

In [96]: preds = rlfm.predict(query)
         preds.to_csv("predictions.csv", index=False)
```

Kaggle Score: 0.6864

2 3

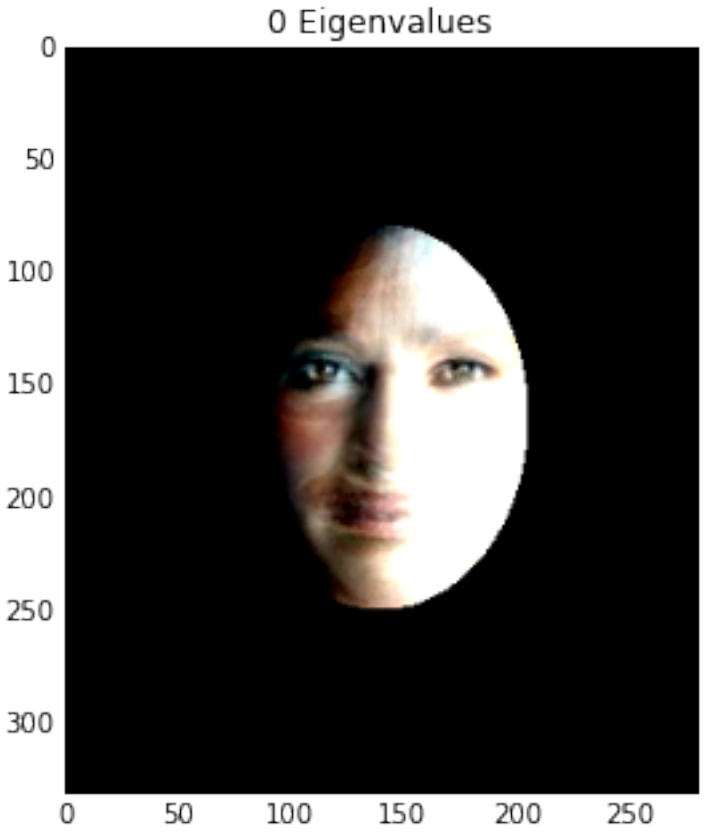
```
In [97]: import scipy.misc
         import scipy.sparse.linalg
         import matplotlib.pyplot as plt
         import scipy.io

In [98]: celebs = !ls eigenfaces_data/CelebrityDatabase/
         students = !ls eigenfaces_data/StudentDatabase/
         mask = sp.io.loadmat("eigenfaces_data/mask.mat")['mask']
         unmasked_pixels = np.where(mask)

         celebs = np.array([sp.misc.imread("eigenfaces_data/CelebrityDatabase/" + x)\
                    .astype(np.uint8)[unmasked_pixels] for x in celebs], dtype=np.uint8)
         students = np.array([sp.misc.imread("eigenfaces_data/StudentDatabase/" + x)\
                      .astype(np.uint8)[unmasked_pixels] for x in students], dtype=np.uint8)

In [99]: def img_to_uint8(f_img): ## Borrowed from Piazza: https://piazza.com/class/idkq8912ql86mq?cid=
                """Convert float image to type uint8"""
                t = np.clip(f_img, 0, 255)
                return t.astype(np.uint8)

         def show_image(im):
             full_im = np.zeros(np.shape(mask), dtype=np.uint8)
             full_im[unmasked_pixels] = img_to_uint8(im)
             plt.imshow(full_im)

In [100]: def plot_eig_face(celebs, celeb_num):
              mean = np.sum(celebs, 0)/float(len(celebs))
              fig = plt.figure(figsize=(15, 5))
              a=fig.add_subplot(1,3,1)
              a.set_title("Original")
              show_image(celebs[celeb_num])
              b=fig.add_subplot(1,3,2)
              b.set_title("10 Eigenvalues")
              U, S, V = sp.sparse.linalg.svds(celebs.astype(float) - mean, k=10)
              show_image(U[celeb_num].dot(np.diag(S).dot(V)) + mean)
              c=fig.add_subplot(1,3,3)
              c.set_title("Error")
              k10_error = ((celebs[celeb_num] - U[celeb_num].dot(np.diag(S).dot(V))) ** 2).sum()
              U, S, V = sp.sparse.linalg.svds(celebs.astype(float) - mean, k=50)
              k50_error = ((celebs[celeb_num] - U[celeb_num].dot(np.diag(S).dot(V))) ** 2).sum()
```

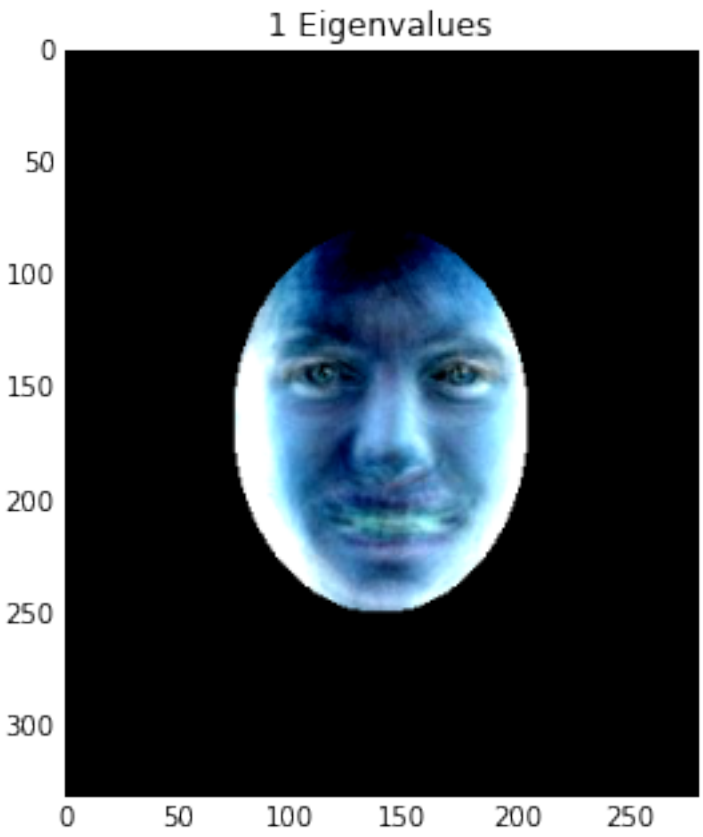
```
U, S, V = sp.sparse.linalg.svds(celebs.astype(float) - mean, k=100)
k100_error = ((celebs[celeb_num] - U[celeb_num].dot(np.diag(S).dot(V))) ** 2).sum()
pd.Series([k10_error, k50_error, k100_error]).plot()
```

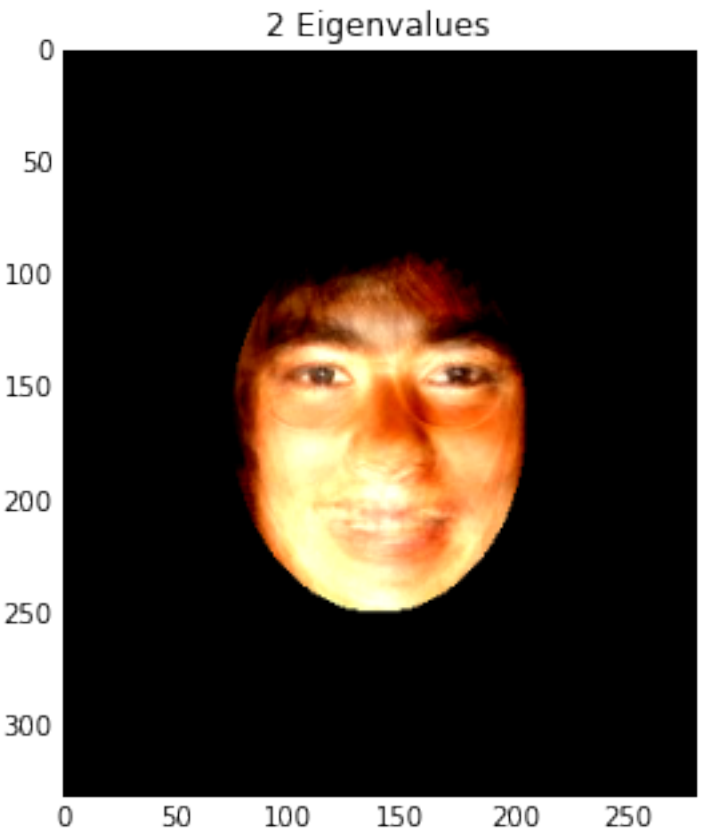
In [101]:
```
def plot_eig_features(celebs, num_eigenfaces):

    U, S, V = sp.linalg.svd(celebs.astype(float) - mean, full_matrices=False)
    for val in range(num_eigenfaces):
        fig = plt.figure(figsize=(5, 5))
        eig_face = np.diag(S).dot(V)[val+1]
        ax=fig.add_subplot(1,1, 1)
        ax.set_title("%i Eigenvalues" % val)
        show_image(eig_face + mean)
```

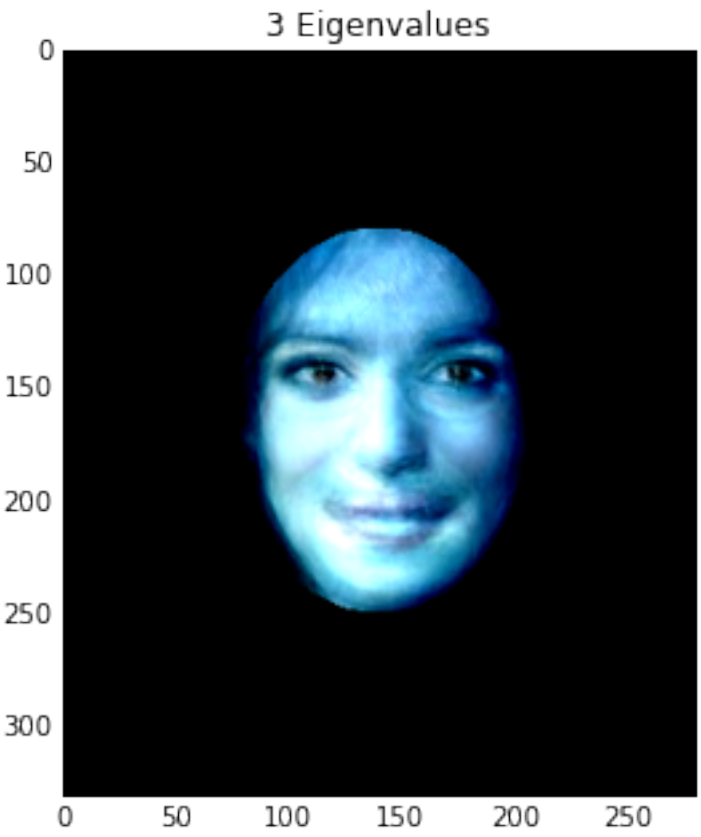
2.1 3.1

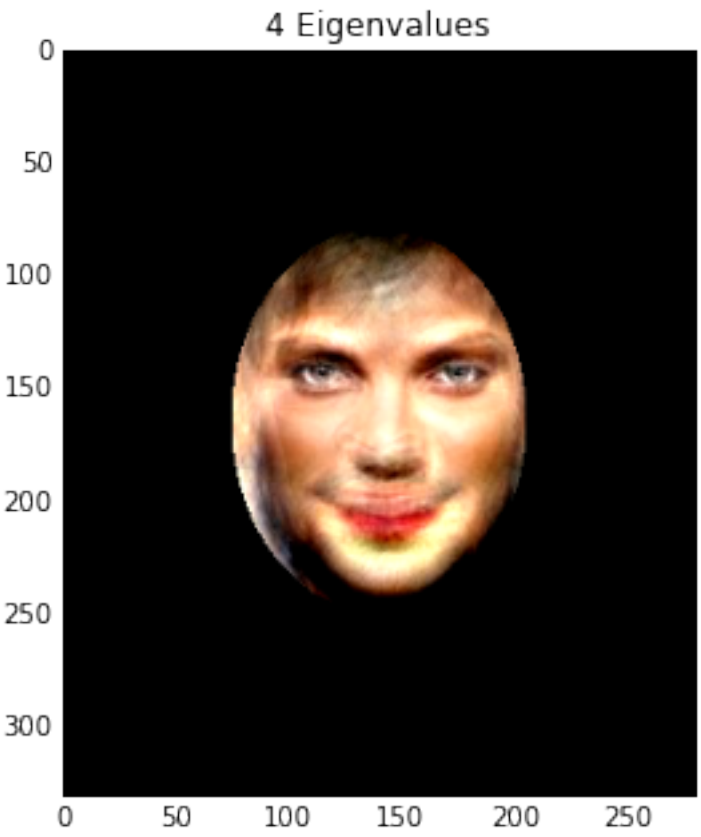
In [102]:
```
plot_eig_features(celebs, 10)
```

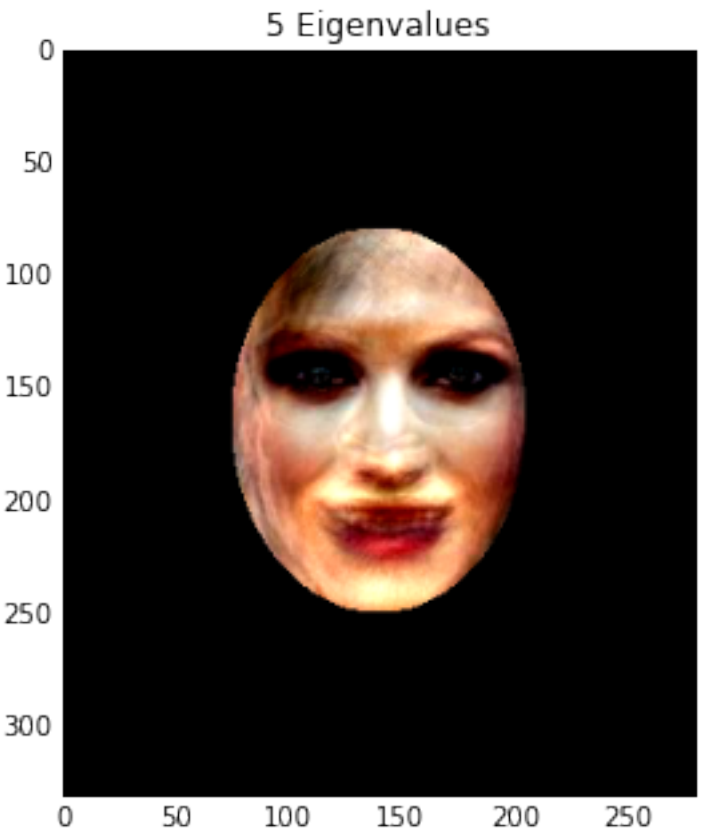


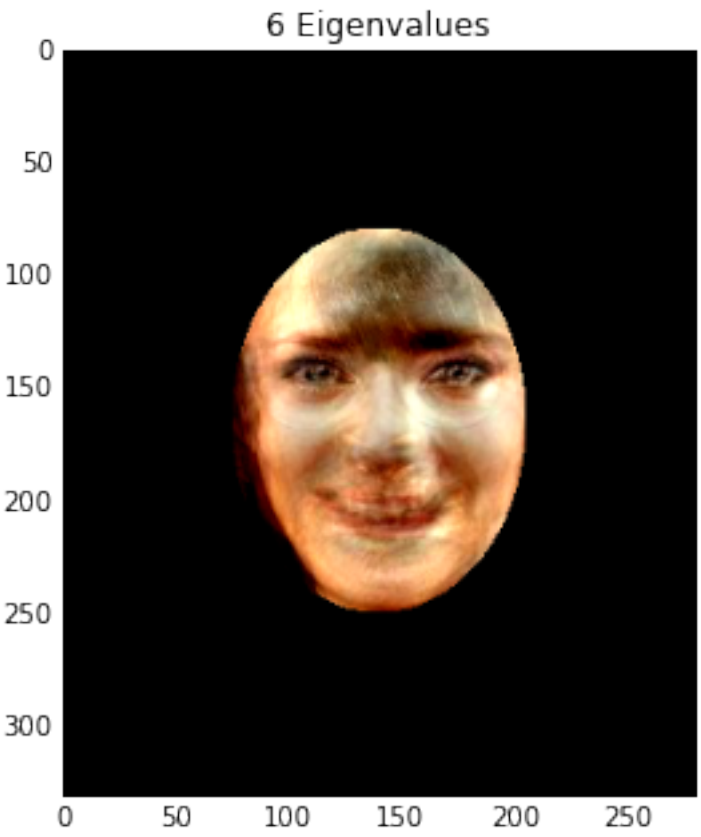

1 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250

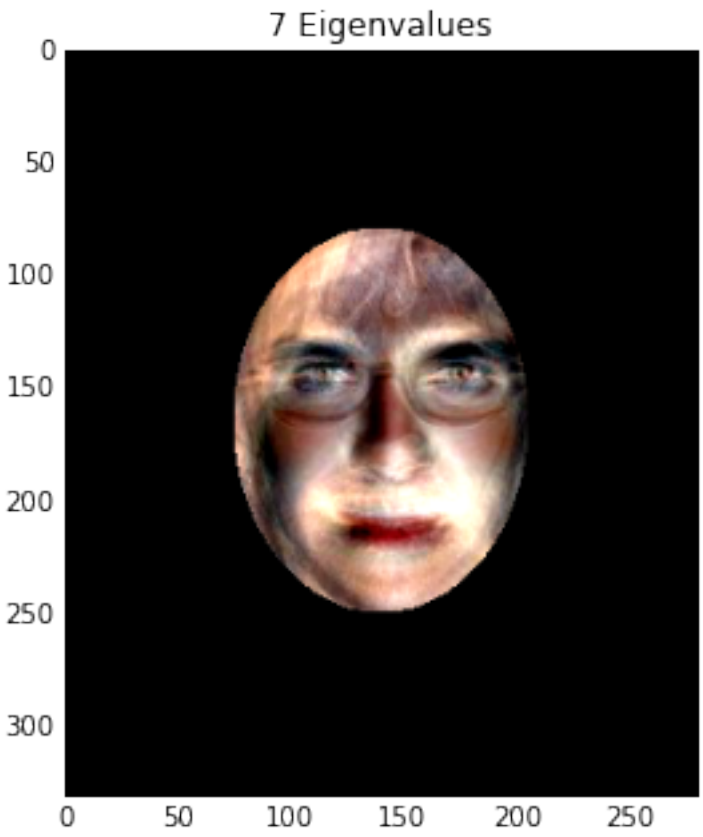

2 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250

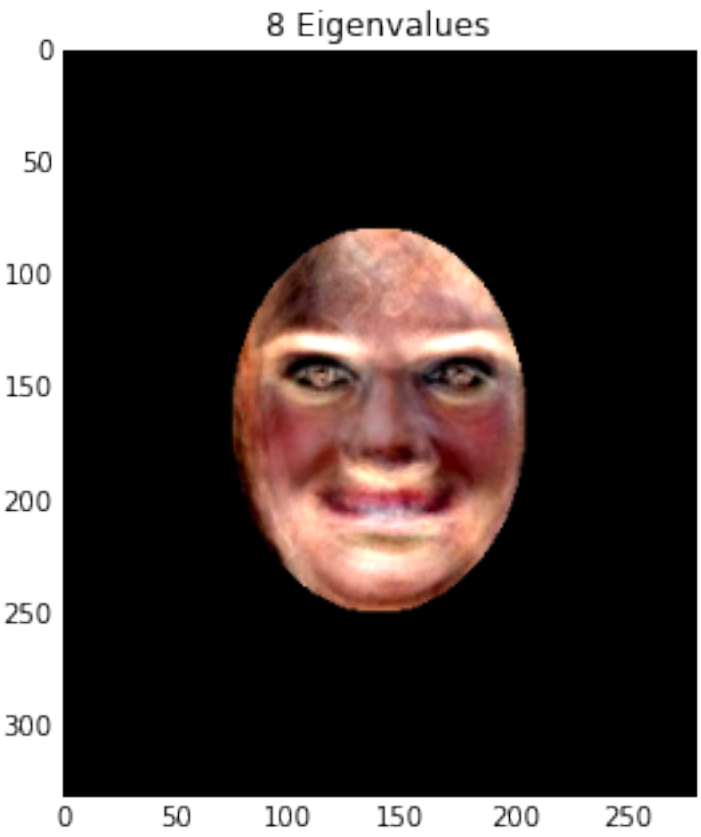

3 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250

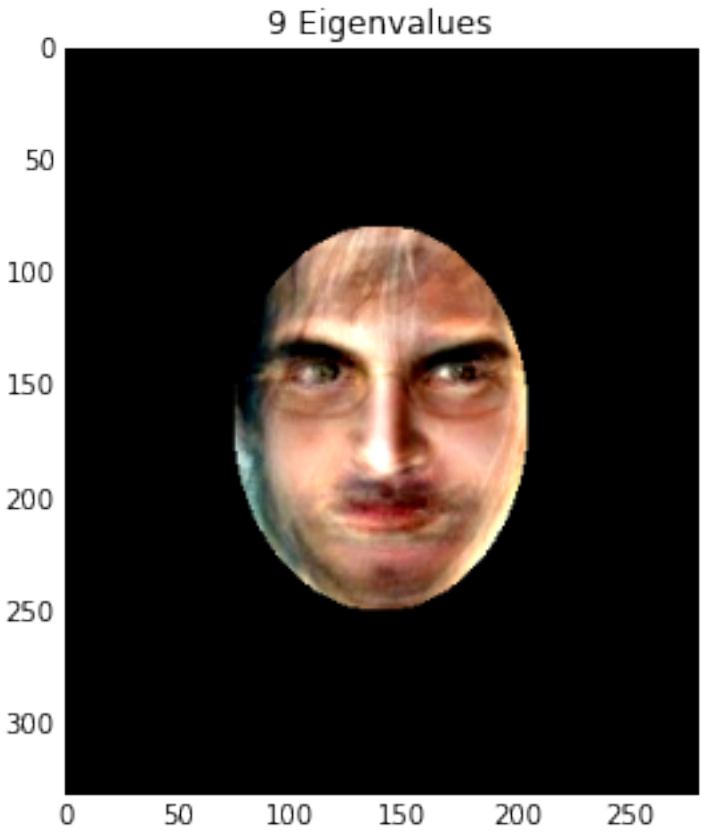

4 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250


5 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250


6 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250


7 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250

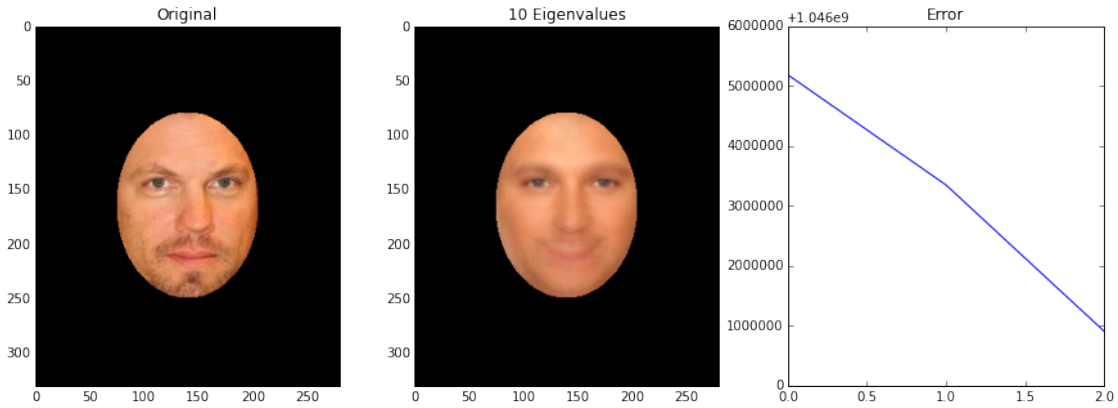

8 Eigenvalues
0
50
100
150
200
250
300
0
50
100
150
200
250



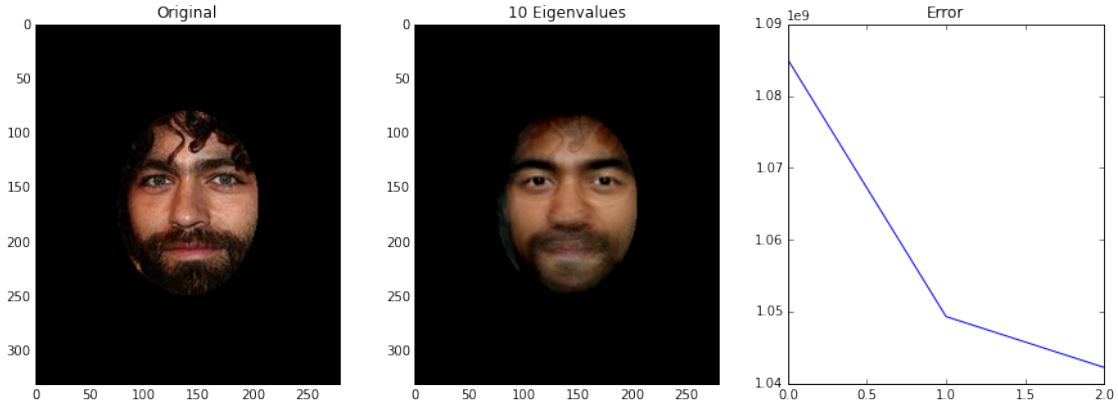
We can see that the core variations are around the mouth. There's a lot of variance around there so it's harder to reconstruct correctly. However the eyes are fairly stable and show up approximately the same (although their direction does vary). There's also a fair amount of variation around the lighting as the other eigenfaces show us.

2.2 3.2

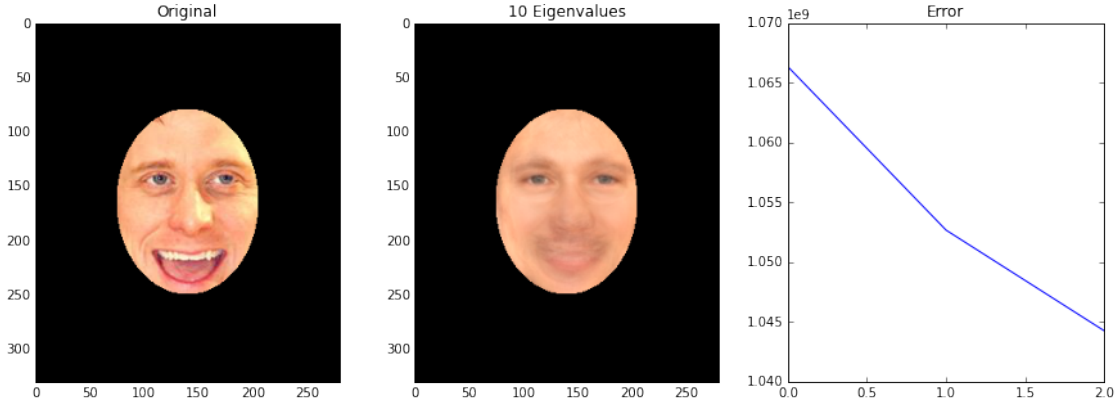
```
In [103]: plot_eig_face(celebs, 0)
```



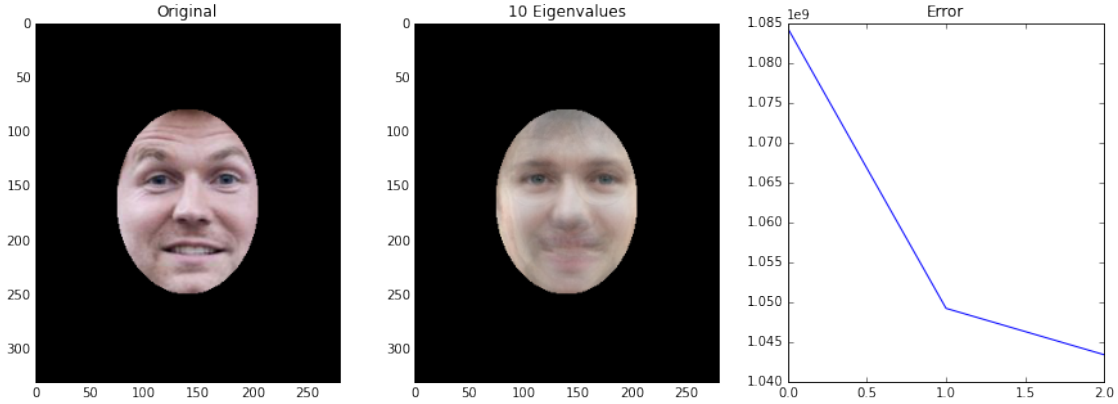
In [104]: `plot_eig_face(celebs, 1)`



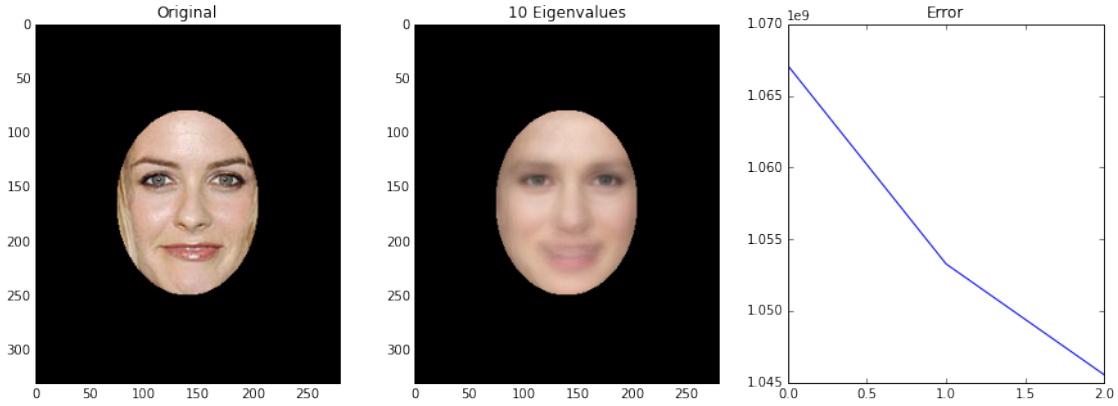
In [105]: `plot_eig_face(celebs, 2)`



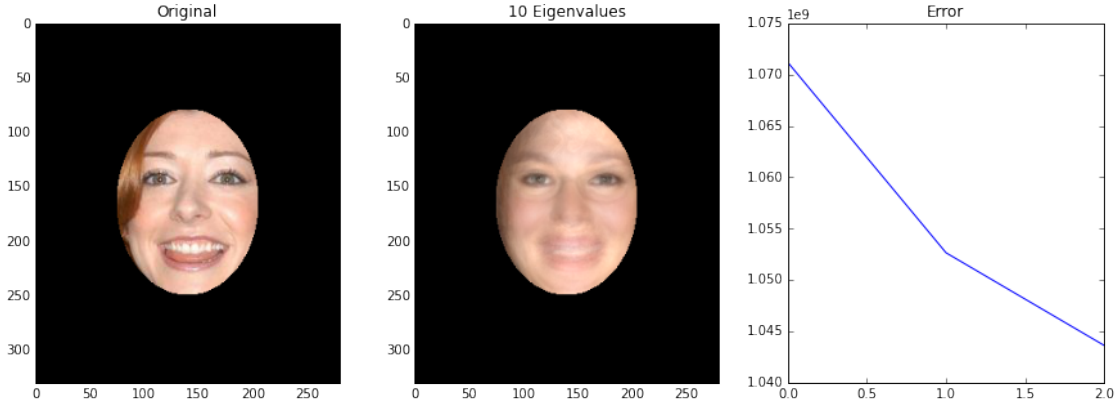
In [106]: `plot_eig_face(celebs, 3)`



In [107]: plot_eig_face(celebs, 4)



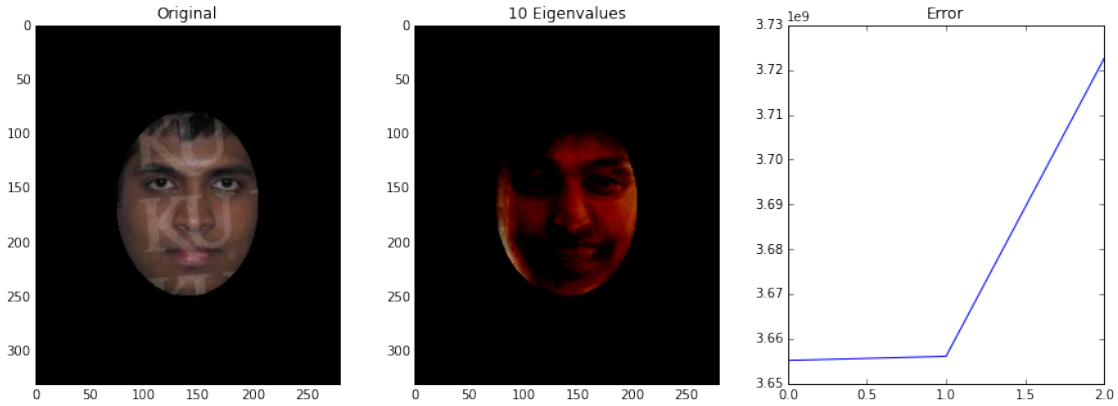
In [108]: plot_eig_face(celebs, 5)



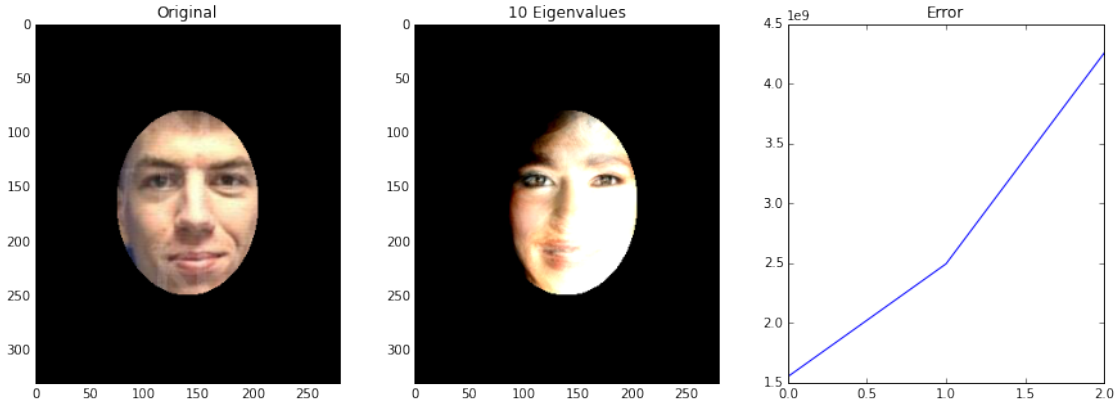

```
In [109]: def plot_eig_face(celebs, students, celeb_num):
              mean = np.sum(celebs, 0)/float(len(celebs))
              fig = plt.figure(figsize=(15, 5))
              a=fig.add_subplot(1,3,1)
              a.set_title("Original")
              show_image(students[celeb_num])

              b=fig.add_subplot(1,3,2)
              b.set_title("10 Eigenvalues")
              U, S, V = sp.sparse.linalg.svds(celebs.astype(float) - mean, k=10)
              U1, S1, V1 = sp.sparse.linalg.svds(students.astype(float) - mean, k=10)
              show_image(U1[celeb_num].dot(np.diag(S).dot(V)) + mean)
              c=fig.add_subplot(1,3,3)
              c.set_title("Error")
              k10_error = ((students[celeb_num] - U1[celeb_num].dot(np.diag(S).dot(V))) ** 2).sum()

              U, S, V = sp.sparse.linalg.svds(celebs.astype(float) - mean, k=11)
```

```
U1, S1, V1 = sp.sparse.linalg.svds(students.astype(float) - mean, k=11)
k50_error = ((students[celeb_num] - U1[celeb_num].dot(np.diag(S).dot(V))) ** 2).sum()

U, S, V = sp.sparse.linalg.svds(celebs.astype(float) - mean, k=12)
U1, S1, V1 = sp.sparse.linalg.svds(students.astype(float) - mean, k=12)
k100_error = ((students[celeb_num] - U1[celeb_num].dot(np.diag(S).dot(V))) ** 2).sum()

pd.Series([k10_error, k50_error, k100_error]).plot()
```

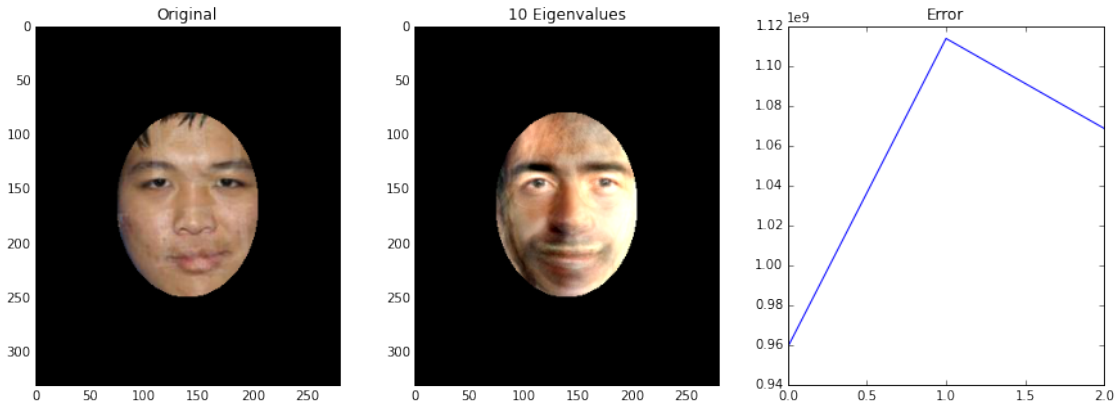
In [110]:
```
plot_eig_face(celebs, students, 0)
```



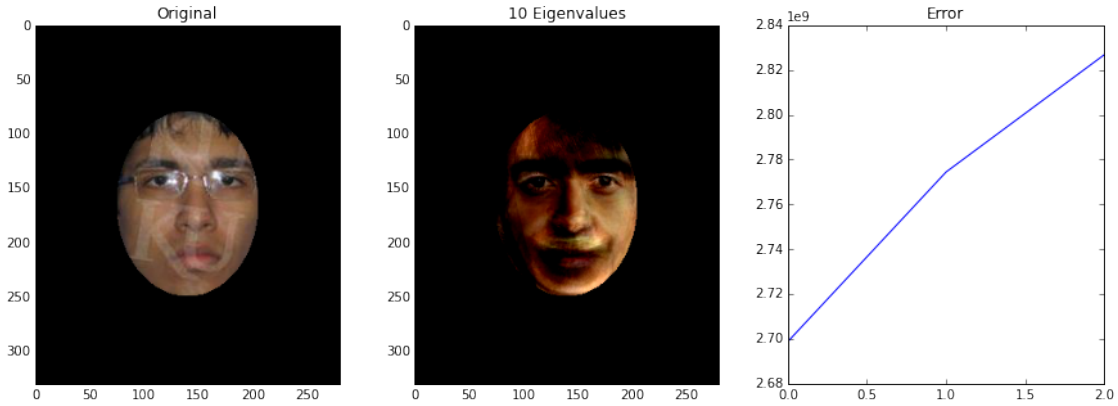
In [111]:
```
plot_eig_face(celebs, students, 1)
```



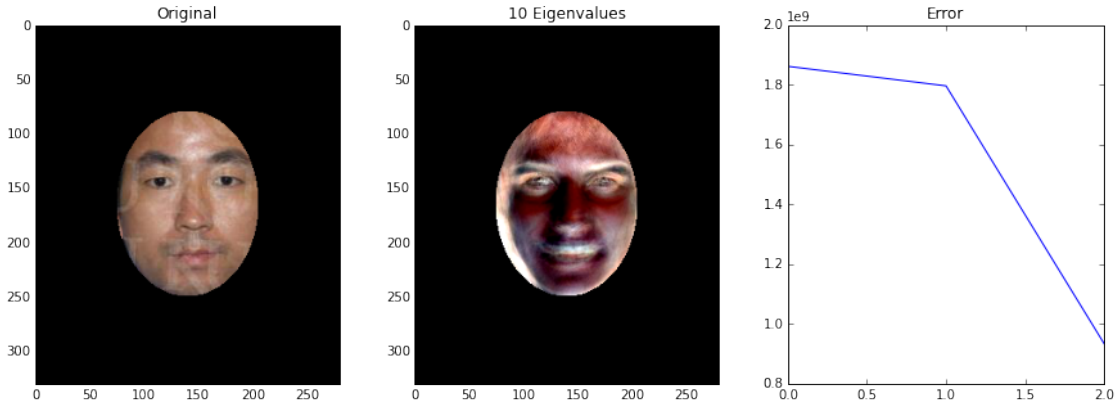
In [112]:
```
plot_eig_face(celebs, students, 2)
```



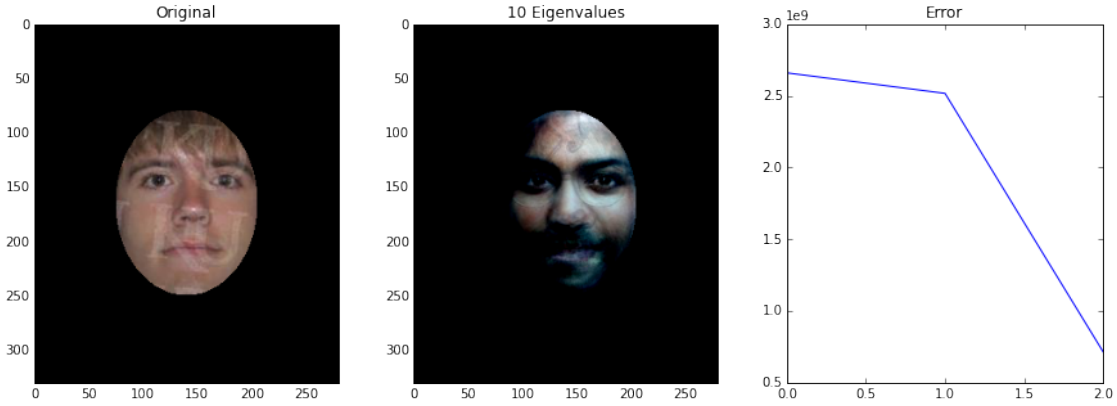
In [113]: plot_eig_face(celebs, students, 3)



In [114]: plot_eig_face(celebs, students, 4)



In [115]: plot_eig_face(celebs, students, 5)


Original
10 Eigenvalues
Error
1e9
0
50
100
150
200
250
300
0.5
1.0
1.5
2.0
2.5
3.0
0.0