In [9]:
```
import numpy as np
import pandas as pd


import matplotlib.pyplot as plt


from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA
from sklearn.svm import SVC
from sklearn.naive_bayes import GaussianNB
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn import metrics
```

In [3]:
```
import warnings
warnings.filterwarnings('ignore')
print("Warnings ignored!!")
```

```
Warnings ignored!!
```

In [6]:
```
data=np.load("olivetti_faces.npy")
target=np.load("olivetti_faces_target.npy")
```

In [10]:
```
print("There are {} images in the dataset".format(len(data)))
print("There are {} unique targets in the dataset".format(len(np.unique(target))))
print("Size of each image is {}x{}".format(data.shape[1],data.shape[2]))
print("Pixel values were scaled to [0,1] interval. e.g:{}".format(data[0][0,:4]))
```

```
There are 400 images in the dataset
There are 40 unique targets in the dataset
Size of each image is 64x64
Pixel values were scaled to [0,1] interval. e.g:[0.30991736 0.3677686  0.41735536 0.44214877]
```

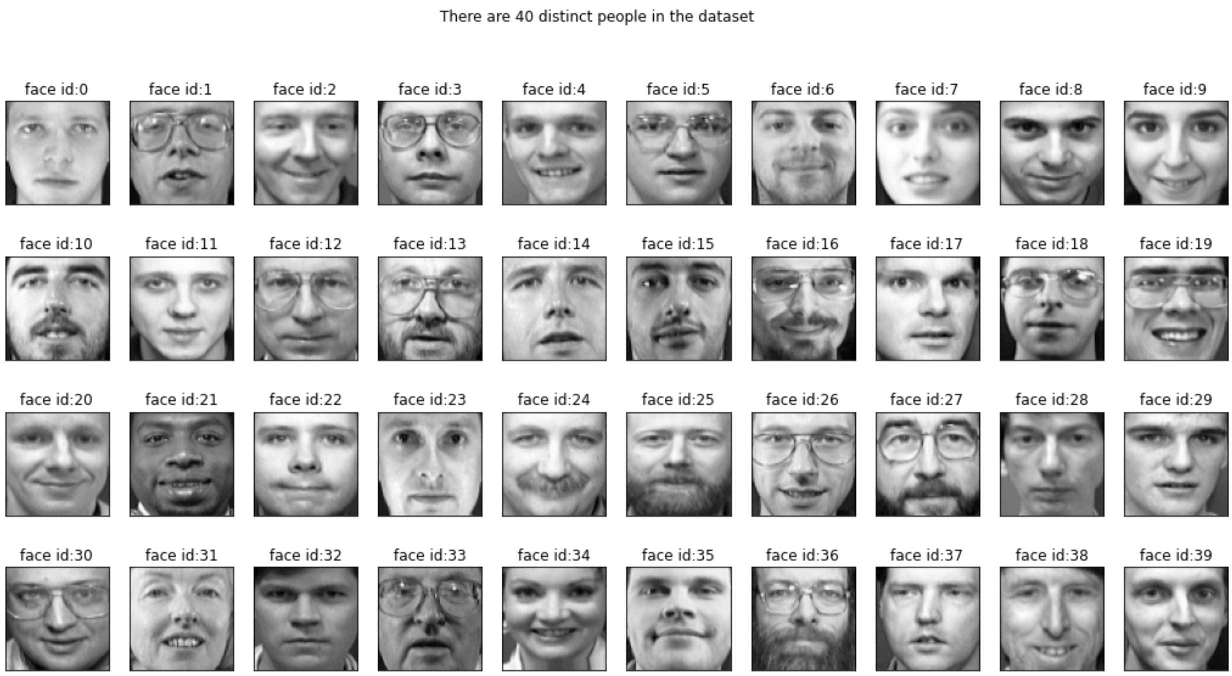
In [11]:
```
print("unique target number:",np.unique(target))
```

```
unique target number: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39]
```

In [12]:
```
def show_40_distinct_people(images, unique_ids):
    #Creating 4X10 subplots in  18x9 figure size
    fig, axarr=plt.subplots(nrows=4, ncols=10, figsize=(18, 9))
    #For easy iteration flattened 4X10 subplots matrix to 40 array
    axarr=axarr.flatten()

    #iterating over user ids
    for unique_id in unique_ids:
        image_index=unique_id*10
        axarr[unique_id].imshow(images[image_index], cmap='gray')
        axarr[unique_id].set_xticks([])
        axarr[unique_id].set_yticks([])
        axarr[unique_id].set_title("face id:{}".format(unique_id))
    plt.suptitle("There are 40 distinct people in the dataset")
```

In [13]:
```
show_40_distinct_people(data, np.unique(target))
```

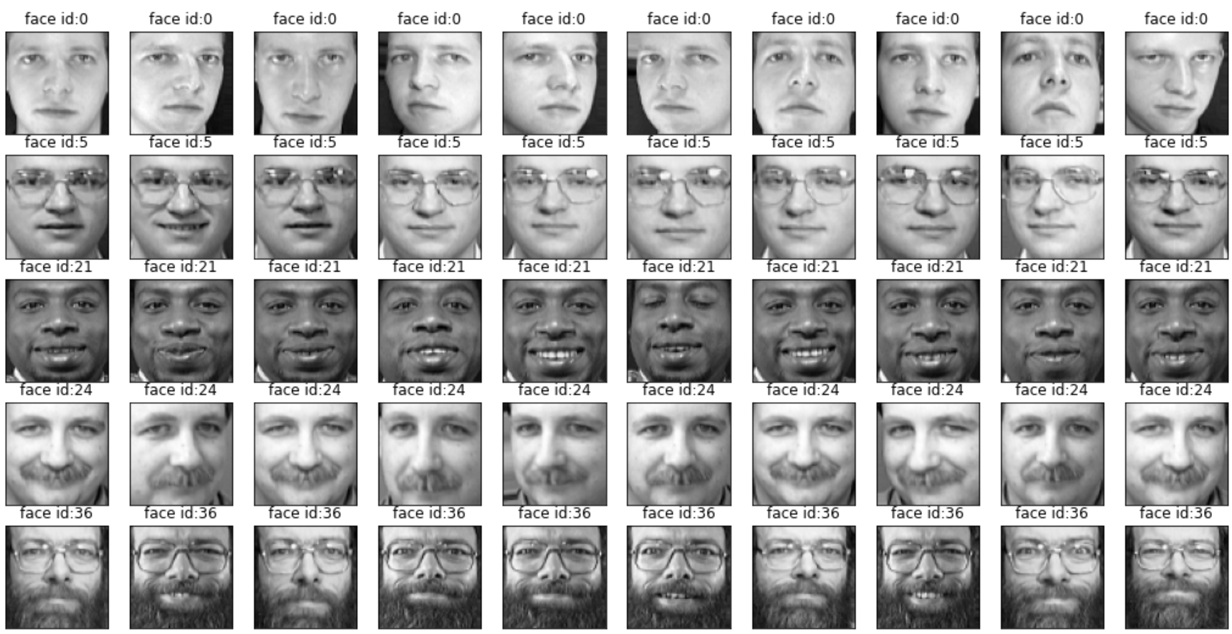


In [14]:
```
def show_10_faces_of_n_subject(images, subject_ids):
    cols=10# each subject has 10 distinct face images
    rows=(len(subject_ids)*10)/cols #
    rows=int(rows)

    fig, axarr=plt.subplots(nrows=rows, ncols=cols, figsize=(18,9))
    #axarr=axarr.flatten()

    for i, subject_id in enumerate(subject_ids):
        for j in range(cols):
            image_index=subject_id*10 + j
            axarr[i,j].imshow(images[image_index], cmap="gray")
            axarr[i,j].set_xticks([])
            axarr[i,j].set_yticks([])
            axarr[i,j].set_title("face id:{}".format(subject_id))
```

In [15]:
```
show_10_faces_of_n_subject(images=data, subject_ids=[0,5, 21, 24, 36])
```



In [16]:
```
X=data.reshape((data.shape[0],data.shape[1]*data.shape[2]))
print("X shape:",X.shape)
```

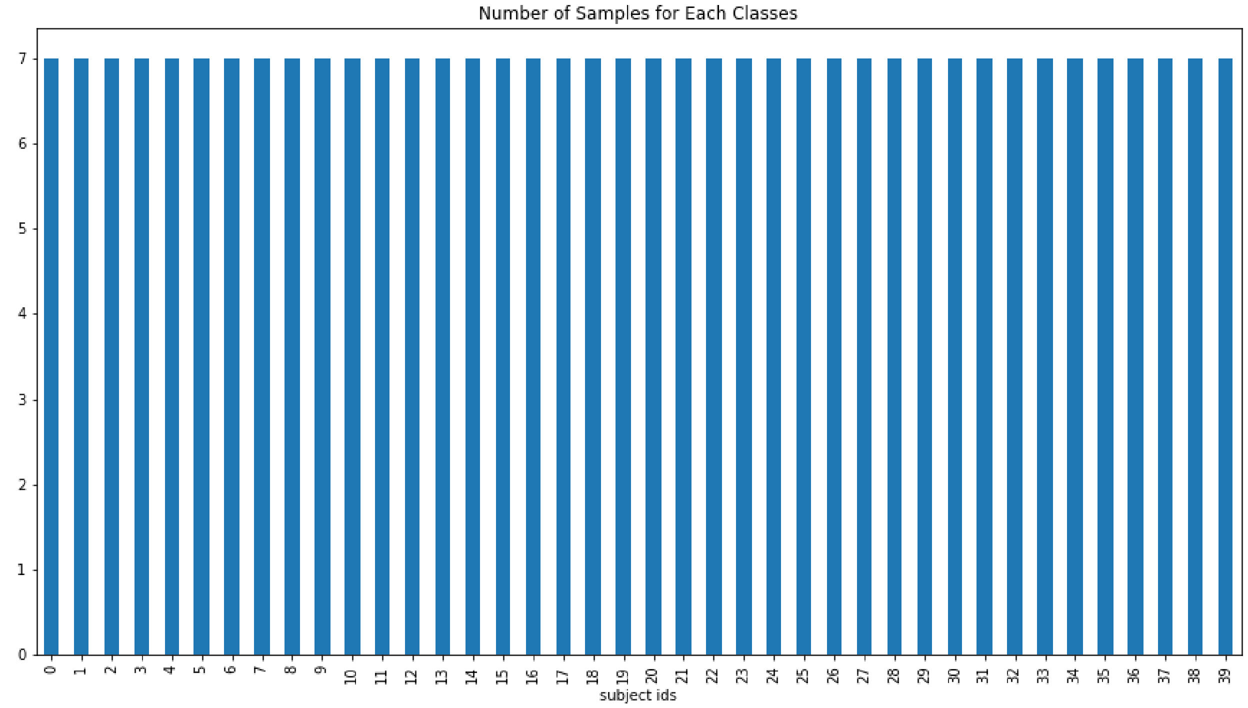
```
X shape: (400, 4096)
```

In [17]:
```
X_train, X_test, y_train, y_test=train_test_split(X, target, test_size=0.3, stratify=target, random_state=
print("X_train shape:",X_train.shape)
print("y_train shape:{}".format(y_train.shape))
```

```
X_train shape: (280, 4096)
y_train shape:(280,)
```

In [18]:
```
y_frame=pd.DataFrame()
y_frame['subject ids']=y_train
y_frame.groupby(['subject ids']).size().plot.bar(figsize=(15,8),title="Number of Samples for Each Classes"
```

Out[18]: `<AxesSubplot:title={'center':'Number of Samples for Each Classes'}, xlabel='subject ids'>`



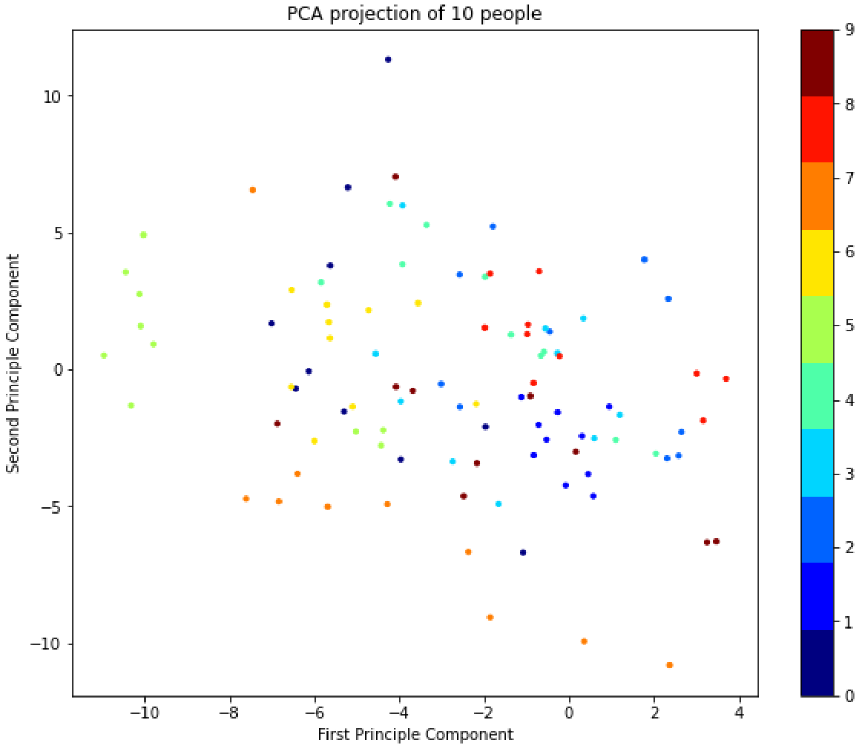
In [20]:
```
from sklearn.decomposition import PCA
pca=PCA(n_components=2)
pca.fit(X)
X_pca=pca.transform(X)
```

In [21]:
```
number_of_people=10
index_range=number_of_people*10
fig=plt.figure(figsize=(10,8))
ax=fig.add_subplot(1,1,1)
scatter=ax.scatter(X_pca[:index_range,0],
            X_pca[:index_range,1],
            c=target[:index_range],
            s=10,
           cmap=plt.get_cmap('jet', number_of_people)
          )

ax.set_xlabel("First Principle Component")
ax.set_ylabel("Second Principle Component")
ax.set_title("PCA projection of {} people".format(number_of_people))

fig.colorbar(scatter)
```

Out[21]: <matplotlib.colorbar.Colorbar at 0x1e2db5ec040>

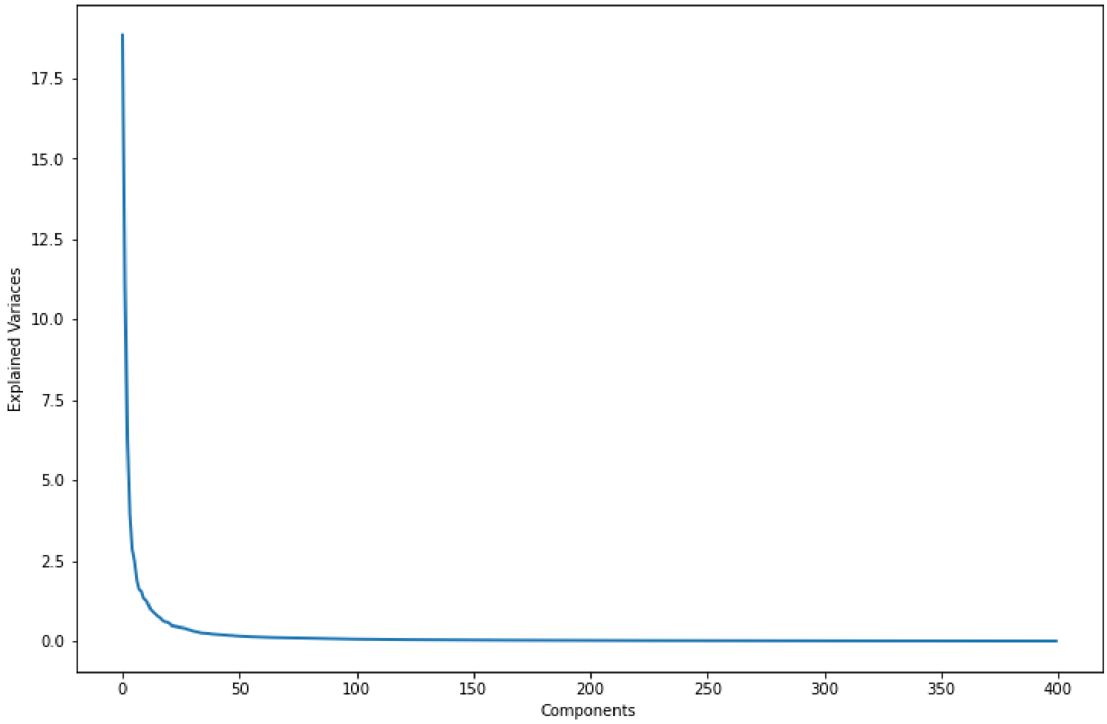


In [22]:
```
pca=PCA()
pca.fit(X)

plt.figure(1, figsize=(12,8))

plt.plot(pca.explained_variance_, linewidth=2)

plt.xlabel('Components')
plt.ylabel('Explained Variaces')
plt.show()
```



In [23]:
```
n_components=90
```

In [24]:
```
pca=PCA(n_components=n_components, whiten=True)
pca.fit(X_train)
```

Out[24]:
```
PCA(n_components=90, whiten=True)
```

In [25]:
```
PCA(copy=True, iterated_power='auto', n_components=90, random_state=None,
  svd_solver='auto', tol=0.0, whiten=True)
```

Out[25]:
```
PCA(n_components=90, whiten=True)
```

In [26]:
```
fig,ax=plt.subplots(1,1,figsize=(8,8))
ax.imshow(pca.mean_.reshape((64,64)), cmap="gray")
ax.set_xticks([])
ax.set_yticks([])
ax.set_title('Average Face')
```

Out[26]: `Text(0.5, 1.0, 'Average Face')`

In [27]:
```
number_of_eigenfaces=len(pca.components_)
eigen_faces=pca.components_.reshape((number_of_eigenfaces, data.shape[1], data.shape[2]))

cols=10
rows=int(number_of_eigenfaces/cols)
fig, axarr=plt.subplots(nrows=rows, ncols=cols, figsize=(15,15))
axarr=axarr.flatten()
for i in range(number_of_eigenfaces):
    axarr[i].imshow(eigen_faces[i],cmap="gray")
    axarr[i].set_xticks([])
    axarr[i].set_yticks([])
    axarr[i].set_title("eigen id:{}".format(i))
plt.suptitle("All Eigen Faces".format(10*"=", 10*"="))
```

Out[27]:
```
Text(0.5, 0.98, 'All Eigen Faces')
```

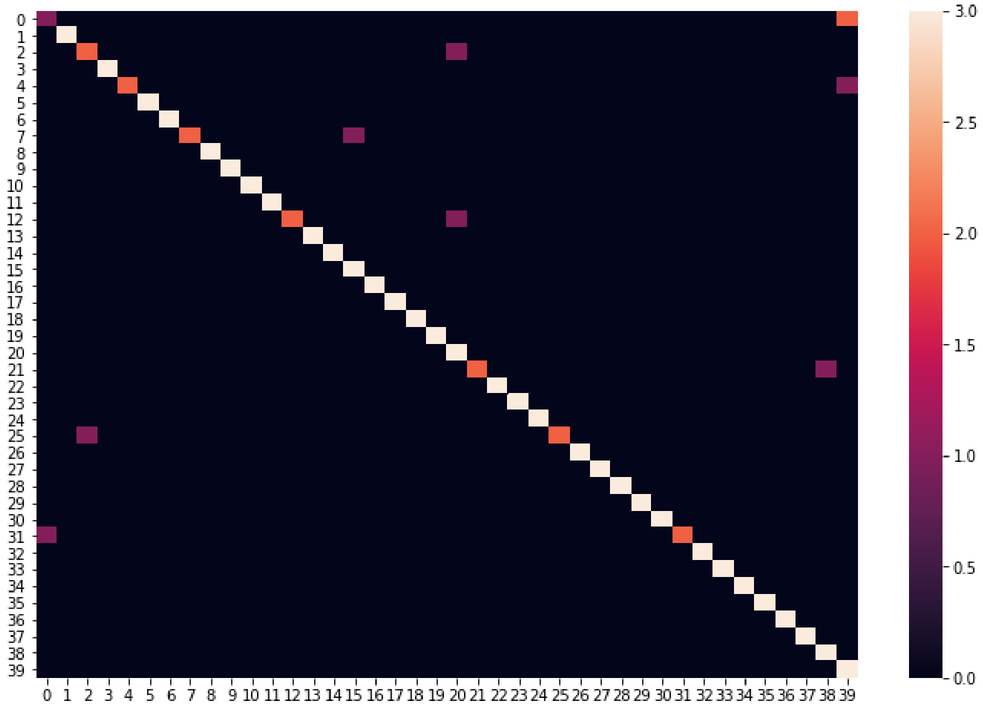
In [28]:
```
X_train_pca=pca.transform(X_train)
X_test_pca=pca.transform(X_test)
```

In [29]:
```
clf = SVC()
clf.fit(X_train_pca, y_train)
y_pred = clf.predict(X_test_pca)
print("accuracy score:{:.2f}".format(metrics.accuracy_score(y_test, y_pred)))
```

```
accuracy score:0.93
```

In [30]:
```
import seaborn as sns
plt.figure(1, figsize=(12,8))
sns.heatmap(metrics.confusion_matrix(y_test, y_pred))
```

Out[30]: <AxesSubplot:>



In [31]:
```
print(metrics.classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.50      0.33      0.40         3
           1       1.00      1.00      1.00         3
           2       0.67      0.67      0.67         3
           3       1.00      1.00      1.00         3
           4       1.00      0.67      0.80         3
           5       1.00      1.00      1.00         3
           6       1.00      1.00      1.00         3
           7       1.00      0.67      0.80         3
           8       1.00      1.00      1.00         3
           9       1.00      1.00      1.00         3
          10       1.00      1.00      1.00         3
          11       1.00      1.00      1.00         3
          12       1.00      0.67      0.80         3
          13       1.00      1.00      1.00         3
          14       1.00      1.00      1.00         3
          15       0.75      1.00      0.86         3
          16       1.00      1.00      1.00         3
          17       1.00      1.00      1.00         3
          18       1.00      1.00      1.00         3
          19       1.00      1.00      1.00         3
          20       0.60      1.00      0.75         3
          21       1.00      0.67      0.80         3
          22       1.00      1.00      1.00         3
          23       1.00      1.00      1.00         3
          24       1.00      1.00      1.00         3
          25       1.00      0.67      0.80         3
          26       1.00      1.00      1.00         3
          27       1.00      1.00      1.00         3
          28       1.00      1.00      1.00         3
          29       1.00      1.00      1.00         3
          30       1.00      1.00      1.00         3
          31       1.00      0.67      0.80         3
          32       1.00      1.00      1.00         3
          33       1.00      1.00      1.00         3
          34       1.00      1.00      1.00         3
          35       1.00      1.00      1.00         3
          36       1.00      1.00      1.00         3
          37       1.00      1.00      1.00         3
          38       0.75      1.00      0.86         3
          39       0.50      1.00      0.67         3

    accuracy                           0.93       120
   macro avg       0.94      0.93      0.92       120
weighted avg       0.94      0.93      0.92       120
```

In [32]:
```
models=[]
models.append(('LDA', LinearDiscriminantAnalysis()))
models.append(("LR",LogisticRegression()))
models.append(("NB",GaussianNB()))
models.append(("KNN",KNeighborsClassifier(n_neighbors=5)))
models.append(("DT",DecisionTreeClassifier()))
models.append(("SVM",SVC()))


for name, model in models:

    clf=model

    clf.fit(X_train_pca, y_train)

    y_pred=clf.predict(X_test_pca)
    print(10*"=","{} Result".format(name).upper(),10*"=")
    print("Accuracy score:{:0.2f}".format(metrics.accuracy_score(y_test, y_pred)))
    print()
```

```
========== LDA RESULT ==========
Accuracy score:0.93

========== LR RESULT ==========
Accuracy score:0.93

========== NB RESULT ==========
Accuracy score:0.87

========== KNN RESULT ==========
Accuracy score:0.70

========== DT RESULT ==========
Accuracy score:0.61

========== SVM RESULT ==========
Accuracy score:0.93
```

In [33]:
```
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
pca=PCA(n_components=n_components, whiten=True)
pca.fit(X)
X_pca=pca.transform(X)
for name, model in models:
    kfold=KFold(n_splits=5, shuffle=True, random_state=0)

    cv_scores=cross_val_score(model, X_pca, target, cv=kfold)
    print("{} mean cross validations score:{:.2f}".format(name, cv_scores.mean()))
```

```
LDA mean cross validations score:0.98
LR mean cross validations score:0.93
NB mean cross validations score:0.80
KNN mean cross validations score:0.68
DT mean cross validations score:0.46
SVM mean cross validations score:0.87
```

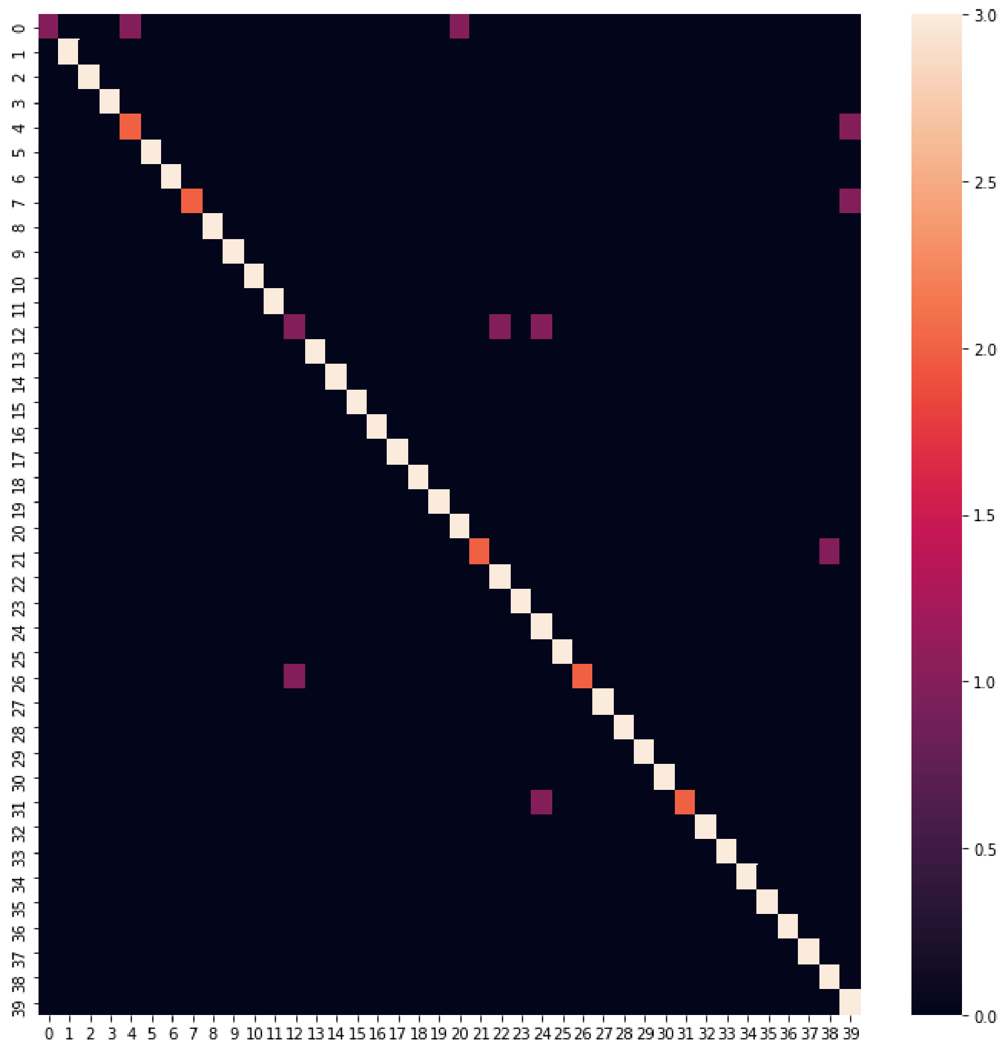
In [34]:
```
lr=LinearDiscriminantAnalysis()
lr.fit(X_train_pca, y_train)
y_pred=lr.predict(X_test_pca)
print("Accuracy score:{:.2f}".format(metrics.accuracy_score(y_test, y_pred)))
```

```
Accuracy score:0.93
```

In [35]:
```
cm=metrics.confusion_matrix(y_test, y_pred)

plt.subplots(1, figsize=(12,12))
sns.heatmap(cm)
```

Out[35]: <AxesSubplot:>



In [36]:
```
print("Classification Results:\n{}".format(metrics.classification_report(y_test, y_pred)))
```

```
Classification Results:
              precision    recall  f1-score   support

           0       1.00      0.33      0.50         3
           1       1.00      1.00      1.00         3
           2       1.00      1.00      1.00         3
           3       1.00      1.00      1.00         3
           4       0.67      0.67      0.67         3
           5       1.00      1.00      1.00         3
           6       1.00      1.00      1.00         3
           7       1.00      0.67      0.80         3
           8       1.00      1.00      1.00         3
           9       1.00      1.00      1.00         3
          10       1.00      1.00      1.00         3
          11       1.00      1.00      1.00         3
          12       0.50      0.33      0.40         3
          13       1.00      1.00      1.00         3
          14       1.00      1.00      1.00         3
          15       1.00      1.00      1.00         3
          16       1.00      1.00      1.00         3
          17       1.00      1.00      1.00         3
          18       1.00      1.00      1.00         3
          19       1.00      1.00      1.00         3
          20       0.75      1.00      0.86         3
          21       1.00      0.67      0.80         3
          22       0.75      1.00      0.86         3
          23       1.00      1.00      1.00         3
          24       0.60      1.00      0.75         3
          25       1.00      1.00      1.00         3
          26       1.00      0.67      0.80         3
          27       1.00      1.00      1.00         3
          28       1.00      1.00      1.00         3
          29       1.00      1.00      1.00         3
          30       1.00      1.00      1.00         3
          31       1.00      0.67      0.80         3
          32       1.00      1.00      1.00         3
          33       1.00      1.00      1.00         3
          34       1.00      1.00      1.00         3
          35       1.00      1.00      1.00         3
          36       1.00      1.00      1.00         3
          37       1.00      1.00      1.00         3
          38       0.75      1.00      0.86         3
          39       0.60      1.00      0.75         3

    accuracy                           0.93       120
   macro avg       0.94      0.93      0.92       120
weighted avg       0.94      0.93      0.92       120
```

In [37]:
```
from sklearn.model_selection import LeaveOneOut
loo_cv=LeaveOneOut()
clf=LogisticRegression()
cv_scores=cross_val_score(clf,
                         X_pca,
                         target,
                         cv=loo_cv)
print("{} Leave One Out cross-validation mean accuracy score:{:.2f}".format(clf.__class__.__name__,
                                                                          cv_scores.mean()))
```

```
LogisticRegression Leave One Out cross-validation mean accuracy score:0.94
```

In [38]:
```
from sklearn.model_selection import LeaveOneOut
loo_cv=LeaveOneOut()
clf=LinearDiscriminantAnalysis()
cv_scores=cross_val_score(clf,
                         X_pca,
                         target,
                         cv=loo_cv)
print("{} Leave One Out cross-validation mean accuracy score:{:.2f}".format(clf.__class__.__name__,
                                                                          cv_scores.mean()))
```

```
LinearDiscriminantAnalysis Leave One Out cross-validation mean accuracy score:0.98
```

In [39]:
```
from sklearn.model_selection import GridSearchCV
```

In [42]:
```
lr=LogisticRegression(C=1.0, penalty="l2")
lr.fit(X_train_pca, y_train)
print("lr score:{:.2f}".format(lr.score(X_test_pca, y_test)))
```

```
lr score:0.93
```

In [43]:
```
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier

Target=label_binarize(target, classes=range(40))
print(Target.shape)
print(Target[0])

n_classes=Target.shape[1]
```

```
(400, 40)
[1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
 0 0 0]
```

In [44]:
```
X_train_multiclass, X_test_multiclass, y_train_multiclass, y_test_multiclass=train_test_split(X,
                                                                                               Target,
                                                                                              test_size=0.3
                                                                                              stratify=Targ
                                                                                      random_state=0)
```

In [45]:
```
pca=PCA(n_components=n_components, whiten=True)
pca.fit(X_train_multiclass)

X_train_multiclass_pca=pca.transform(X_train_multiclass)
X_test_multiclass_pca=pca.transform(X_test_multiclass)
```

In [46]:
```
oneRestClassifier=OneVsRestClassifier(lr)

oneRestClassifier.fit(X_train_multiclass_pca, y_train_multiclass)
y_score=oneRestClassifier.decision_function(X_test_multiclass_pca)
```

In [47]:
```
# For each class
precision = dict()
recall = dict()
average_precision = dict()
for i in range(n_classes):
    precision[i], recall[i], _ = metrics.precision_recall_curve(y_test_multiclass[:, i],
                                                        y_score[:, i])
    average_precision[i] = metrics.average_precision_score(y_test_multiclass[:, i], y_score[:, i])

# A "micro-average": quantifying score on all classes jointly
precision["micro"], recall["micro"], _ = metrics.precision_recall_curve(y_test_multiclass.ravel(),
    y_score.ravel())
average_precision["micro"] = metrics.average_precision_score(y_test_multiclass, y_score,
                                                     average="micro")
print('Average precision score, micro-averaged over all classes: {0:0.2f}'
      .format(average_precision["micro"]))
```

```
Average precision score, micro-averaged over all classes: 0.97
```

In [49]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
```

In [52]:
```
print("Accuracy score:{:.2f}".format(metrics.accuracy_score(y_test, y_pred)))
print("Classification Results:\n{}".format(metrics.classification_report(y_test, y_pred)))
```

```
Accuracy score:0.93
Classification Results:
              precision    recall  f1-score   support

           0       1.00      0.33      0.50         3
           1       1.00      1.00      1.00         3
           2       1.00      1.00      1.00         3
           3       1.00      1.00      1.00         3
           4       0.67      0.67      0.67         3
           5       1.00      1.00      1.00         3
           6       1.00      1.00      1.00         3
           7       1.00      0.67      0.80         3
           8       1.00      1.00      1.00         3
           9       1.00      1.00      1.00         3
          10       1.00      1.00      1.00         3
          11       1.00      1.00      1.00         3
          12       0.50      0.33      0.40         3
          13       1.00      1.00      1.00         3
          14       1.00      1.00      1.00         3
          15       1.00      1.00      1.00         3
          16       1.00      1.00      1.00         3
          17       1.00      1.00      1.00         3
          18       1.00      1.00      1.00         3
          19       1.00      1.00      1.00         3
          20       0.75      1.00      0.86         3
          21       1.00      0.67      0.80         3
          22       0.75      1.00      0.86         3
          23       1.00      1.00      1.00         3
          24       0.60      1.00      0.75         3
          25       1.00      1.00      1.00         3
          26       1.00      0.67      0.80         3
          27       1.00      1.00      1.00         3
          28       1.00      1.00      1.00         3
          29       1.00      1.00      1.00         3
          30       1.00      1.00      1.00         3
          31       1.00      0.67      0.80         3
          32       1.00      1.00      1.00         3
          33       1.00      1.00      1.00         3
          34       1.00      1.00      1.00         3
          35       1.00      1.00      1.00         3
          36       1.00      1.00      1.00         3
          37       1.00      1.00      1.00         3
          38       0.75      1.00      0.86         3
          39       0.60      1.00      0.75         3

    accuracy                           0.93       120
   macro avg       0.94      0.93      0.92       120
weighted avg       0.94      0.93      0.92       120
```

In [53]:
```
from sklearn.pipeline import Pipeline
```

In [55]:
```
print("Accuracy score:{:.2f}".format(metrics.accuracy_score(y_test, y_pred)))
print("Classification Results:\n{}".format(metrics.classification_report(y_test, y_pred)))
```

```
Accuracy score:0.93
Classification Results:
              precision    recall  f1-score   support

           0       1.00      0.33      0.50         3
           1       1.00      1.00      1.00         3
           2       1.00      1.00      1.00         3
           3       1.00      1.00      1.00         3
           4       0.67      0.67      0.67         3
           5       1.00      1.00      1.00         3
           6       1.00      1.00      1.00         3
           7       1.00      0.67      0.80         3
           8       1.00      1.00      1.00         3
           9       1.00      1.00      1.00         3
          10       1.00      1.00      1.00         3
          11       1.00      1.00      1.00         3
          12       0.50      0.33      0.40         3
          13       1.00      1.00      1.00         3
          14       1.00      1.00      1.00         3
          15       1.00      1.00      1.00         3
          16       1.00      1.00      1.00         3
          17       1.00      1.00      1.00         3
          18       1.00      1.00      1.00         3
          19       1.00      1.00      1.00         3
          20       0.75      1.00      0.86         3
          21       1.00      0.67      0.80         3
          22       0.75      1.00      0.86         3
          23       1.00      1.00      1.00         3
          24       0.60      1.00      0.75         3
          25       1.00      1.00      1.00         3
          26       1.00      0.67      0.80         3
          27       1.00      1.00      1.00         3
          28       1.00      1.00      1.00         3
          29       1.00      1.00      1.00         3
          30       1.00      1.00      1.00         3
          31       1.00      0.67      0.80         3
          32       1.00      1.00      1.00         3
          33       1.00      1.00      1.00         3
          34       1.00      1.00      1.00         3
          35       1.00      1.00      1.00         3
          36       1.00      1.00      1.00         3
          37       1.00      1.00      1.00         3
          38       0.75      1.00      0.86         3
          39       0.60      1.00      0.75         3

    accuracy                           0.93       120
   macro avg       0.94      0.93      0.92       120
weighted avg       0.94      0.93      0.92       120
```