```
## Import libraries
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from skimage.color import rgb2gray
import pylab as pl
import pandas as pd
```

```
from google.colab import drive
drive.mount('/content/drive', force_remount=True)
```

```
Mounted at /content/drive
```

```
ls "/content/drive/My Drive/Colab Notebooks/"
```

```
ls: cannot access '/content/drive/My Drive/Colab Notebooks/': No such file or dir
```

```
X=np.load('/content/drive/My Drive/train_data.npy')
Y=np.load('/content/drive/My Drive/train_labels.npy')
labels = ['A','B','C','D','E','F','G','H','I']
X.shape, Y.shape
```

```
((1844, 100, 100, 3), (1844, 1))
```

```
# Vectorize origional data so other preprocessing techniques can be used.
Xtrain2 = []
for k in range(len(X)):
        X_train1 = rgb2gray(X[k,:,:,:])
        Xtrain2 += [X_train1.ravel()]
Xtrain2 = np.array(Xtrain2)
Xtrain2.shape, X.shape, len(X)
```

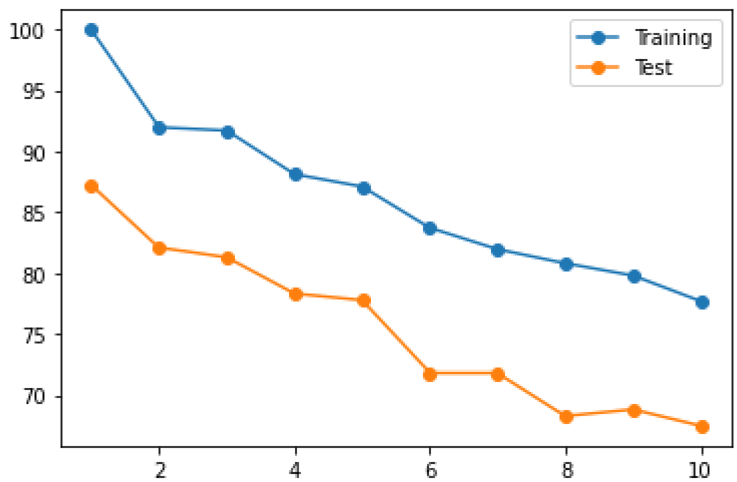
```
((1844, 10000), (1844, 100, 100, 3), 1844)
```

```
## Normalize and separate data into training and validation sets.
from sklearn.model_selection import train_test_split

X_train_norm = Xtrain2/255

X_train, X_test, y_train, y_test = train_test_split(X_train_norm, Y, test_size=0.2)
y_train = np.array(y_train.ravel())
y_test = np.array(y_test.ravel())
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

```
((1475, 10000), (369, 10000), (1475,), (369,))
```

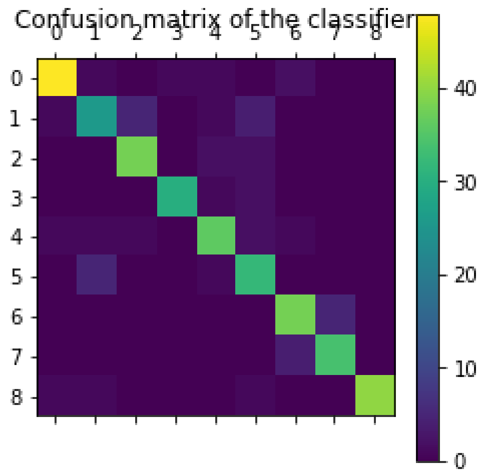
```
import sys
from sklearn.metrics import confusion_matrix
```

```
from sklearn.neighbors import KNeighborsClassifier

N = 10
kset = np.arange(1,N+1)
Acc = np.zeros((N,2))

for k in kset:
    clf = KNeighborsClassifier(n_neighbors=k, weights='uniform',metric = 'minkowski', 
    clf.fit(X_train, y_train)
    Acc[k-1,:] = [round(clf.score(X_train, y_train.ravel())*100,2),round(clf.score(X_t

plt.plot(kset, Acc[:,0], '-o', label = 'Training')
plt.plot(kset, Acc[:,1], '-o', label = 'Test')
plt.legend();
```




```
# plot confusion matrix
# Recalculate  KNN with best value of K
clf = KNeighborsClassifier(n_neighbors=1, weights = 'uniform', metric = 'minkowski', p
model     = clf.fit(X_train, y_train)
predicted = clf.predict(X_test)


cm = confusion_matrix(predicted, y_test)
print(cm)

pl.matshow(cm)
pl.title('Confusion matrix of the classifier')

pl.colorbar()

pl.show()
```

```
[[48  1  0  1  1  0  2  0  0]
 [ 1 26  5  0  1  4  0  0  0]
 [ 0  0 38  0  2  2  0  0  0]
 [ 0  0  0 30  1  2  0  0  0]
 [ 1  1  1  0 36  2  1  0  0]
 [ 0  5  0  0  1 32  0  0  0]
 [ 0  0  0  0  0  0 38  5  0]
 [ 0  0  0  0  0  0  4 34  0]
 [ 1  1  0  0  0  1  0  0 40]]
```




```
clf = KNeighborsClassifier(n_neighbors=1, weights = 'uniform',metric = 'minkowski', p
clf.fit(X_train, y_train)
ACC = clf.score(X_train, y_train)
ACC2 = clf.score(X_test, y_test)
print("Best KNN training Accuracy: ", ACC)
print("Best KNN test Accuracy: ", ACC2)
```

```
Best KNN training Accuracy:  1.0
Best KNN test Accuracy:  0.8726287262872628
```

```
# BASICALLY THE WHOLE LAB USING KNN CLASSIFIER
import numpy as np
from scipy import ndimage
from skimage.color import rgb2gray
from skimage import data, filters
from sklearn.preprocessing import FunctionTransformer
from sklearn.pipeline import Pipeline

def grayscale_img(X):
    """Convert RGB image to grayscale image"""
    if(X.shape[1:] != (100, 100, 3)):
        raise ValueError('Grayscale: shape must be (k, 100, 100, 3)!')
    output=np.asarray(a=[rgb2gray(X[k,:,:,:]) for k in range(len(X))]).reshape(X.shape
    print('Grayscale: X.shape:\t{}\n'.format(output.shape))
    return output


def vectorize_img(X):
```

```
def vectorize_img(X):
    """Flatten image into a 1D vector"""
    if(X.shape[1:] != (100, 100, 1)):
        raise ValueError('Vectorize: shape must be (k, 100, 100, 1)!')
    output=np.asarray(a=[X[k].flatten() for k in range(len(X))])
    print('Vectorize: X.shape:\t{}\n'.format(output.shape))
    return output

# testing only
def vectorize_img_inv(X):
    """Inverse of vectorize_img by converting flattened image into 100x100 grayscale i
    if(X.ndim != 2):
        raise ValueError('Vectorize_Inv: each image must be 1D!')
    output=X.reshape(X.shape[0], 100, 100, 1)
    print('Vectorize_Inv: X.shape:\t{}\n'.format(output.shape))
    return output

def normalize_img(X_vector):
    """Normalize each pixel intensity value in vectorized image"""
    if(X_vector.ndim != 2):
        raise ValueError('Normalize: each image must be 1D!')
    output=X_vector/255
    print('Normalize: X.shape:\t{}\n'.format(output.shape))
    return output

# testing only
def normalize_img_inv(X_vector):
    """Inverse of normalize_img by scaling intensity of each pixel by 255"""
    if(X_vector.ndim != 2):
        raise ValueError('Normalize_Inv: each image must be 1D!')
    output=X_vector*255
    print('Normalize_Inv: X.shape:\t{}\n'.format(output.shape))
    return output

# converting each function to FunctionTransformer type to be compatible in Pipeline
grayscale_img_func=FunctionTransformer(func=grayscale_img)
vectorize_img_func=FunctionTransformer(func=vectorize_img, inverse_func=vectorize_img_
normalize_img_func=FunctionTransformer(func=normalize_img, inverse_func=normalize_img_

from sklearn.neighbors import KNeighborsClassifier
estimators = [
    ('Grayscale', grayscale_img_func),
    ('Vectorize', vectorize_img_func),
    ('Normalize', normalize_img_func),
    ('KNN', KNeighborsClassifier(n_neighbors=1, weights='uniform', metric='minkowski',
]
img_pipeline=Pipeline(estimators)

# generating scores
def pipeline_score(X_train, X_test, y_train, y_test):
    """
        Compute the score for model trained by pipeline-preprocessed training set and
```

```
        then tested on the testing set.
    """
    ip_model=img_pipeline.fit(X=X_train, y=y_train)
    return ip_model.score(X=X_test, y=y_test)

# example
from sklearn.model_selection import train_test_split

# use below when running from local desktop
# X=np.load('train_data.npy')
# Y=np.load('train_labels.npy')

# use below when running on Google collab
X=np.load('/content/drive/My Drive/train_data.npy')
Y=np.load('/content/drive/My Drive/train_labels.npy')

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, shuffle=True)
print('X_train.shape:\t{}\n'.format(X_train.shape))
print('X_test.shape:\t{}\n'.format(X_test.shape))
print('y_train.shape:\t{}\n'.format(y_train.shape))
print('y_test.shape:\t{}\n'.format(y_test.shape))
print('Score:\t{}\n'.format(
    pipeline_score(X_train=X_train, X_test=X_test, y_train=y_train, y_test=y_test)
))
```

```
X_train.shape:  (1475, 100, 100, 3)

X_test.shape:   (369, 100, 100, 3)

y_train.shape:  (1475, 1)

y_test.shape:   (369, 1)

Grayscale: X.shape:     (1475, 100, 100, 1)

Vectorize: X.shape:     (106, 10000)

Vectorize_Inv: X.shape: (106, 100, 100, 1)

Vectorize: X.shape:     (1475, 10000)

Normalize: X.shape:     (106, 10000)

Normalize_Inv: X.shape: (106, 10000)

Normalize: X.shape:     (1475, 10000)

/usr/local/lib/python3.6/dist-packages/sklearn/pipeline.py:354: DataConversionWar
  self._final_estimator.fit(Xt, y, **fit_params)
Grayscale: X.shape:     (369, 100, 100, 1)

Vectorize: X.shape:     (369, 10000)

Normalize: X.shape:     (369, 10000)

Score:  0.9051490514905149
```

Steps of Pipeline:

1. Each image is converted to grayscale using rgb2gray from skimage.color. This is in preparation only focuses on change between brightness or intensity of color, rather than the rgb value. Conv to entirely focus on intensity of the pixels.
2. Vectorizing i.e. flattening each image into a single 1D vector allows streamlined performance an importantly, this reduces the dimensionality of X data set to 2 dimensions with shape (k, 10000) with sklearn estimators.
3. Normalizing the intensity of each pixel for all images puts the images on a more equal playing fi background lighting may cause a greater variation of average pixel intensities across images foı each image to the same but smaller interval of allowed values (0 to 1). This reduces the variatio
4. As empirically discovered in Lab 3, SVM beats the other tested estimators as having the best ac data set as input into SVM, which is configured with optimal values for C and gamma from empi to form the best pipeline.

Double-click (or enter) to edit