CSC 421 Assignment 1

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Knn

This notebook imports the CIFAR-10 image dataset and separates the data into two sets containing 50000 train / 10000 test images. The data is not shuffled, since it was not required to be (except in the 5-fold validation section). The Knn machine learning algorithm is then used to train on the 50000 train images, and classify on the 10000 test images (using various values of k). The accuracies of the predictions for each k value are calculated and compared.

Import statements

In [1]:
```
import matplotlib.pyplot as plt  #Used for plotting different k values, as well as displ
import numpy as np
import torch                     #torch and other libraries are only being used to downl
from torch.utils.data import DataLoader
import torchvision
from torchvision import datasets
from torchvision.transforms import ToTensor, Compose
from collections import Counter
import cv2                       #Used for displaying images during testing
```

In [2]:
```
import ssl                       #for resolving a known certificate error with downloadi
ssl._create_default_https_context = ssl._create_unverified_context
```

The ssl code above is for resolving a known certificate error with CIFAR-10 in torchvision

RGB values for Grayscale conversion

In [3]:
```
RED = 0.299
GREEN = 0.587
BLUE = 0.114
```

Seed value for shuffling data

In [4]:
```
seedval = 2022 #seed used in k-fold validation
```

Importing and partitioning data into test and train datasets

The data is imported and stored in two arrays. Each image of the dataset is a 32x32 image, and each pixel has BGR values.

In [5]:
```
train_dataset = datasets.CIFAR10(root='data/', download=True, train=True, transform=ToTe
test_dataset = datasets.CIFAR10(root='data/', download=True, train=False, transform=ToTe
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [6]:
```
X_train = train_dataset.data
y_train = np.array(train_dataset.targets)
X_test = test_dataset.data
y_test = np.array(test_dataset.targets)
classes = train_dataset.classes
```

In [7]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(50000, 32, 32, 3)
(10000, 32, 32, 3)
```

Function Definitions

Grayscale conversion function to be performed on every pixel when called in preProcess function

In [8]:
```
def toBWArray(itemarray):
    global RED,BLUE,GREEN
    val = np.uint8(np.dot(itemarray, [BLUE,GREEN,RED]))
    return val
```

Pre-processing of each image. Flattens the array, converts it to grayscale, and scales each pixel value between 0-1.

In [9]:
```
def preProcess(itemarray):
    arrcopy = np.empty((len(itemarray), 32, 32, 3))
    np.copyto(arrcopy, itemarray)
    arrcopy = arrcopy.reshape((len(itemarray), 1024, 3))
    bwArray = np.empty((len(itemarray),1024), np.uint8)
    for i in range(len(itemarray)):
        bwArray[i] = toBWArray(arrcopy[i])
    bwArray = bwArray / 256
    return bwArray
```

Distance computation. Calculates the distances between every image in X_test and every image in X_train. In this case, outputs an array of size (10000, 50000)

In [10]:
```
def computeDist(X_train, X_test):
    distance_array = np.empty((len(X_test),len(X_train)), np.float32)
    for n in range(len(X_test)):
        #print(f'calculating distances for image {n}')
        results_array = np.empty((len(X_train)))
        for i in range(len(X_train)):
            results_array[i] = np.sqrt(np.sum(np.square(X_train[i] - X_test[n])))
        distance_array[n] = results_array
    return distance_array
```

User-facing function used to "train" the dataset. It really just calls computeDist.

In [11]:
```
def trainThis(X_train, y_train, X_test):
    distance_array = computeDist(X_train, X_test)
    return distance_array
```

This function uses global values of k to take the k-closest X_train images from the corresponding distance list for each image of X_test. It then takes the indexes of those closest images, counts the most common occurance, and stores that value in a results_array whose index corresponds to the index of X_test

In [12]:
```
def classifyThis(distance_array, y_train):
    global k
    results_array = np.empty(len(distance_array), np.uint8)
    for n in range(len(results_array)):
        classeslist = np.empty(k)
```

```
        distancesortedindexes = np.argsort(distance_array[n])
        for i in range(len(classeslist)):
            classeslist[i] = y_train[distancesortedindexes[i]]
        c = Counter(classeslist)
        results_array[n] = c.most_common(1)[0][0]
    return results_array
```

Compares the answers of the test set to the predicted set and returns the accuracy of the predicted set

In [13]:
```
def evalThis(results_array, y_test):
    val = np.sum(results_array == y_test) / len(y_test)
    return val
```

Computation

Both the X_train and X_test arrays are preprocessed.

In [14]:
```
X_train_proc = preProcess(X_train)
print('X_train preprocessed')
X_test_proc = preProcess(X_test)
print('X_test preprocessed')
```

```
X_train preprocessed
X_test preprocessed
```

The arrays are now reshaped, converted to grayscale, and scaled

In [15]:
```
print(X_train_proc)
```

```
[[0.23828125 0.17578125 0.1796875  ... 0.6796875  0.43359375 0.34765625]
 [0.69140625 0.52734375 0.39453125 ... 0.52734375 0.53515625 0.53515625]
 [0.99609375 0.98828125 0.98828125 ... 0.32421875 0.32421875 0.328125  ]
 ...
 [0.6953125  0.69921875 0.703125   ... 0.21875    0.18359375 0.1328125 ]
 [0.84765625 0.83203125 0.828125   ... 0.703125   0.71875    0.71875   ]
 [0.90234375 0.93359375 0.93359375 ... 0.6875     0.63671875 0.6328125 ]]
```

In [16]:
```
print(X_train_proc.shape)
```

```
(50000, 1024)
```

In [17]:
```
print(X_test_proc.shape)
```

```
(10000, 1024)
```

Distance array is calculated for every image in X_test.

In [18]:
```
distance_array = trainThis(X_train_proc, y_train, X_test_proc)
```

In [19]:
```
print(distance_array)
```

```
[[ 6.6806     8.814243  12.311892  ... 11.074615  11.5746565  9.574177 ]
 [13.959751  11.588673   9.104533  ... 10.0869     8.199101  11.366525 ]
 [10.890447   9.228642   8.495009  ...  8.555114   7.6023664  9.010739 ]
 ...
 [ 9.362952  13.998307  17.503193  ... 14.580839  18.182764  14.695854 ]
 [ 6.9926567  9.95874   13.610982  ... 12.150267  12.8435955 10.490734 ]
 [ 8.088964   9.4295435 11.073403  ...  9.540804  11.611938   8.405117 ]]
```

In [20]:
```
k = 3
results_array = classifyThis(distance_array, y_train)
k3 = evalThis(results_array, y_test)
print(k3)
```

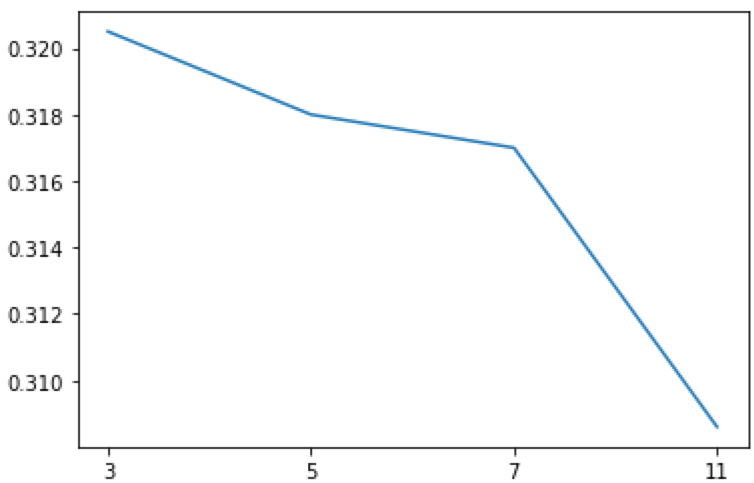
```
k = 5
results_array = classifyThis(distance_array, y_train)
k5 = evalThis(results_array, y_test)
print(k5)
k = 7
results_array = classifyThis(distance_array, y_train)
k7 = evalThis(results_array, y_test)
print(k7)
k = 11
results_array = classifyThis(distance_array, y_train)
k11 = evalThis(results_array, y_test)
print(k11)
```

```
0.3205
0.318
0.317
0.3086
```

Accuracy Chart

In [21]:
```
vals = {'3':k3, '5':k5, '7':k7, '11':k11}
plt_x = list(vals.keys())
plt_y = list(vals.values())
plt.plot(plt_x, plt_y)
```

Out[21]:
```
[<matplotlib.lines.Line2D at 0x1df65a129a0>]
```



As we can see, k = 3 has the highest accuracy at around 32%

5-fold Validation

In [22]:
```
def fiveFoldVal(X_train, X_test, y_train, y_test):
    global k
    folds = 5
    np.random.seed(seedval)

    X_set_OG = np.concatenate((X_train, X_test))
    y_set_OG = np.concatenate((y_train, y_test))

    X_set_OG = preProcess(X_set_OG)

    indices = np.arange(X_set_OG.shape[0])
    np.random.shuffle(indices)
    X_set = X_set_OG[indices]
    y_set = y_set_OG[indices]
```

```python
    #size reduction for testing
    #X_set = X_set[:1000]
    #y_set = y_set[:1000]

    #This is assuming (X_set = y_set = 60000) is divisible by (folds = 5)
    #I didn't bother to write the case where it isn't
    subset_size = int(X_set.shape[0] / folds)

    X_sets = np.empty((folds, subset_size, 1024), np.float32)
    for i in range(folds):
        X_sets[i] = X_set[(i * subset_size):((i+1) * subset_size)]

    y_sets = np.empty((folds, subset_size), np.uint8)
    for i in range(folds):
        y_sets[i] = y_set[(i * subset_size):((i+1) * subset_size)]

    accuracies = np.empty((folds, 4), np.float32)

    for i in range(folds):
        print(f'Fold: {(i+1)}')
        X_test = X_sets[i]
        y_test = y_sets[i]

        X_train = np.empty(shape=[0, 1024], dtype=np.float32)
        y_train = np.empty(shape=[0], dtype=np.uint8)

        for j in range(folds):
            if(j!=i):
                X_train = np.append(X_train, X_sets[j], axis=0)
                y_train = np.append(y_train, y_sets[j])

        distance_array = trainThis(X_train, y_train, X_test)

        k = 3
        results_array = classifyThis(distance_array, y_train)
        k3 = evalThis(results_array, y_test)
        accuracies[i][0] = k3
        print(k3)

        k = 5
        results_array = classifyThis(distance_array, y_train)
        k5 = evalThis(results_array, y_test)
        accuracies[i][1] = k5
        print(k5)

        k = 7
        results_array = classifyThis(distance_array, y_train)
        k7 = evalThis(results_array, y_test)
        accuracies[i][2] = k7
        print(k7)

        k = 11
        results_array = classifyThis(distance_array, y_train)
        k11 = evalThis(results_array, y_test)
        accuracies[i][3] = k11
        print(k11)
        print()
        print()
    return accuracies
```

In [23]:

```python
accuracies = fiveFoldVal(X_train, X_test, y_train, y_test)
```

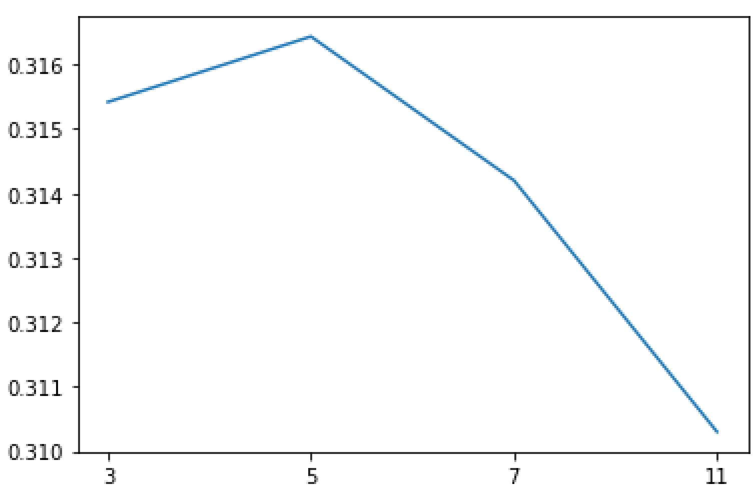
```
Fold: 1
0.3155
0.31983333333333336
0.31566666666666665
0.3145


Fold: 2
0.31475
0.3134166666666667
0.3125
0.3075833333333333


Fold: 3
0.31908333333333333
0.3205
0.31758333333333333
0.3144166666666667


Fold: 4
0.30866666666666664
0.31266666666666665
0.3119166666666667
0.3085833333333333


Fold: 5
0.31908333333333333
0.31575
0.31333333333333335
0.30641666666666667
```

In [24]:

```python
avg_k3 = np.mean(accuracies[:,0])
avg_k5 = np.mean(accuracies[:,1])
avg_k7 = np.mean(accuracies[:,2])
avg_k11 = np.mean(accuracies[:,3])
vals = {'3':avg_k3, '5':avg_k5, '7':avg_k7, '11':avg_k11}
plt_x = list(vals.keys())
plt_y = list(vals.values())
plt.plot(plt_x, plt_y)
```

Out[24]:

```
[<matplotlib.lines.Line2D at 0x1df63cb59a0>]
```

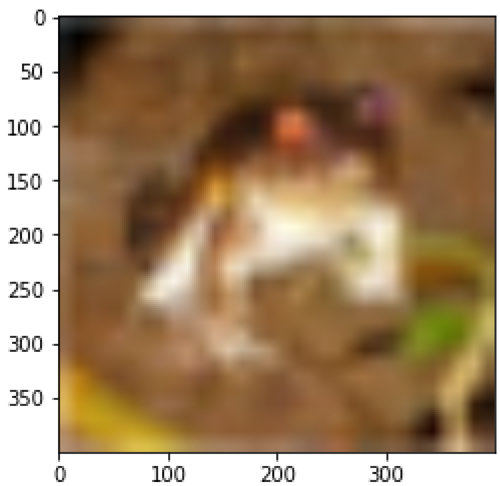


After performing 5-fold validation, it is clear that the best value of k for Knn in this model is actually k = 5, with around 31.65% accuracy

Image Printing

This section was used for testing and can be ignored.

In [25]:
```
IMGNUM = 0
#img_colored = cv2.cvtColor(X_train[IMGNUM], cv2.COLOR_BGR2RGB)
#img_resized = cv2.resize(img_colored, (400,400))
#plt.imshow(img_resized)

#X_train = X_train.reshape((50000,32,32))
#print(X_train)
img_resized = cv2.resize(X_train[IMGNUM],(400,400))
#img_resized2 = cv2.resize(X_train_proc[IMGNUM],(400,400))

plt.imshow(img_resized)
plt.show()
#plt.imshow(img_resized2, cmap='gray', vmin=0, vmax=255)
#plt.show()
```



Kmeans

My Kmeans implementation was created in its own notebook, and as such uses a seperate memory space / kernel. This notebook imports the CIFAR-10 image dataset and separates the data into two sets containing 50000 train / 10000 test images. The data is not shuffled, since it was not required to be (except in the 5-fold validation section). The Kmeans machine learning algorithm is then used to train on the 50000 train images, and classify on the 10000 test images (using various values of k). The accuracies of the predictions for each k value are calculated and compared.

Import statements

In [1]:
```
import matplotlib.pyplot as plt
import numpy as np
import torch
from torch.utils.data import DataLoader
import torchvision
from torchvision import datasets
from torchvision.transforms import ToTensor, Compose
from collections import Counter
import cv2
```

In [2]:
```
import ssl #This is for resolving a known certificate error with CIFAR-10 in torchvision
ssl._create_default_https_context = ssl._create_unverified_context
```

The ssl code above is for resolving a known certificate error with CIFAR-10 in torchvision

RGB values for Grayscale conversion

In [3]:
```
#Global colour values for greyscale conversion
RED = 0.299
BLUE = 0.114
GREEN = 0.587
```

Seed value for shuffling data

In [4]:
```
seedval = 2022 #seed used for picking random centroids and in k-fold validation
```

Importing and partitioning data into test and train datasets

The data is imported and stored in two arrays. Each image of the dataset is a 32x32 image, and each pixel has BGR values.

In [5]:
```
train_dataset = datasets.CIFAR10(root='data/', download=True, train=True, transform=ToTe
test_dataset = datasets.CIFAR10(root='data/', download=True, train=False, transform=ToTe
```

```
Files already downloaded and verified
Files already downloaded and verified
```

In [6]:
```
X_train = train_dataset.data
y_train = np.array(train_dataset.targets)
X_test = test_dataset.data
y_test = np.array(test_dataset.targets)
classes = train_dataset.classes
```

Function Definitions

Grayscale conversion function to be performed on every pixel when called in preProcess function

In [7]:
```
def toBWArray(itemarray):
    global RED,BLUE,GREEN
    val = np.uint8(np.dot(itemarray, [BLUE,GREEN,RED]))
    return val
```

Pre-processing of each image. Flattens the array, converts it to grayscale, and scales each pixel value between 0-1.

In [8]:
```
def preProcess(itemarray):
    arr_copy = np.empty((len(itemarray), 32, 32, 3))
    np.copyto(arr_copy, itemarray)
    arr_copy = arr_copy.reshape((len(itemarray), 1024, 3))
    bwArray = np.empty((len(itemarray),1024), np.uint8)
    for i in range(len(itemarray)):
        bwArray[i] = toBWArray(arr_copy[i])
    bwArray = bwArray / 256
    return bwArray
```

Distance computation. Calculates the distances between every image in X_test and every image in arr_centroids. In this case, outputs an array of size (10000, k)

In [9]:
```
def computeDist(X_test, arr_centroids):
    distance_array = np.empty((len(X_test),len(arr_centroids)), np.float32)
    for n in range(len(X_test)):
        results_array = np.empty((len(arr_centroids)))
        for i in range(len(arr_centroids)):
            results_array[i] = np.sqrt(np.sum(np.square(arr_centroids[i] - X_test[n])))
        distance_array[n] = results_array
    return distance_array
```

Computes the cluster value for each image in X_train. Outputs an array of size 50000. The index of the array is the image id in X_train and the value is the id of the centroid it belongs to in arr_centroids.

In [10]:
```
def computeClusters(X_train, arr_centroids):
    arr_clusters = np.empty((len(X_train)), np.uint8)
    for n in range(len(X_train)):
        distance_array = np.empty((len(arr_centroids)),np.float32)
        for i in range(len(arr_centroids)):
            distance_array[i] = np.sqrt(np.sum(np.square(X_train[n] - arr_centroids[i])))
        distancesortedindexes = np.argsort(distance_array)
        arr_clusters[n] = distancesortedindexes[0]
    return arr_clusters
```

Function that picks the initial centroids for the algorithm. Outputs a semi-random array of images to be used as centroids of size (k). When (k <= the size of the feature set) the chosen images will all be different classes. When (k > the size of the feature set), the shuffled sequence of classes to be chosen will repeat. (Ex. when k = 10, arr_centroids = [8 5 0 9 2 3 7 1 6 4] and when k= 15, arr_centroids = [8 5 0 9 2 3 7 1 6 4 8 5 0 9 2]

In [11]:
```
def pickCentroids(X_train, y_train):
    global k
    global seedval
    np.random.seed(seedval)
    arr_centroids_id = np.empty((k), np.uint32)
    arr_centroids = np.empty((k, len(X_train[0])))
    indices = np.arange(X_train.shape[0])
    np.random.shuffle(indices)
```

```
    shuffled_classes = np.arange(len(classes))
    np.random.shuffle(shuffled_classes)
    picked_classes = np.empty((k), np.uint8)

    for i in range(picked_classes.shape[0]):
        picked_classes[i] = shuffled_classes[int(i % (len(classes)))]

    #print(picked_classes[::-1])

    loop_c = 0
    while(picked_classes.size != 0):
        if y_train[indices[loop_c]] in picked_classes:
            arr_centroids_id[(len(picked_classes) - 1)] = indices[loop_c]
            index_of_found_value = np.where(picked_classes == y_train[indices[loop_c]])[
            if(index_of_found_value.size != 1):
                index_of_found_value = index_of_found_value[0]
            picked_classes = np.delete(picked_classes, index_of_found_value)
        loop_c += 1

    for i in range(k):
        arr_centroids[i] = X_train[arr_centroids_id[i]]

    #print(arr_centroids_id)

    return arr_centroids
```

Function that recomputes the centroids based on the current clusters

In [12]:
```
def recomputeCentroids(arr_centroids, arr_clusters, X_train):
    avgs = np.zeros((len(arr_centroids),1024), np.float32)
    for i in range(len(arr_clusters)):
        avgs[arr_clusters[i]] += X_train[i]
    arr_count = np.bincount(arr_clusters)
    for j in range(len(avgs)):
        avgs[j] = avgs[j] /  arr_count[j]
    return avgs
```

User-facing function for training the model. Sets up initial centroids, clusters, the base case for recursiveTrain, and calls recursiveTrain. Returns arr_clusters and arr_centroids to be used for classification.

In [13]:
```
def trainThis(X_train, y_train):
    arr_centroids = pickCentroids(X_train, y_train)
    arr_clusters = computeClusters(X_train, arr_centroids)
    prev_centroids = np.zeros((len(arr_centroids),arr_centroids.shape[1]),np.float32)
    tupled = recursiveTrain(arr_clusters, arr_centroids, prev_centroids, X_train)
    return tupled[0], tupled[1]
```

Recursively trains the model. Returns multiple variables uses in recursion, but only the final arr_clusters and arr_centroids are relevant to the user.

In [14]:
```
def recursiveTrain(arr_clusters, arr_centroids, prev_centroids, X_train):
    diff = 0.0
    for i in range(len(arr_centroids)):
        diff += (arr_centroids[i] - prev_centroids[i]).sum()
    #print(diff)
    if(diff == 0.0):
        return arr_clusters, arr_centroids, prev_centroids, X_train
    else:
        np.copyto(prev_centroids, arr_centroids)
        arr_clusters = computeClusters(X_train, arr_centroids)
        arr_centroids = recomputeCentroids(arr_centroids, arr_clusters, X_train)
        return recursiveTrain(arr_clusters, arr_centroids, prev_centroids, X_train)
```

Classifies the test data based on arr_clusters, and arr_centroids. Somewhat unintuitively requires y_train to be passed to it because the k features are also labelled in this function.

In [15]:

```
def classifyThis(X_train, X_test, y_train, arr_clusters, arr_centroids):
    results_array = np.empty((X_test.shape[0]), np.uint8)

    arr_clusters_counts = np.zeros((arr_centroids.shape[0], len(classes)), np.int32)
    for i in range(arr_clusters.shape[0]):
        arr_clusters_counts[arr_clusters[i]][y_train[i]] += 1

    centroid_labels = np.empty((arr_centroids.shape[0]), np.uint8)

    for i in range(arr_clusters_counts.shape[0]):
        sorted_cluster_indexes = np.argsort(arr_clusters_counts[i])
        centroid_labels[i] = sorted_cluster_indexes[(sorted_cluster_indexes.shape[0] - 1

    distance_array = computeDist(X_test, arr_centroids)
    for i in range(distance_array.shape[0]):
        distancesortedindexes = np.argsort(distance_array[i])
        results_array[i] = centroid_labels[distancesortedindexes[0]]
    return results_array
```

Compares the answers of the test set to the predicted set and returns the accuracy of the predicted set

In [16]:

```
def evalThis(results_array, y_test):
    val = np.sum(results_array == y_test) / len(y_test)
    return val
```

Computation

Both the X_train and X_test arrays are preprocessed.

In [17]:

```
X_train_proc = preProcess(X_train)
print('X_train preprocessed')
X_test_proc = preProcess(X_test)
print('X_test preprocessed')
```

```
X_train preprocessed
X_test preprocessed
```

The arrays are now reshaped, converted to grayscale, and scaled

In [18]:

```
k = 3
```

Global k value is now set

The arr_clusters and arr_centroids are created by training:

In [19]:

```
arr_clusters, arr_centroids = trainThis(X_train_proc, y_train)
```

Classify the X_test data and return the predicted results:

In [20]:

```
results = classifyThis(X_train_proc, X_test_proc, y_train, arr_clusters, arr_centroids)
```

Accuracy is returned and saved in k3:

In [21]:

```
k3 = evalThis(results, y_test)
print(k3)
```

```
0.1738
```

The training->classifying->evaluating process is repeated for k = 5,7, and 11

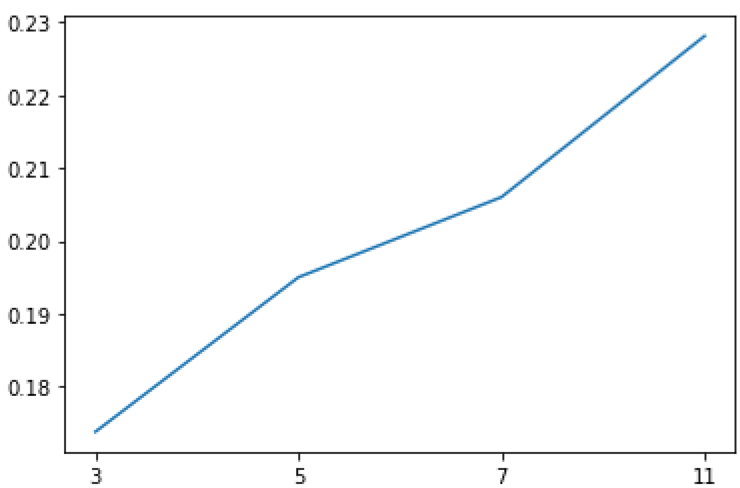
In [22]:
```
k = 5
arr_clusters, arr_centroids = trainThis(X_train_proc, y_train)
results_array = classifyThis(X_train_proc, X_test_proc, y_train, arr_clusters, arr_centr
k5 = evalThis(results_array, y_test)
print(k5)

k = 7
arr_clusters, arr_centroids = trainThis(X_train_proc, y_train)
results_array = classifyThis(X_train_proc, X_test_proc, y_train, arr_clusters, arr_centr
k7 = evalThis(results_array, y_test)
print(k7)

k = 11
arr_clusters, arr_centroids = trainThis(X_train_proc, y_train)
results_array = classifyThis(X_train_proc, X_test_proc, y_train, arr_clusters, arr_centr
k11 = evalThis(results_array, y_test)
print(k11)
```

```
0.195
0.206
0.2281
```

Accuracy Chart

In [23]:
```
vals = {'3':k3, '5':k5, '7':k7, '11':k11}
plt_x = list(vals.keys())
plt_y = list(vals.values())
plt.plot(plt_x, plt_y)
```

Out[23]:
```
[<matplotlib.lines.Line2D at 0x181c696df70>]
```



As we can see, k = 11 has the highest accuracy at around 23%

5-fold Validation

In [24]:
```
def fiveFoldVal(X_train, X_test, y_train, y_test):
    global k
    global seedval
    folds = 5
    np.random.seed(seedval)

    X_set_OG = np.concatenate((X_train, X_test))
    y_set_OG = np.concatenate((y_train, y_test))
```

```
X_set_OG = preProcess(X_set_OG)

indices = np.arange(X_set_OG.shape[0])
np.random.shuffle(indices)
X_set = X_set_OG[indices]
y_set = y_set_OG[indices]

#size reduction for testing
X_set = X_set[:1000]
y_set = y_set[:1000]

#This is assuming (X_set = y_set = 60000) is divisible by (folds = 5)
#I didn't bother to write the case where it isn't
subset_size = int(X_set.shape[0] / folds)

X_sets = np.empty((folds, subset_size, 1024), np.float32)
for i in range(folds):
    X_sets[i] = X_set[(i * subset_size):((i+1) * subset_size)]

y_sets = np.empty((folds, subset_size), np.uint8)
for i in range(folds):
    y_sets[i] = y_set[(i * subset_size):((i+1) * subset_size)]

accuracies = np.empty((folds, 4), np.float32)

for i in range(folds):
    print(f'Fold: {(i+1)}')
    X_test = X_sets[i]
    y_test = y_sets[i]

    X_train = np.empty(shape=[0, 1024], dtype=np.float32)
    y_train = np.empty(shape=[0], dtype=np.uint8)

    for j in range(folds):
        if(j!=i):
            X_train = np.append(X_train, X_sets[j], axis=0)
            y_train = np.append(y_train, y_sets[j])

    k = 3
    arr_clusters, arr_centroids = trainThis(X_train, y_train)
    results_array = classifyThis(X_train, X_test, y_train, arr_clusters, arr_centroi
    k3 = evalThis(results_array, y_test)
    accuracies[i][0] = k3
    print(k3)

    k = 5
    arr_clusters, arr_centroids = trainThis(X_train, y_train)
    results_array = classifyThis(X_train, X_test, y_train, arr_clusters, arr_centroi
    k5 = evalThis(results_array, y_test)
    accuracies[i][1] = k5
    print(k5)

    k = 7
    arr_clusters, arr_centroids = trainThis(X_train, y_train)
    results_array = classifyThis(X_train, X_test, y_train, arr_clusters, arr_centroi
    k7 = evalThis(results_array, y_test)
    accuracies[i][2] = k7
    print(k7)

    k = 11
    arr_clusters, arr_centroids = trainThis(X_train, y_train)
    results_array = classifyThis(X_train, X_test, y_train, arr_clusters, arr_centroi
    k11 = evalThis(results_array, y_test)
    accuracies[i][3] = k11
    print(k11)
```

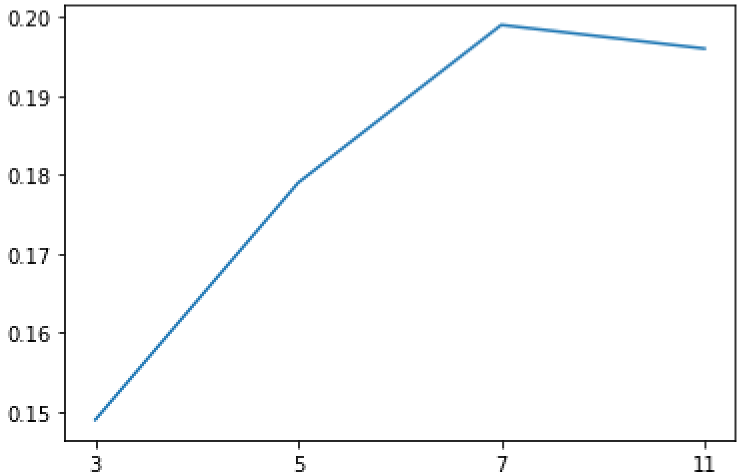
```python
        print()
        print()
    return accuracies
```

In [25]:
```python
accuracies = fiveFoldVal(X_train, X_test, y_train, y_test)
```

```
Fold: 1
0.155
0.2
0.205
0.205


Fold: 2
0.15
0.22
0.24
0.195


Fold: 3
0.15
0.17
0.16
0.16


Fold: 4
0.16
0.13
0.17
0.195


Fold: 5
0.13
0.175
0.22
0.225
```

In [26]:
```python
avg_k3 = np.mean(accuracies[:,0])
avg_k5 = np.mean(accuracies[:,1])
avg_k7 = np.mean(accuracies[:,2])
avg_k11 = np.mean(accuracies[:,3])
vals = {'3':avg_k3, '5':avg_k5, '7':avg_k7, '11':avg_k11}
plt_x = list(vals.keys())
plt_y = list(vals.values())
plt.plot(plt_x, plt_y)
```

Out[26]:
```
[<matplotlib.lines.Line2D at 0x181c5bdde50>]
```



After performing 5-fold validation, it seems that the best value of k for Kmeans in this model is between k = 7, and k=11 with around 20% accuracy. This makes sense since k is roughly equal to the size of the classes set.