knncifar

April 30, 2018

0.1 K-Nearest Neighbors

Using K-Nearest Neighbor to classify image from the CIFAR-10 dataset.

```
In [1]: import cifar10
        %matplotlib inline
        import matplotlib.pyplot as plt
        import numpy as np
        import math

        cifar10.maybe_download_and_extract()

        class_names = cifar10.load_class_names()
        print(class_names)
```

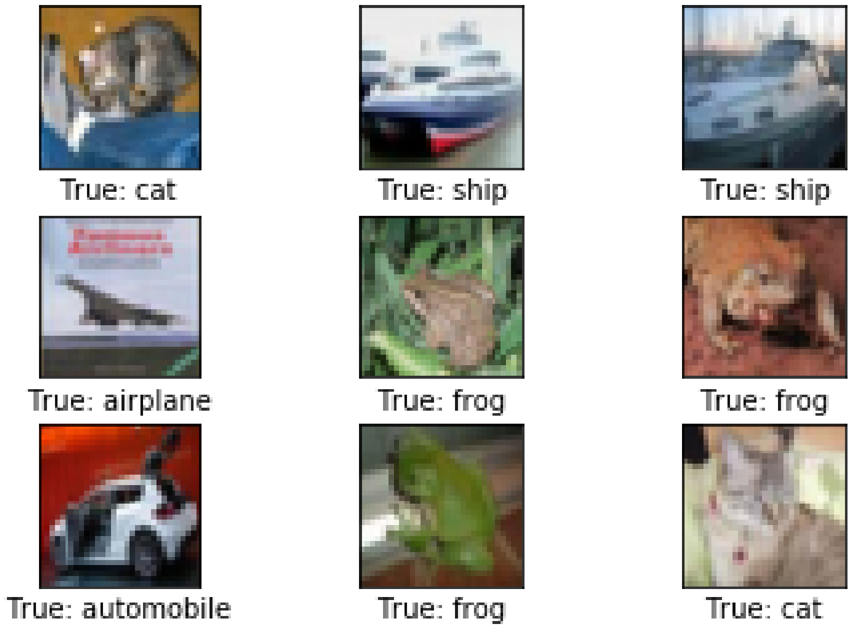
```
Data has apparently already been downloaded and unpacked.
Loading data: data/CIFAR-10/cifar-10-batches-py/batches.meta
['airplane', 'automobile', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse', 'ship', 'truck']
```

```
In [14]: images_train, cls_train, labels_train = cifar10.load_training_data()
         images_test, cls_test, labels_test = cifar10.load_test_data()
         print("Size of:")
         print("- Training-set:\t\t{}".format(len(images_train)))
         print("- Test-set:\t\t{}".format(len(images_test)))

         def plot_images(images, cls_true, cls_pred=None, smooth=True):

             assert len(images) == len(cls_true) == 9

             # Create figure with sub-plots.
             fig, axes = plt.subplots(3, 3)

             # Adjust vertical spacing if we need to print ensemble and best-net.
             if cls_pred is None:
                 hspace = 0.3
             else:
                 hspace = 0.6
             fig.subplots_adjust(hspace=hspace, wspace=0.3)
```

```
        for i, ax in enumerate(axes.flat):
            # Interpolation type.
            if smooth:
                interpolation = 'spline16'
            else:
                interpolation = 'nearest'

            # Plot image.
            ax.imshow(images[i, :, :, :],
                      interpolation=interpolation)

            # Name of the true class.
            cls_true_name = class_names[cls_true[i]]

            # Show true and predicted classes.
            if cls_pred is None:
                xlabel = "True: {0}".format(cls_true_name)
            else:
                # Name of the predicted class.
                cls_pred_name = class_names[cls_pred[i]]

                xlabel = "True: {0}\nPred: {1}".format(cls_true_name, cls_pred_name)

            # Show the classes as the label on the x-axis.
            ax.set_xlabel(xlabel)

            # Remove ticks from the plot.
            ax.set_xticks([])
            ax.set_yticks([])

        # Ensure the plot is shown correctly with multiple plots
        # in a single Notebook cell.
        plt.show()

    # Get the first images from the test-set.
    images = images_test[0:9]

    # Get the true classes for those images.
    cls_true = cls_test[0:9]

    # Plot the images and labels using our helper-function above.
    plot_images(images=images, cls_true=cls_true, smooth=False)
```

```
Loading data: data/CIFAR-10/cifar-10-batches-py/data_batch_1
Loading data: data/CIFAR-10/cifar-10-batches-py/data_batch_2
Loading data: data/CIFAR-10/cifar-10-batches-py/data_batch_3
Loading data: data/CIFAR-10/cifar-10-batches-py/data_batch_4
```

```
Loading data: data/CIFAR-10/cifar-10-batches-py/data_batch_5
Loading data: data/CIFAR-10/cifar-10-batches-py/test_batch
Size of:
- Training-set:                 50000
- Test-set:                 10000
```



0.1.1 a) Apply K-Nearest Neighbor algorithm with k = 1 on the test samples.

- Classification error rate, Pe = (Number of Wrongly Classified Test Samples / Total Number of Test Samples)

In [22]:
```
num_test = len(images_test)
num_train = len(images_train)
#dists = np.zeros((num_test, num_train))

num_test = 49
num_train = 199
train = images_train[0:num_train]
test = images_test[0:num_test]
dists = np.zeros((num_test, num_train))

print("Test: ", images_test.shape)
print("Trn:  ", images_train.shape)
print("Dist: ", dists.shape)
```

```
for i in range(0, num_test):
    for j in range(0, num_train):
        a_sq = 0
        for k in range(0, 3):
            for x in range(0, 32):
                for y in range(0, 32):
                    a = (test[i][x][y][k] - train[j][x][y][k])
                    a_sq = a_sq + a*a
        dists[i][j] = math.sqrt(a_sq)
```

```
Test:  (10000, 32, 32, 3)
Trn:   (50000, 32, 32, 3)
Dist:  (49, 199)
```

```
In [26]: # images_train, cls_train, labels_train
         k = [1, 2, 5, 10, 20 ]
         prob_errors = []
         err_count = 0
         new_label = -1
         visited = np.zeros(10)
         n_10_n = np.zeros((10,10))
         for a in range(0,5):
             idx_min = []
             err_count = 0
             new_label = -1
             for i in range(0, num_test-1):
                 for j in range(0,k[a]):
                     max_label_count = np.zeros(10)
                     idx_min = np.argsort(np.array(dists[i]), axis=0)[:k[a]]
                     for index in idx_min:
                         label_idx = cls_train[index]
                         max_label_count[label_idx] = max_label_count[label_idx] + 1
                         new_label = np.argmax(max_label_count)

                     ## a random image from test data and its 10 nearest neighbours
                     if((k[a] == 10) & (visited[(cls_test[i])] == 0)):# & (cls_test[i])
                         visited[(cls_test[i])] = 1
                         n_10_n[(cls_test[i])] = idx_min
                         print((cls_test[i])," Class - idx_min",idx_min)
                 if((new_label != cls_test[i]) & (new_label != -1)):
                     err_count = err_count+1

             prob_error = err_count/(num_test+1)
             print("\nK : ",k[a],"Probability of Error = " , 100*prob_error, "%")
             prob_errors.append(prob_error)
```

```
K :  1 Probability of Error =  80.0 %
```

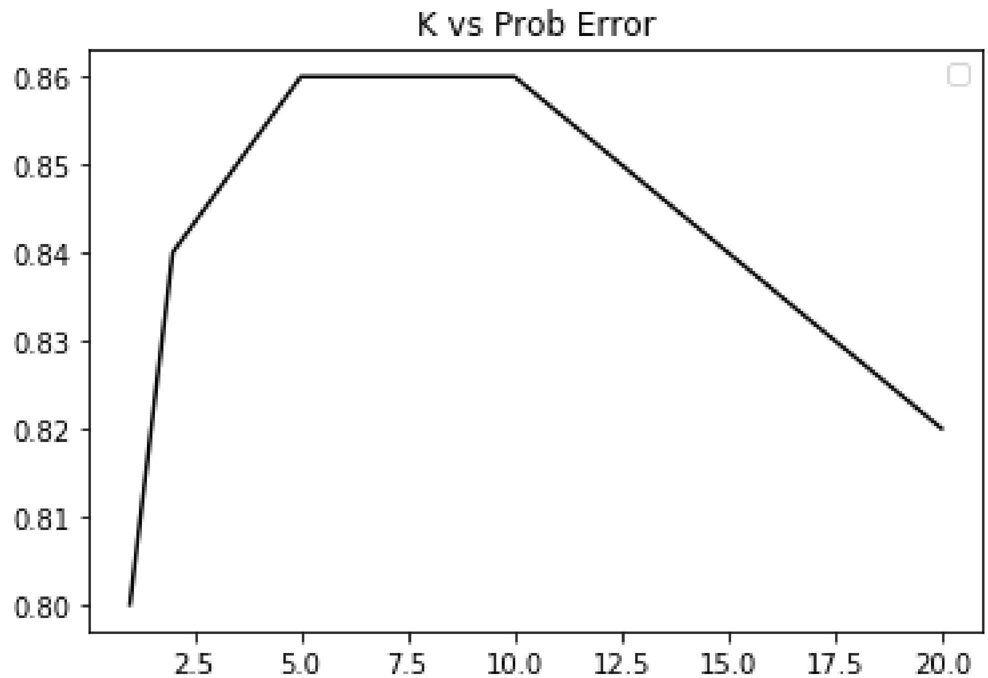
```
K :  2 Probability of Error =  84.0 %

K :  5 Probability of Error =  86.0 %
3  Class - idx_min [ 82  58  75  39 177  47 130  23 173 196]
8  Class - idx_min [139 126 185 193  16  31 192 122 169 154]
0  Class - idx_min [137 185 100 144 193  15 192  69 126 189]
6  Class - idx_min [197 130  86  58  39  98 187 180 132 157]
1  Class - idx_min [ 22  54   3 180  17  10 132 196  57 124]
9  Class - idx_min [139  69 154 117 193 165 126 144 170  94]
5  Class - idx_min [  3 132 197   0  98 142 157  17  39 180]
7  Class - idx_min [132 163  22  77   3 162  10  54  96  57]
4  Class - idx_min [ 47  10 196 173 180  37  27 132  50 179]
2  Class - idx_min [ 69 117 130 196  75  82 170 121 193  58]

K :  10 Probability of Error =  86.0 %

K :  20 Probability of Error =  82.0 %
```

0.1.2 b) Repeat last step for k = 2, 5, 10, 20 on test

- Classification error rate, Pe = (Number of Wrongly Classified Test Samples / Total Number of Test Samples)
- Here we can see that by increasing "K" we need not gain accuracy.
- At high value of K, there may be points which can influence the classification even though they are far

In [24]:
```
plt.plot(k, prob_errors, 'k-')
plt.legend()
plt.title('K vs Prob Error')
plt.show()
```

```
No handles with labels found to put in legend.
```



0.1.3 (c) For each of the ten classes, pick a random image from test data and report its 10 nearest neighbors.

Here are the Image indices of the 10 nearest neighbor from the test data

for each of the classes as computed in previous step

- 3 Class - idx_min [82 58 75 39 177 47 130 23 173 196]
- 8 Class - idx_min [139 126 185 193 16 31 192 122 169 154]
- 0 Class - idx_min [137 185 100 144 193 15 192 69 126 189]
- 6 Class - idx_min [197 130 86 58 39 98 187 180 132 157]
- 1 Class - idx_min [22 54 3 180 17 10 132 196 57 124]
- 9 Class - idx_min [139 69 154 117 193 165 126 144 170 94]
- 5 Class - idx_min [3 132 197 0 98 142 157 17 39 180]
- 7 Class - idx_min [132 163 22 77 3 162 10 54 96 57]
- 4 Class - idx_min [47 10 196 173 180 37 27 132 50 179]
- 2 Class - idx_min [69 117 130 196 75 82 170 121 193 58]