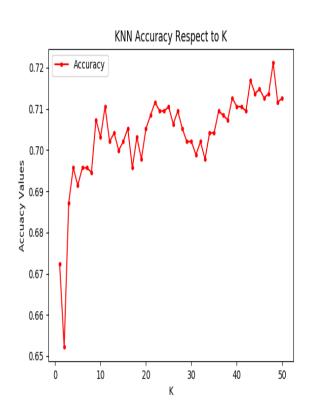
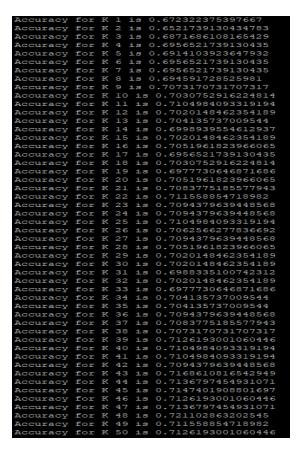
## K nearest Neighbor Report:

## (1) a brief description of how you formulated the problem

As how KNN algorithm goes, I took every test examples and calculated the distance with all training examples. Then, the distance was ordered in least to ascending order. I used this ordered list and extracted K closest training points with the test set. These training points will have their votes for classifying the test class label, which is their own class label. We estimate the test data's class as the class with the most votes. Let's say if K=5, then we get 5 closest points from the training. 5 training points will have their class and these will be votes for the test data. In ['90','90','180', '270', '0'], it will estimate the test example's class as '90'.

Since K is the user-defined parameter and ultimate K which works for every data doesn't exist, I tried multiple Ks for the best accuracy. Testing from K=1 to 10, I saw an increase of the accuracy, so I tried increasing K. Till K=30, I got the highest accuracy at K=22 but wasn't sure if it was the local maximum or global maximum, so I tried till 50. Below is the plot I earned from K=1 to 50 and output of the accuracy of the results. At K=48, I got about 0.7211, which was the highest among the 3 algorithms we implemented. If I had more time, I hoped to run till K=100 to check how the accuracy goes.





Changing K values didn't change the process time. This is because most of the operation time is calculating Euclidean distance not extracting K training points.

```
LOADING DATA...
                                                LOADING DATA...
                                                DATA LOADED...
DATA LOADED...
                                                Computing Euclidean Distance for KNN...
Computing Euclidean Distance for KNN...
                                                Computing Euclidean Distance is NOW COMPLETED...
Computing Euclidean Distance is NOW COMPLETED
                                                Estimating CLASS Based on Distance...
Estimating CLASS Based on Distance...
                                                Accuracy for K = 1 is 0.672322375397667
Accuracy for K = 50 is 0.7126193001060446
                                                real
                                                        7m46.978s
real
        7m31.168s
                                                        7m42.354s
                                                user
        7m26.848s
user
                                                        0m6.692s
```

## (2) Brief description of how your program works

My program is composed of 3 functions : *readfile*(file), *k\_nearest neighbors*(K, train\_px, train\_ot), and *get\_accuracy*(test\_label, est\_label).

readfile reads in the data and returns the list of photo\_id, the list of orientation of the photos (which is the class we want to estimate) and the list of pixel values. k\_nearest\_neighbors takes K, training pixel values and train orientation and uses the algorithm explained above and returns estimated class for the test sets. get\_accuracy will take the estimated class the previous function returned and compare it with the test label to calculate the performance of the algorithm.

After the execution of the above functions, it will create the document called *output.txt,* which writes the test id and the estimated class of the test sets.

My implementation can take different values for K. As a default, it takes K that had the highest accuracy, which is K=48. However, user can give the list of values for K, for instance; K=[i for i in range(1,11)] and it will test for K's 1 to 10. This may be useful, if you want to get the best K for estimating the test's orientation.

If you also want a plot for multiple Ks, you can also uncomment the plot part in the bottom, and you will get the accuracy graph as given in (1).

## (3) Discussion of any problems, assumptions or simplifications

Making Euclidean distance calculation to be simple and cheap as possible was the main theme for solving the problem efficiently. If we assume that the number of test examples to be N, training examples as M and number of dimensions as D, it will be O(N\*M\*D), which calculating distance alone, is very expensive.

At my first implementation, I tried using numpy.linalg.norm(test\_array-train\_array) but it was not converging for 10 minutes. So, I changed the algorithm to be cheaper by taking step by step approach: take difference-> np.square->np.sum. This made the algorithm converge in 8 minute.

Also my previous program used to calculate Euclidean distance each time for each K, and extract K training points(which is O(NMDK + NK) and output the estimate class, which was very inefficient. I changed my program to calculate Euclidean distance once and extract different K in one huge distance list (O(NMD + NK)). (NK is for choosing K closest training point for N test data)

Things that I can try to make my program better are as follows. I would have tried taking Manhatten distance other than the Euclidean since it may imply different meaning and classification accuracy.

Also, I could have tried dimension reduction since I have found from R coding that some variables are more important than the other. (PCA etc..)