3) k-NN for a classification problem on the Iris dataset

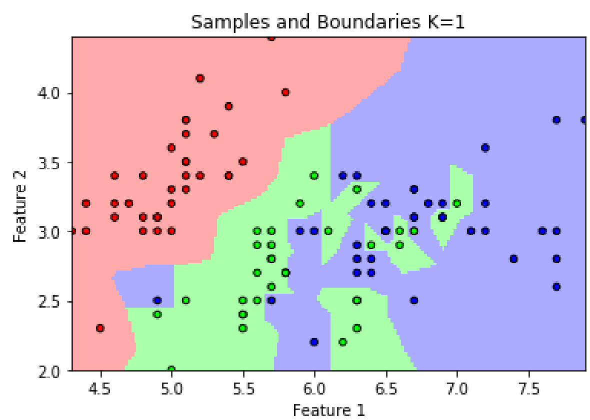
1)Implemented in the python file

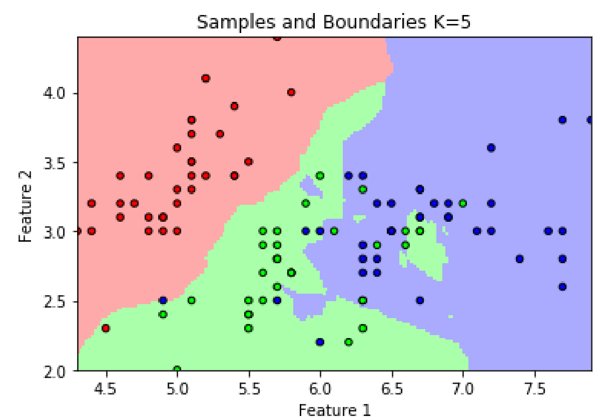
```
X = iris.data[:, :2]
Y = iris.target
```

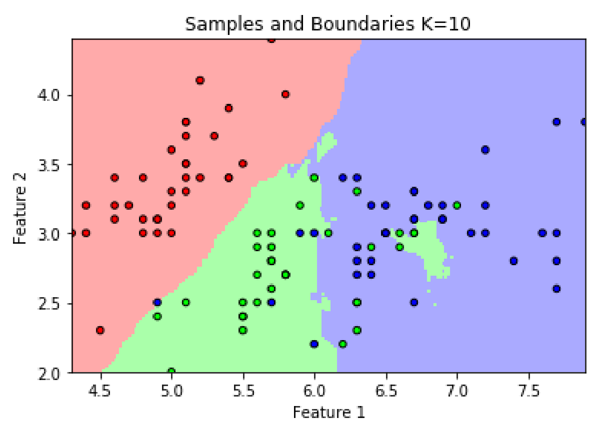
2)Implemented in the python file

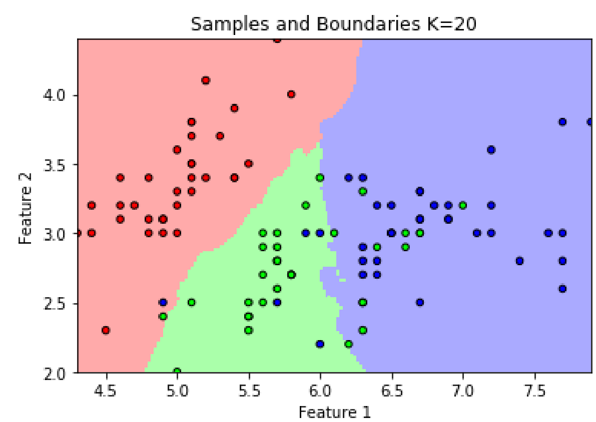
```
X_train, X_val, Y_train, Y_val = train_test_split(X, Y, test_size = 0.3, random_state = 0)
```

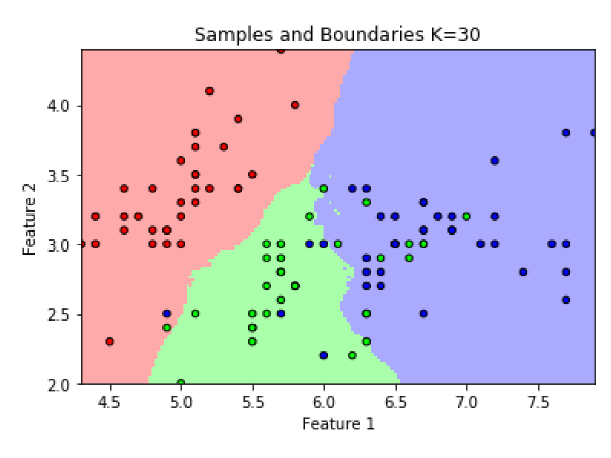
3)Implemented in the python file

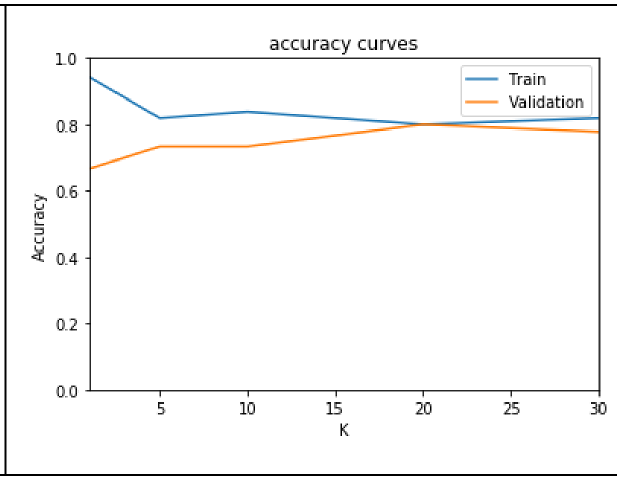












4) For K=30, since after K=20, the validation accuracy decreases while the training accuracy increases.

5) This is not happening since there are samples in the training set with the exact same values for their two selected features but different classes.

The code:

```
#!/usr/bin/env python
# coding: utf-8

# In[1]:


import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
from sklearn import neighbors, datasets, model_selection
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split


# In[20]:


### Iris dataset preprocessing
# Load Iris dataset:
iris = datasets.load_iris()
# Store the first 2 features in a matrix X:
```

```
X = iris.data[:, :2] #[0,3]
# Store the labels in a vector Y:
Y = iris.target
# Split the data into train and validation sets with a ratio of 0.7/0.3:

X_train, X_val, Y_train, Y_val = train_test_split(X, Y, test_size = 0.3, random_state = 0)
# X[0:round(X.shape[0]*.7),:],\
# X[round(X.shape[0]*.7)+1:X.shape[0],:],\
# Y[0:round(X.shape[0]*.7)],\
# Y[round(X.shape[0]*.7)+1:X.shape[0]]
# Store number of datapoints in train and validation sets:
N_train = len(Y_train)
N_val = len(Y_val)


# In[21]:


### Plot parameters:
# Step size in the mesh:
h = .02
# Light colors for decision boundaries plots:
cmap_light = ListedColormap(['#FFAAAA', '#AAFFAA', '#AAAAFF'])
# Bold colors for training points scatterplots:
cmap_bold = ListedColormap(['#FF0000', '#00FF00', '#0000FF'])

### k-NN parameters:
# k: Number of nearest neighbors taken into account:
k_list = [1, 5, 10, 20, 30]


# In[32]:


### k-NN on the Iris dataset for different values of k:
# Create vectors to store the results for each k:
train_accuracies = []
val_accuracies = []

# Main work here:
for idx, k in enumerate(k_list):
	# Create an instance of the KNeighborsClassifier class for current value of k:
	neigh = KNeighborsClassifier(n_neighbors=k)
	# Fit the train data:
	neigh.fit(X_train, Y_train)

	### Decision boundaries plotting:
```

```
        # Generate the axis associated to the first feature:
        x_min = np.amin(X[:,0])
        x_max = np.amax(X[:,0])
        x_axis = np.arange(x_min, x_max, h)
        # Generate the axis associated to the second feature:
        y_min = np.amin(X[:,1])
        y_max = np.amax(X[:,1])
        y_axis = np.arange(y_min, y_max, h)
        # Generate a meshgrid (2D grid) from the 2 axis:
        x_grid, y_grid = np.meshgrid(x_axis, y_axis)
        # Vectorize the grids into column vectors:
        x_grid_vectorized = x_grid.flatten()
        x_grid_vectorized = np.expand_dims(x_grid_vectorized, axis=1)
        y_grid_vectorized = y_grid.flatten()
        y_grid_vectorized = np.expand_dims(y_grid_vectorized, axis=1)
        # Concatenate the vectorized grids:
        concat_grids = np.concatenate((x_grid_vectorized, y_grid_vectorized),
                                                        axis=1)
        # Predict concatenated features to get the decision boundaries:
        decision_boundaries = neigh.predict(np.c_[x_grid.ravel(), y_grid.ravel()])
        # Reshape the decision boundaries into a 2D matrix:
        decision_boundaries = decision_boundaries.reshape(x_grid.shape)
        # Plot the decision boundaries:
        plt.figure(idx)
        plt.pcolormesh(x_grid, y_grid, decision_boundaries, cmap=cmap_light)
        # Overlay the training points:
        plt.scatter(X_train[:,0], X_train[:,1], c=Y_train, cmap=cmap_bold, edgecolor='k', s=20)
        plt.xlim(np.amin(X[:,0]),np.amax(X[:,0]))
        plt.ylim(np.amin(X[:,1]),np.amax(X[:,1]))
        plt.xlabel("Feature 1")
        plt.ylabel("Feature 2")
        plt.title('Samples and Boundaries K=%i' %k)

        ### Model evaluation:
        # Evaluate train set:
#     accuracy_score(Y_train,neigh.predict(X_train))
        train_accuracies.append(accuracy_score(Y_train,neigh.predict(X_train)))
        # Evaluate validation set:
#     accuracy_score(Y_val,neigh.predict(X_val))
        val_accuracies.append(accuracy_score(Y_val,neigh.predict(X_val)))

print("Train accuracy for every K:",*train_accuracies)
print("Validation accuracy for every K:",*val_accuracies)
# Plot accuracy curves:
plt.figure(len(k_list))
plt.plot(k_list,train_accuracies) # train accuracy plot
plt.plot(k_list,val_accuracies) # validation accuracy plot
```

```
plt.xlim(np.amin(k_list),np.amax(k_list))
plt.ylim(0,1)
plt.xlabel("K")
plt.ylabel("Accuracy")
plt.legend(['Train', 'Validation'], loc='best')
plt.title("accuracy curves")

# Display plots:
plt.show()
```