K-Nearest-Neighbor Decision Tree

kNearestNeighbor

- Lazy learner: defers model construction until test tuple arrives
- Based on learning by analogy
- Compares a given test tuple with all the training tuples
- Searches for the k training tuples that are **closest** to the unknown tuple
- ‘Closeness’ measure - a distance metric such as Euclidean distance between two tuples

kNearestNeighbor

- For classification:
  - ‘k’ closest points are selected
  - test tuple’s class: the majority class appearing among k neighbors
- For regression:
  - ‘k’ closest points are selected
  - test tuple’s prediction: avg. of labels associated with k neighbors

Drawbacks

- Computationally expensive for large training data
- Choice of k depends upon the training tuples
- Uses distance-based comparisons: need to convert binary, ordinal, and nominal data to numeric data
- Data normalization required to cancel the effects of large differences in attribute values

Algorithm

- m - the number of training data samples; p - an unknown point.
- Store the training samples in an array of tuple (x, y).
- for i=0 to m:

  Calculate Euclidean distance d(arr[i], p).
- Obtain a set S of K smallest distances obtained and return the majority label among S.

Iris Dataset

- Contains 50 samples from each of three species of Iris
- They are **Iris setosa, Iris virginica, and Iris versicolor**
- Four features describe each class
- The features are sepal length, sepal width, petal length, and petal width

	SepalLength	SepalWidth	PetalLength	PetalWidth	Name
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

Implementation

```
# distance between testInstance and each trainingSet
for i in range(len(trainingSet)):

      dist = manhattanDistance(testInstance, trainingSet.iloc[i], length)
    dist = euclideanDistance(testInstance, trainingSet.iloc[i], length)

    distances[i] = dist
```

```
sorted_d = sorted(distances.items(), key=lambda kv: kv[1])

# get k neighbors closest to the testInstance
neighbors = []

for i in range(k):
    neighbors.append(sorted_d[i][0])

# count of classes among neighbors
classVotes = {}

for x in range(len(neighbors)):

    class_label = trainingSet.iloc[neighbors[x]][-1]

    if class_label in classVotes:
        classVotes[class_label] += 1
    else:
        classVotes[class_label] = 1

sorted_v = sorted(classVotes.items(), key=lambda kv: kv[1], reverse=True)
```

Output

- With the value of k = 1 (no. of nearest neighbors); accuracy was about: 94.285714285714285%

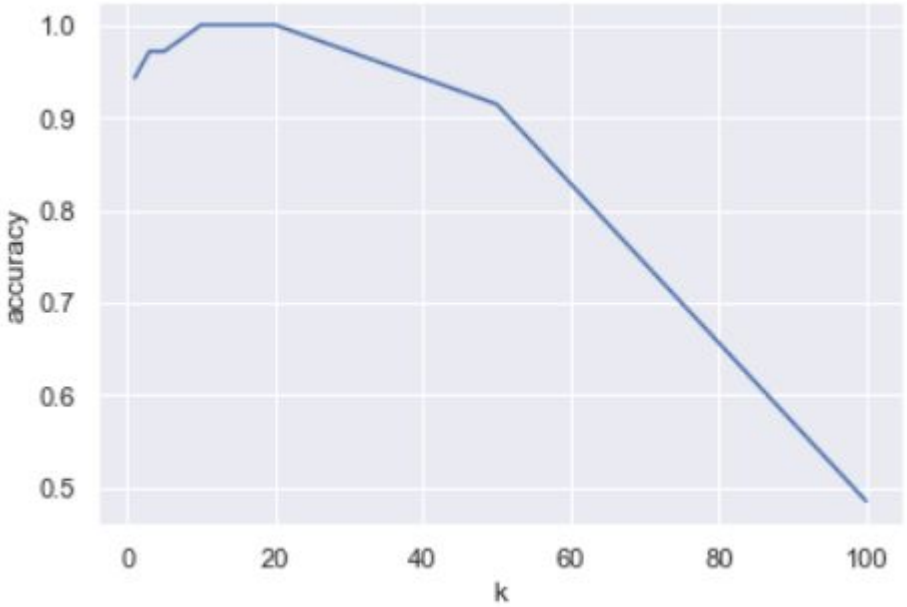
```
train, test = load_iris2()
KNearestNeighbor(train, test, 1)
```

```
For tuple 0; correct label is Iris-setosa; predicted lable is Iris-setosa
For tuple 1; correct label is Iris-setosa; predicted lable is Iris-setosa
For tuple 2; correct label is Iris-virginica; predicted lable is Iris-virginica
For tuple 3; correct label is Iris-setosa; predicted lable is Iris-setosa
Error ****************************************  For tuple 4; correct label is Iris-virginica;
predicted lable is Iris-versicolor
```

```
# varying the value of k

list_k = [1, 3, 5, 10, 20, 50, 100]
def test_for_k(train, test):

    accuracy = []
    for k in list_k:
        test_len = test.shape[0]

        correct = 0
        for i in range(test_len):

            result, neighbors = KNN(train, test.iloc[i][:-1], k)
            if result == test.iloc[i]['Name']:
                correct += 1

        accuracy.append(correct / test_len)

    plt.xlabel('k')
    plt.ylabel('accuracy')
    plt.plot(list_k, accuracy)
```

Varying k

- Accuracy was found maximum when value of k was between 10 and 20



Decision tree

- Flowchart-like tree structure, with internal node making a decision, and leaf node holds a classification of a tuple
- Are easy to understand and interpret
- Can handle both categorical and continuous data
- Provides clear indication of prominent field for classification/prediction using attribute selection measures like information gain, gini index, etc.

Drawbacks

- Less appropriate for training with many classes and less examples
- Computationally expensive for large datasets
- No incremental training
- Unstable: small change in data leads to large change in the output of decison tree

Algorithm

- Find the best splitting criteria for the entire dataset
- Label root node with splitting criteria
- For each outcome *k* of splitting criteria
  - Find tuples satisfying k
    - If the size of tuples is empty, attach a leaf with majority class
    - Else attach the node returned by calling the algorithm with the remaining attribute list recursively

Implementation

Partition the dataset based on the question

i.e. Is SepalLenght >= 1.0 ?

Into two distinct partitions

```
def partitions(rows, question):
    """Partition the dataset into 'true rows' or
    'false rows' based on the matching with question
    """

    true_rows, false_rows = [], []
    for row in rows:
        if question.match(row):
            true_rows.append(row)
        else:
            false_rows.append(row)
    return true_rows, false_rows
```

Implementation

Calculate the Gini impurity for a given split of dataset

i.e. $= 1 - \sum_{i=1}^{J} {p_i}^2$

```
def gini(rows):
    """Calculates the Gini Impurity for a list of rows"""

    counts = class_counts(rows)
    impurity = 1
    for lbl in counts:
        prob_lbl = counts[lbl] / float(len(rows))
        impurity -= prob_lbl**2
    return impurity
```

```
mixed_dataset = [['Iris-versicolor'],
                 ['Iris-versicolor'],
                 ['Iris-setosa'],
                 ['Iris-versicolor'],
                 ['Iris-versicolor']]
gini(mixed_dataset)
```

```
0.31999999999999984
```

Implementation

The information gain from the split based on a certain value of the attribute

```
def info_gain(left, right, current_uncertainty):
    """
    Calculate information gain i.e.
    uncertainty of starting node minus the weighted impurity
    of two child nodes
    """
    p = float(len(left)) / (len(left) + len(right))
    return current_uncertainty - p*gini(left) - (1-p)*gini(right)
```

```
    best_gain = 0
    best_question = None
    current_uncertainty = gini(rows)
    n_features = len(rows[0]) - 1

    for col in range(n_features):

        values = set([row[col] for row in rows])

        for val in values:

            question = Question(col, val)
            true_rows, false_rows = partitions(rows, question)

            if len(true_rows) == 0 or len(false_rows) == 0:
                continue # no need to split

            gain = info_gain(true_rows, false_rows, current_uncertainty)

            if gain >= best_gain:
                best_gain, best_question = gain, question

    return best_gain, best_question
```

```
    Builds the tree
    """

    # get the gain and the question with highest gain
    gain, question = find_best_split(rows)

    # all classes are the same
    if gain == 0 or depth == 3:
        return Leaf(rows)

    true_rows, false_rows = partitions(rows, question)

    # build the true subtree
    true_branch = build_tree(true_rows, depth=depth+1)

    # build the false subtree
    false_branch = build_tree(false_rows, depth=depth+1)

    # the Question node i.e question to ask at this node
    return DecisionNode(question, true_branch, false_branch)
```

```
print_tree(my_tree)
```

```
Is PetalWidth >= 1.0?
--> True:
  Is PetalWidth >= 1.8?
  --> True:
    Is PetalLength >= 4.9?
    --> True:
      Predict {'Iris-virginica': 31}
    --> False:
      Predict {'Iris-virginica': 2, 'Iris-versicolor': 1}
  --> False:
    Is PetalLength >= 5.0?
    --> True:
      Predict {'Iris-virginica': 2, 'Iris-versicolor': 1}
    --> False:
      Predict {'Iris-versicolor': 39}
--> False:
  Predict {'Iris-setosa': 39}
```

```
def classify(row, node):
    """
    classify a given test data - row
    the root of decision tree - node
    """

    if isinstance(node, Leaf):
        return node.predictions

    if node.question.match(row):
        return classify(row, node.true_branch)
    else:
        return classify(row, node.false_branch)
```

```
classify(test_data[3], my_tree)
```

```
{'Iris-versicolor': 39}
```