kNN-Study-Validation-Set-Approach

November 26, 2018

1 K-Nearest Neighbours - Validation Set Approach

Basically trying to implement common distance calculation algorithms and would like to try KNN using those on Iris Data Set.

From this trying to observe overfitting/underfitting behaviour when we do not have cross validation

Referece 1. [http://dataaspirant.com/2015/04/11/five-most-popular-similarity-measures-implementation-in-python/] 2. [https://www.itl.nist.gov/div898/software
3. Introduction to Statistical Learning

- Implemented required distance functions (yet to review its accuracy)
- Loaded Irsi dataset
- splitted into training and test dataset 80%, 20%
- for each distance algorith, running k-NN from 1 to 9 and printing its accuracy

```
In [1]: # Importing required modules
        from math import * # for math operation
        from decimal import Decimal # for decimal approximation
        import operator # for selection
        import pandas as pd # for handling iris dataset
        from sklearn.model_selection import train_test_split # for splitting dataset into train/test
        from sklearn.preprocessing import StandardScaler # for Column Standardization
        from matplotlib import pyplot as plt
```

```
In [2]: # My test vector

        v1 = [1.0, 3.2, 4.8, 0.1, 3.2, 0.6, 2.2, 1.1]
        v2 = [0.1, 5.2, 1.9, 4.2, 1.9, 0.1, 0.1, 6.0]
```

1.1 Distance Algorthm Implementations

1.1.1 Manhattan Distance

Also referred as L1 Norm

$$L_1 Norm = ||x-y||_1 = \left(\sum_{i=1}^{n} |(x_i - y_i)|\right)$$

```
In [3]: def manhanttan_dist(v1, v2):
            '''
            returns manhattan distance between vector v1 and v2 having same dimension d
            numeric components for vectors v1 and v2 are assumed
            '''
            return round(Decimal(sum(abs(a-b) for a, b in zip(v1, v2))),3)

        print(manhanttan_dist(v1,v1), manhanttan_dist(v2,v2))
        print(manhanttan_dist(v1, v2), manhanttan_dist(v2, v1))
```

```
0.000 0.000
18.700 18.700
```

1.1.2 Euclidean Distance

Also referred as L2 Norm

$$L_2 Norm = ||x-y||_2 = \sqrt{\left(\sum_{i=1}^{d} (x_{1i} - y_{2i})^2\right)} = \sqrt{(x-y)^T (x-y)}$$

$$L_2 Norm = ||x-y||_2 = \left(\sum_{i=1}^{d} (x_{1i} - y_{2i})^2\right)^{\frac{1}{2}}$$

```
In [4]: def eucd_dist(v1,v2):
            '''
            returns euclidean distance between vector v1 and v2 having same dimension d
            numeric components for vectors v1 and v2 are assumed
            '''
            return round(Decimal(sqrt(sum(pow(a-b,2) for a,b in zip(v1,v2)))),3)
```

```
In [5]: print(eucd_dist(v1,v1), eucd_dist(v2,v2))
        print(eucd_dist(v1, v2), eucd_dist(v2, v1))
```

```
0.000 0.000
7.771 7.771
```

1.1.3 Minkowski Distance

Also referred as Lp Norm, where **p > 0**
Can be used for both 'Ordinal' and 'Quantitative' Values

$$L_p Norm = ||x - y||_p = \left(\sum_{i=1}^{d} |x_{1i} - y_{2i}|^p \right)^{\frac{1}{p}}$$

Observations of Minkowski:

$$L_1 Norm = ManhattanDistance$$

$$L_2 Norm = EuclideanDistance$$

$$L_\infty Norm = ChebyshevDistance = L_{max} Norm$$

```
In [6]: def getNthRoot(val, n_root):
            '''
            returns n_th root of the given value
            '''
            return round(Decimal(val) ** Decimal(Decimal(1.0)/n_root),3)

        def minkowski_dist(v1, v2, p):
            '''
            returns minkowski distance between vectors v1 and v2 of same dimension d
                numeric components for vectors v1 and v2 are assumed
                v1, v2 ==> vectors
                p ==> p-form that need to be calcualted
            '''
            return getNthRoot(sum(pow(abs(a-b),p) for a,b in zip(v1, v2)), p)

        #print(getNthRoot(2,9))
        #print(minkowski_dist([0,3,4,5], [7,6,3,-1], 3))


        for p in range(1,5):
            print("p :", p, minkowski_dist(v1, v2, p), minkowski_dist(v2, v1, p))
```

```
p : 1 18.700 18.700
p : 2 7.771 7.771
p : 3 6.138 6.138
p : 4 5.579 5.579
```

1.1.4 Consine Similarity

$$\cos\theta = \frac{a.b}{||a||\ ||b||}$$

$$\cos\theta = \frac{a^T b}{||a||\ ||b||}$$

$$\cos\theta = \left(\frac{a}{||a||}\right)^T \left(\frac{b}{||b||}\right)$$

if both a and b are unit vectors, then cosine similarity is the dot product of both vectors a and b

$$\cos\theta = a.b$$

Dot Product (Alebraic Equation)
Let, x = [x1, x2, ..., xd] a vector, y = [y1, y2, ..., yd] a vector
the Dot product of x.y is (Algebraic)

$$x.y = x^T y$$

$$x.y = x_1 y_1 + x_2 y_2 + ... + x_d y_d$$

$$x.y = \sum_{i=1}^{d} x_i y_i$$

Algebraic Dot Product of two vectors tells how similar those two vectors are. Usefull in Text Processing to find how two vectors are similar
Dot Product (Geometric Equation)

$$x.y = ||x||\ ||y||\ \cos\theta$$

cosine and euclidean distance are same if the vectors are in unit length
[https://www.machinelearningplus.com/nlp/cosine-similarity/ - It is a metrix used to measure how similar the documents are irrespective of their size - Mahtematically it measures the cosine of the angle between two vectors projected in a multi-dimensional space
When to use Cosine
https://cmry.github.io/notes/euclidean-v-cosine

- Cosine Similarity is generally used as a metric for measuring distance when the magnitude of the vectors does not matter. This happens for example when working with text data represented by word counts.

In [7]:
```
def dot_product(v1, v2):
    '''
    returns algebraic dot product of two vectors v1 and v2
    '''
    return Decimal(sum(a*b for a,b in zip(v1,v2)))

def getLength(v1):
    '''
    returns length/magniture of the given vector
    '''
    return Decimal(sqrt(sum(x*x for x in v1)))

def scalarMultiply(v1, c):
    '''
    performs scalar multiplication over given vector v1
    '''
    return [round(Decimal(x*c),3) for x in v1]

def normalize(v1):
    '''
    returns the unit vector of given vector v1
    '''
    l = getLength(v1)
    if(l == 0):
        return 0; # TO DO - Raise Exception

    return scalarMultiply(v1,(Decimal(1.0)/l))

def cosine_similarity(v1,v2):
    '''
    returns consine similarity between vectors v1 and v2
    '''
    numerator = dot_product(v1, v2)
    denominator = getLength(v1) * getLength(v2)
    return round(Decimal(numerator / denominator), 3)
```

In [8]:
```
# Validation

a = [5,3]
b = [1,4]

print('Euclidean_Distance(a,b): ', eucd_dist(a,b))
print('Unit Vecor of a: ', normalize(a))
print('Unit Vecor of b: ', normalize(b))
print('cos_similarity(a,b): ', cosine_similarity(a,b))
```

```
Euclidean_Distance(a,b):  4.123
Unit Vecor of a:  [Decimal('0.857'), Decimal('0.514')]
Unit Vecor of b:  [Decimal('0.243'), Decimal('0.970')]
cos_similarity(a,b):  0.707
```

In [9]:
```
# https://masongallo.github.io/machine/learning,/python/2016/07/29/cosine-similarity.html
import numpy as np

def cos_sim(a, b):
    """Takes 2 vectors a, b and returns the cosine similarity according
    to the definition of the dot product
    """
    dot_product = np.dot(a, b)
    norm_a = np.linalg.norm(a)
    norm_b = np.linalg.norm(b)
    return dot_product / (norm_a * norm_b)
```

```
# the counts we computed above
sentence_m = np.array([1, 1, 1, 1, 0, 0, 0, 0, 0])
sentence_h = np.array([0, 0, 1, 1, 1, 1, 0, 0, 0])
sentence_w = np.array([0, 0, 0, 1, 0, 0, 1, 1, 1])

# We should expect sentence_m and sentence_h to be more similar
print(cos_sim(sentence_m, sentence_h)) # 0.5
print(cos_sim(sentence_m, sentence_w)) # 0.25
```

```
0.5
0.25
```

1.1.5 Cosine Dissimlarity

$$1 - cosine\_similarity(x, y)$$

```
In [10]: def consine_dissimilarity(v1, v2):
             '''
             returns cosine dissimilarity between vectors v1 and v2
             '''
             return (1-cosine_similarity(v1,v2))

In [11]: print('cos_similarity(a,b): ', consine_dissimilarity(a,b))
```

```
cos_similarity(a,b):  0.293
```

2 k-NN Implementation (for Iris DataSet)

2.1 Load DataSet

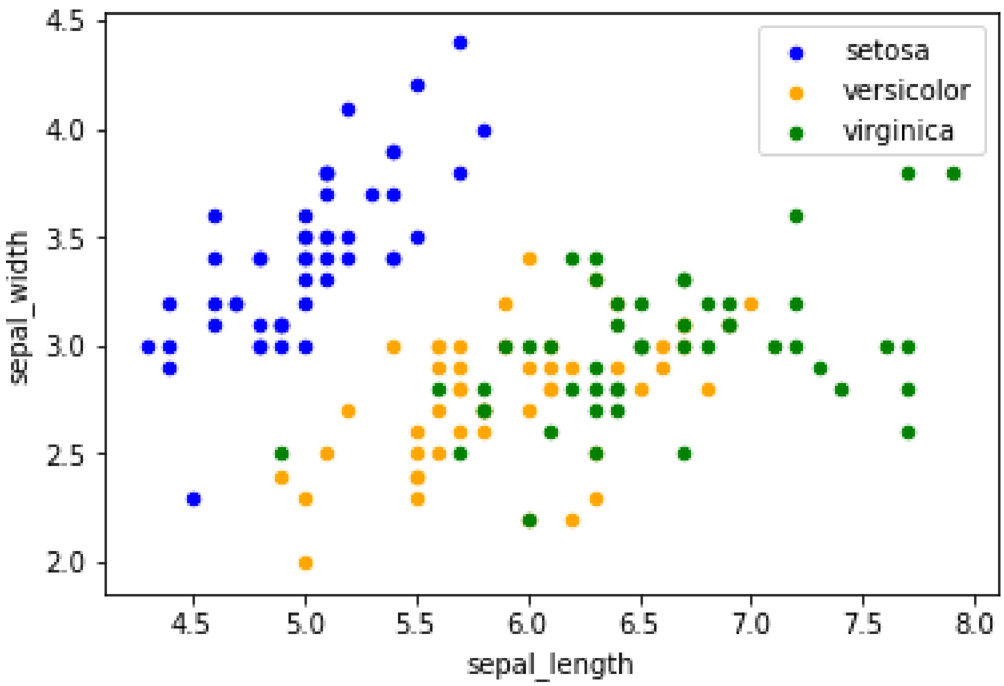
```
In [12]: df = pd.read_csv('./iris.data')
         df.head()
```

Out[12]:

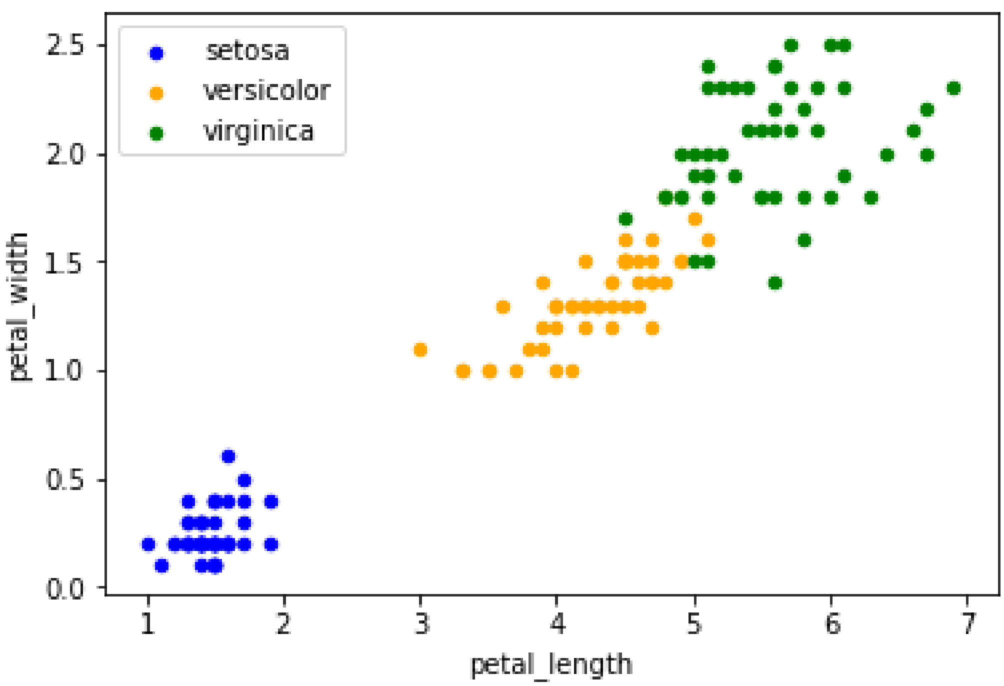
	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

2.2 Visual Observation

```
In [13]: # Checking how images are classifiable
         ax = df[df['species'] == 'setosa'].plot.scatter(x='sepal_length', y='sepal_width', c = 'blue', label='setosa')
         ax = df[df['species'] == 'versicolor'].plot.scatter(x='sepal_length', y='sepal_width', c = 'orange', label='versicolor', ax=ax)
         ax = df[df['species'] == 'virginica'].plot.scatter(x='sepal_length', y='sepal_width', c = 'green', label='virginica', ax=ax)
         ax

Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x7f107b174c50>
```




```
In [14]: # Checking how images are classifiable
         ax = df[df['species'] == 'setosa'].plot.scatter(x='petal_length', y='petal_width', c = 'blue', label='setosa')
         ax = df[df['species'] == 'versicolor'].plot.scatter(x='petal_length', y='petal_width', c = 'orange', label='versicolor', ax=ax)
         ax = df[df['species'] == 'virginica'].plot.scatter(x='petal_length', y='petal_width', c = 'green', label='virginica', ax=ax)
         ax

Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x7f107ae10198>
```



2.3 Split DataSet

```
In [15]: # Split the data and labels for easy handling
         # 80% training
```

```
# 20% for testing
df_train, df_test = train_test_split(df, test_size=0.3)

#df_data = df[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']]
#df_labels = df[['species']]
#print(df_data.head())
#print(df_labels.head())
```

In [16]:
```
print('Training Dataset:')
print(df_train.shape)
print(df_train.head())
print(df_train.describe())
```

```
Training Dataset:
(105, 5)
     sepal_length  sepal_width  petal_length  petal_width     species
133           6.3          2.8           5.1          1.5   virginica
147           6.5          3.0           5.2          2.0   virginica
63            6.1          2.9           4.7          1.4  versicolor
95            5.7          3.0           4.2          1.2  versicolor
140           6.7          3.1           5.6          2.4   virginica
       sepal_length  sepal_width  petal_length  petal_width
count    105.000000   105.000000     105.00000   105.000000
mean       5.796190     3.021905       3.70381     1.177143
std        0.797101     0.434339       1.65767     0.730155
min        4.400000     2.000000       1.00000     0.100000
25%        5.100000     2.800000       1.60000     0.300000
50%        5.700000     3.000000       4.20000     1.300000
75%        6.400000     3.300000       4.90000     1.700000
max        7.900000     4.400000       6.40000     2.500000
```

In [17]:
```
print('Test Dataset:')
print(df_test.shape)
print(df_test.head())
print(df_test.describe())
```

```
Test Dataset:
(45, 5)
     sepal_length  sepal_width  petal_length  petal_width    species
120           6.9          3.2           5.7          2.3  virginica
127           6.1          3.0           4.9          1.8  virginica
47            4.6          3.2           1.4          0.2     setosa
122           7.7          2.8           6.7          2.0  virginica
130           7.4          2.8           6.1          1.9  virginica
       sepal_length  sepal_width  petal_length  petal_width
count     45.000000    45.000000     45.000000    45.000000
mean       5.953333     3.128889      3.886667     1.248889
std        0.895849     0.427265      2.005855     0.841703
min        4.300000     2.200000      1.100000     0.100000
25%        5.200000     2.800000      1.500000     0.200000
50%        5.900000     3.000000      4.600000     1.400000
75%        6.500000     3.400000      5.600000     1.900000
max        7.700000     4.200000      6.900000     2.500000
```

2.4 Calculating Neighbors

In [18]:
```
def getNeighbours(training_data_set, query_point, k, algo='euct', p=3):
    '''
    returns list having k neighbors to the given query data point
    input:
        training_data_set: Pandas DataFrame
        query_point: Pandas DataSeries
        k: Number of Neighbors to calculate
        algo: type of distance algorithm to use
            euct (euclidean distance default)
            maht (manhattan)
            mink (minkowski)
            coss (cosine similarity)
            cods (cosine dissimilarity/ cosine distance)
        p: minkowski required p norm (default 3)
    Output:
        List of nearest data points
    '''
    distances = [] # list to hold all the neighbors
```

```
    # calcualte distance between query_point and every point in data set
    # create a list
    for x in range(len(training_data_set)):
        # stip non-numeric label - in training data
        v1 = training_data_set.iloc[x]
        v1 = v1[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']]
        #print(type(v1), v1)

        # stip non-numeric label - in query data
        q_v = query_point[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']]
        if algo == 'maht':
            dist = manhanttan_dist(q_v, v1)
        elif algo == 'mink':
            dist = minkowski_dist(q_v, v1, p)
        elif algo == 'coss':
            dist = cosine_similarity(q_v, v1)
        elif algo == 'cods':
            dist = consine_dissimilarity(q_v, v1)
        else:
            dist = eucd_dist(q_v, v1)
        distances.append((dist, training_data_set.iloc[x]))

    # sort the list in ascending order
    distances.sort(key=lambda tup:tup[0])
    #print(distances)

    # select k nearest neighbors and return it
    neighbors = []
    for i in range(k):
        neighbors.append(distances[i][1])
    return neighbors
```

2.5 Calculating Responses

In [19]:
```
def getClassLabel(neighbors):
    '''
    returns the class label having majority vote
    Note that it doesn't handle 'Not Sure' case yet
    '''
    class_votes = {} # dictionary keys are flowers, values are its counts
    for x in range(len(neighbors)):
        class_label = neighbors[x][-1]
        if class_label in class_votes:
            class_votes[class_label] += 1
        else:
            class_votes[class_label] = 1

    response = max(class_votes.items(), key=operator.itemgetter(1))[0]
    return response
```

2.6 Accuracy of Predictions

- Try to check accuray for k in range 1 to 9
  - Euclidean Distance
  - Cosine Similarity
  - Manhattan Distance
  - L_3 Norm (minkowski distance)

In [20]:
```
# Max number of k that need to be tried
max_k = 11
```

2.6.1 Euclidean Distance

In [21]:
```
%%time

ecut_dist_results = ['Euclidean-Distance']
for k in range(1,max_k):
    correct_predictions = 0
    for t_index in range(len(df_test)):
        test_data_point = df_test.iloc[t_index]
        neighbors = getNeighbours(df_train, test_data_point, k)
        predicted_class = getClassLabel(neighbors)
        if predicted_class == test_data_point['species']:
            correct_predictions += 1
        #print('Predicted: ', predicted_class, ' Actual: ', test_data_point['species'])
```

```
    accuracy = round((correct_predictions/len(df_test)) * 100,3)
    print('k=',k,' Accuracy: ', accuracy,', Total correct predictions: ', correct_predictions, ' out of ', len(df_test))
    ecut_dist_results.append(accuracy)

print(ecut_dist_results)
```

```
k= 1  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 2  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 3  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 4  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 5  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 6  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 7  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 8  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 9  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 10  Accuracy:  95.556 , Total correct predictions:  43  out of  45
['Euclidean-Distance', 93.333, 93.333, 93.333, 93.333, 95.556, 95.556, 95.556, 95.556, 95.556, 95.556]
CPU times: user 1min 46s, sys: 956 ms, total: 1min 47s
Wall time: 1min 46s
```

2.6.2 Cosine Similarity

In [22]:
```
%%time

# TO-DO
# Standardize the Data
#standardized_data = StandardScaler().fit_transform(final_counts.toarray().astype(np.float64)) #, with_mean=False
#print('Shape of Standardized data', standardized_data.shape)

coss_sim_results = ['Cosine-Similarity']
for k in range(1,max_k):
    correct_predictions = 0
    for t_index in range(len(df_test)):
        test_data_point = df_test.iloc[t_index]
        neighbors = getNeighbours(df_train, test_data_point, k, 'coss')
        predicted_class = getClassLabel(neighbors)
        if predicted_class == test_data_point['species']:
            correct_predictions += 1
        #print('Predicted: ', predicted_class, ' Actual: ', test_data_point['species'])

    accuracy = round((correct_predictions/len(df_test)) * 100,3)
    print('k=',k,' Accuracy: ', accuracy,', Total correct predictions: ', correct_predictions, ' out of ', len(df_test))
    coss_sim_results.append(accuracy)

print(coss_sim_results)
```

```
k= 1  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 2  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 3  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 4  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 5  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 6  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 7  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 8  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 9  Accuracy:  0.0 , Total correct predictions:  0  out of  45
k= 10  Accuracy:  0.0 , Total correct predictions:  0  out of  45
['Cosine-Similarity', 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0, 0.0]
CPU times: user 1min 47s, sys: 999 ms, total: 1min 48s
Wall time: 1min 48s
```

2.6.3 Cosine Distance

In [23]:
```
%%time

# TO-DO
# Standardize the Data
#standardized_data = StandardScaler().fit_transform(final_counts.toarray().astype(np.float64)) #, with_mean=False
#print('Shape of Standardized data', standardized_data.shape)

coss_dissim_results = ['Cosine-Dissimilarity']
for k in range(1,max_k):
    correct_predictions = 0
    for t_index in range(len(df_test)):
        test_data_point = df_test.iloc[t_index]
```

```
            neighbors = getNeighbours(df_train, test_data_point, k, 'cods')
            predicted_class = getClassLabel(neighbors)
            if predicted_class == test_data_point['species']:
                correct_predictions += 1
            #print('Predicted: ', predicted_class, ' Actual: ', test_data_point['species'])

        accuracy = round((correct_predictions/len(df_test)) * 100,3)
        print('k=',k,' Accuracy: ', accuracy,', Total correct predictions: ', correct_predictions, ' out of ', len(df_test))
        coss_dissim_results.append(accuracy)

    print(coss_dissim_results)
```

```
k= 1  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 2  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 3  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 4  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 5  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 6  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 7  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 8  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 9  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 10  Accuracy:  97.778 , Total correct predictions:  44  out of  45
['Cosine-Dissimilarity', 97.778, 97.778, 97.778, 97.778, 97.778, 97.778, 95.556, 97.778, 97.778, 97.778]
CPU times: user 1min 48s, sys: 981 ms, total: 1min 49s
Wall time: 1min 48s
```

2.6.4 Manhattan Distance

In [24]:
```
%%time

manhattan_results = ['Manhattan']
for k in range(1,max_k):
    correct_predictions = 0
    for t_index in range(len(df_test)):
        test_data_point = df_test.iloc[t_index]
        neighbors = getNeighbours(df_train, test_data_point, k, 'maht')
        predicted_class = getClassLabel(neighbors)
        if predicted_class == test_data_point['species']:
            correct_predictions += 1
        #print('Predicted: ', predicted_class, ' Actual: ', test_data_point['species'])

    accuracy = round((correct_predictions/len(df_test)) * 100,3)
    print('k=',k,' Accuracy: ', accuracy,', Total correct predictions: ', correct_predictions, ' out of ', len(df_test))
    manhattan_results.append(accuracy)

print(manhattan_results)
```

```
k= 1  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 2  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 3  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 4  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 5  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 6  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 7  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 8  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 9  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 10  Accuracy:  95.556 , Total correct predictions:  43  out of  45
['Manhattan', 93.333, 93.333, 93.333, 93.333, 93.333, 93.333, 95.556, 95.556, 95.556, 95.556]
CPU times: user 1min 45s, sys: 954 ms, total: 1min 45s
Wall time: 1min 45s
```

2.6.5 Minkowski Distance with p=3

In [25]:
```
%%time

minkowsi_results_3 = ['Minkowski p=3']
for k in range(1,max_k):
    correct_predictions = 0
    for t_index in range(len(df_test)):
        test_data_point = df_test.iloc[t_index]
        neighbors = getNeighbours(df_train, test_data_point, k, 'mink')
        predicted_class = getClassLabel(neighbors)
        if predicted_class == test_data_point['species']:
            correct_predictions += 1
        #print('Predicted: ', predicted_class, ' Actual: ', test_data_point['species'])
```

```
        accuracy = round((correct_predictions/len(df_test)) * 100,3)
        print('k=',k,' Accuracy: ', accuracy,', Total correct predictions: ', correct_predictions, ' out of ', len(df_test))
        minkowsi_results_3.append(accuracy)

    print(minkowsi_results_3)
```

```
k= 1  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 2  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 3  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 4  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 5  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 6  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 7  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 8  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 9  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 10  Accuracy:  95.556 , Total correct predictions:  43  out of  45
['Minkowski p=3', 93.333, 93.333, 93.333, 93.333, 97.778, 95.556, 95.556, 95.556, 97.778, 95.556]
CPU times: user 1min 56s, sys: 892 ms, total: 1min 57s
Wall time: 1min 56s
```

2.6.6 Minkowski Distance with p=4

In [26]:
```
%%time

minkowsi_results_4 = ['Minkowski p=4']
for k in range(1,max_k):
    correct_predictions = 0
    for t_index in range(len(df_test)):
        test_data_point = df_test.iloc[t_index]
        neighbors = getNeighbours(df_train, test_data_point, k, 'mink')
        predicted_class = getClassLabel(neighbors)
        if predicted_class == test_data_point['species']:
            correct_predictions += 1
        #print('Predicted: ', predicted_class, ' Actual: ', test_data_point['species'])

    accuracy = round((correct_predictions/len(df_test)) * 100,3)
    print('k=',k,' Accuracy: ', accuracy,', Total correct predictions: ', correct_predictions, ' out of ', len(df_test))
    minkowsi_results_4.append(accuracy)

print(minkowsi_results_4)
```

```
k= 1  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 2  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 3  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 4  Accuracy:  93.333 , Total correct predictions:  42  out of  45
k= 5  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 6  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 7  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 8  Accuracy:  95.556 , Total correct predictions:  43  out of  45
k= 9  Accuracy:  97.778 , Total correct predictions:  44  out of  45
k= 10  Accuracy:  95.556 , Total correct predictions:  43  out of  45
['Minkowski p=4', 93.333, 93.333, 93.333, 93.333, 97.778, 95.556, 95.556, 95.556, 97.778, 95.556]
CPU times: user 1min 57s, sys: 918 ms, total: 1min 58s
Wall time: 1min 58s
```

2.7 Visualize - Methods Prediction Accuracy

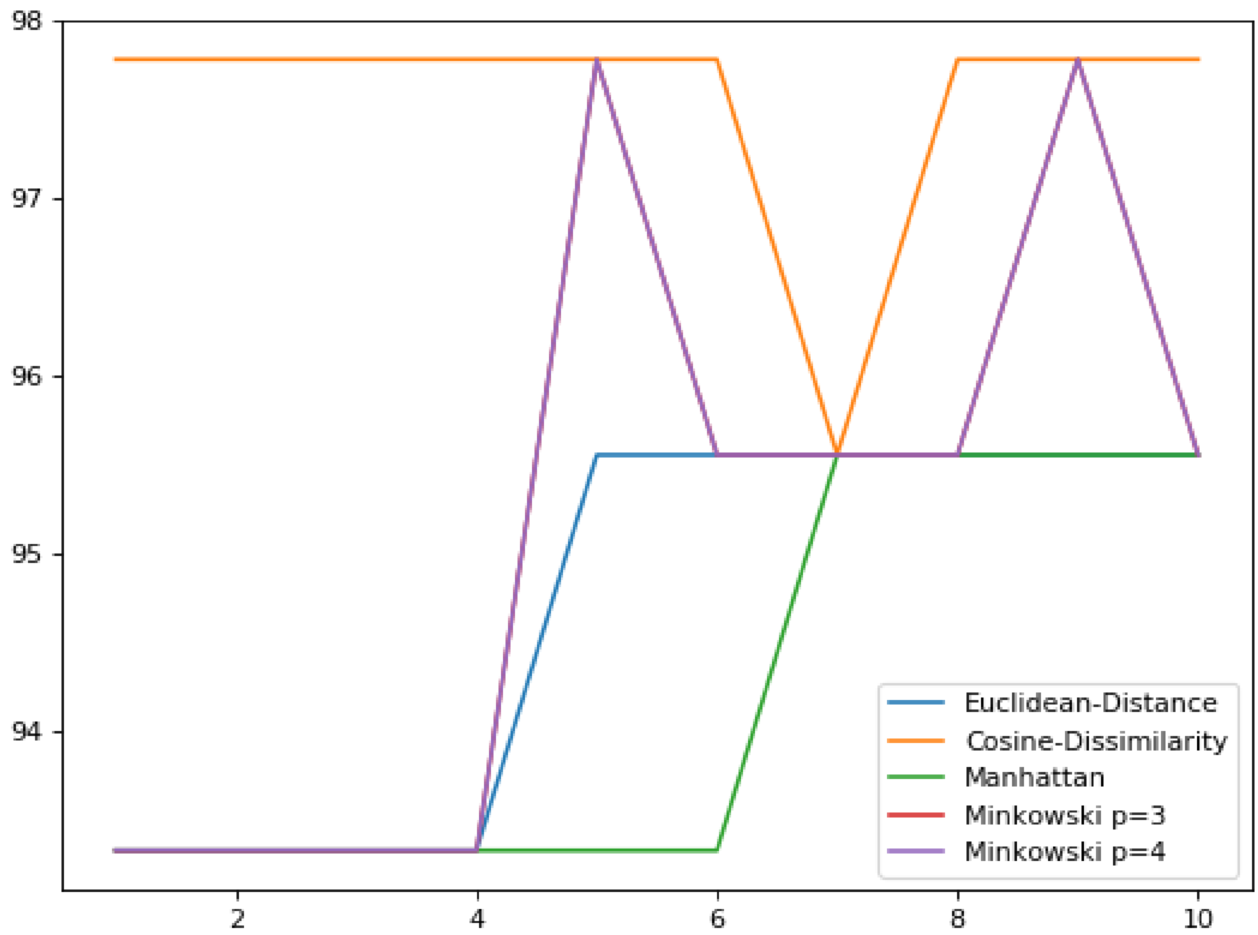
In [27]:
```
col_names = ['Method']
[col_names.append(k) for k in range(1,max_k)]
disp_df = pd.DataFrame([ecut_dist_results, coss_dissim_results, manhattan_results, minkowsi_results_3,minkowsi_results_4], columns=c
disp_df.head(len(disp_df))
```

Out[27]:
```
                 Method       1       2       3       4       5       6  \
0    Euclidean-Distance  93.333  93.333  93.333  93.333  95.556  95.556
1  Cosine-Dissimilarity  97.778  97.778  97.778  97.778  97.778  97.778
2             Manhattan  93.333  93.333  93.333  93.333  93.333  93.333
3         Minkowski p=3  93.333  93.333  93.333  93.333  97.778  95.556
4         Minkowski p=4  93.333  93.333  93.333  93.333  97.778  95.556

        7       8       9      10
0  95.556  95.556  95.556  95.556
1  95.556  97.778  97.778  97.778
2  95.556  95.556  95.556  95.556
```

```
3  95.556  95.556  97.778  95.556
4  95.556  95.556  97.778  95.556
```

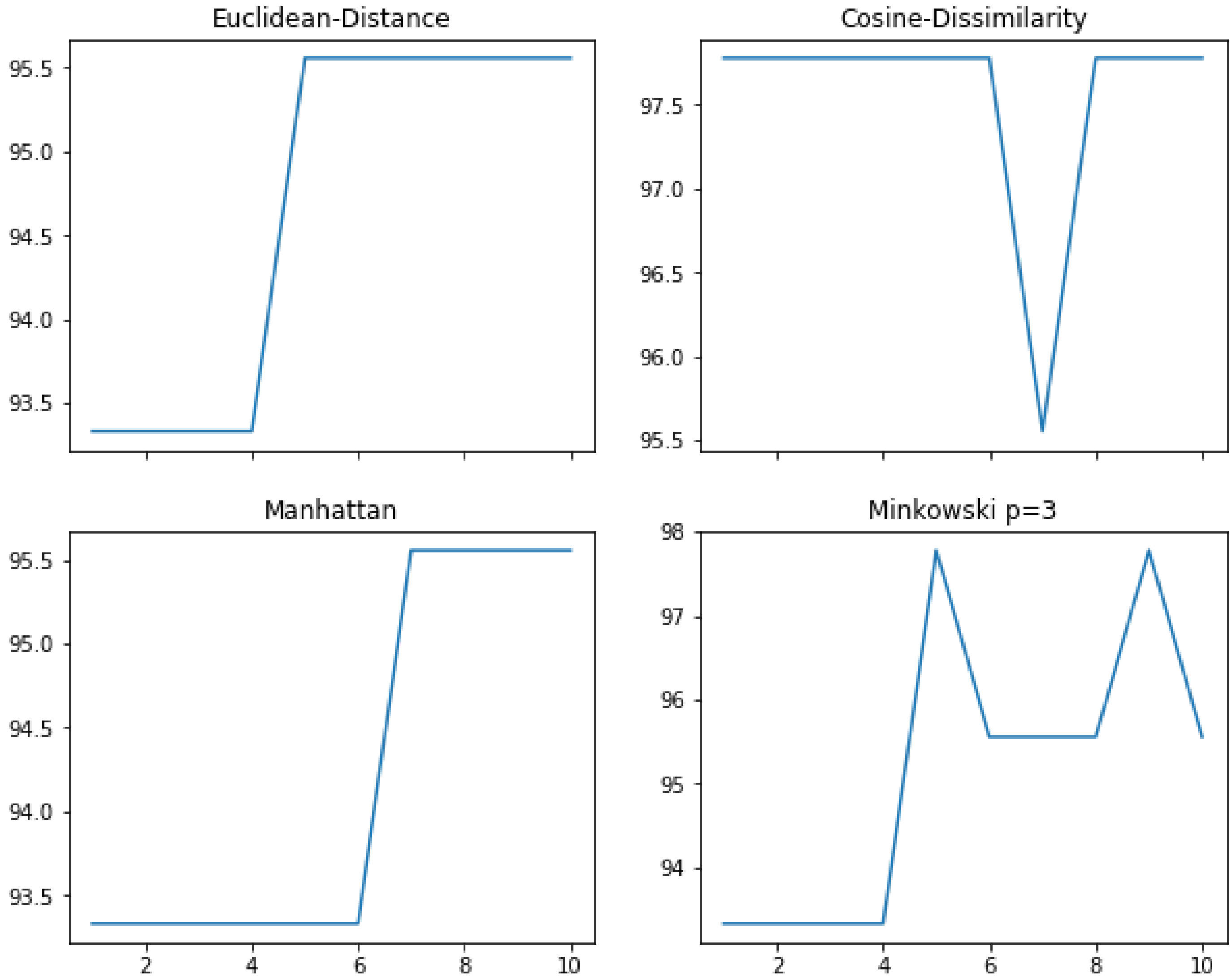
In [28]:
```
# Displaying the various iteration results for bias/variance observation
k_val = [k for k in range(1,max_k)]
plt.figure(num=None, figsize=(8, 6), dpi=80, facecolor='w', edgecolor='k')
for method_index in range(len(disp_df)):
    data_ser = disp_df.iloc[method_index]
    plt.plot(k_val, data_ser[k_val], label=data_ser['Method'])
plt.legend()
```

Out[28]: <matplotlib.legend.Legend at 0x7f107adb33c8>



In [29]:
```
fig, ((ax1, ax2),(ax3, ax4)) = plt.subplots(2, 2, sharex='col')

fig.set_figwidth(10)
fig.set_figheight(8)
data_ser = disp_df.iloc[0]
ax1.plot(k_val, data_ser[k_val])
ax1.set_title(data_ser['Method'])

data_ser = disp_df.iloc[1]
ax2.plot(k_val, data_ser[k_val])
ax2.set_title(data_ser['Method'])

data_ser = disp_df.iloc[2]
ax3.plot(k_val, data_ser[k_val])
ax3.set_title(data_ser['Method'])

data_ser = disp_df.iloc[3]
ax4.plot(k_val, data_ser[k_val])
ax4.set_title(data_ser['Method'])
```

Out[29]: Text(0.5, 1.0, 'Minkowski p=3')



2.8 Bias and Variance Check - Using Euclidean Distance

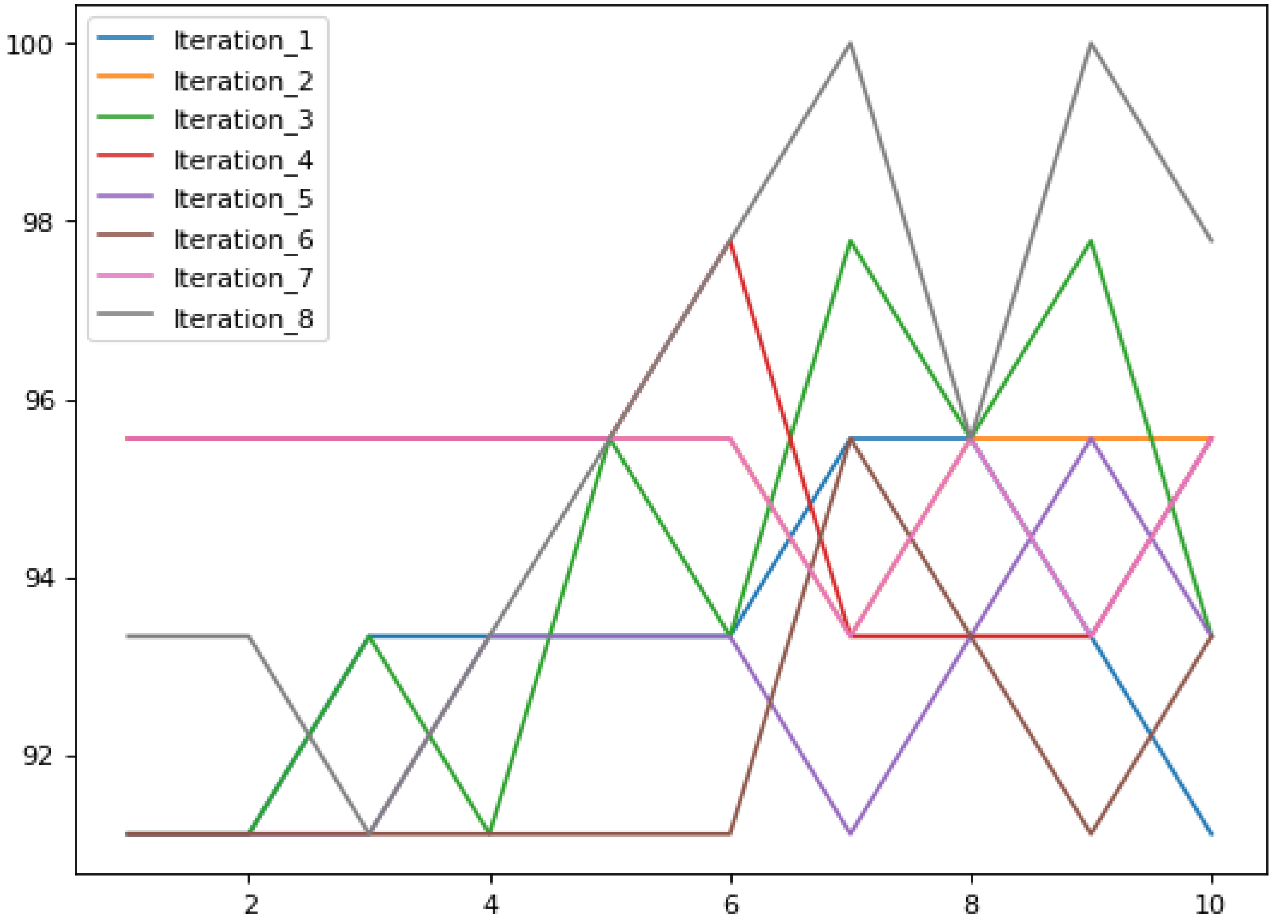
```
In [30]: %%time

         # Max number of test repeation
         # In each trial, creating a new train and test sample dataset
         # getting accuracy of prediction over test dataset from training dataset
         # this will provide bian/variance behaviour of this 'validation set approach'

         max_repeat = 8 # no. of times to repeat the test to get the bias/variance

         test_results = []
         for test_case in range(max_repeat):
             test_result = []
             print("\n", "Iteration : ", test_case+1)
             # Select new data set
             df_train, df_test = train_test_split(df, test_size=0.3)

             # Predict using Euclidean Distance Method
             for k in range(1,max_k):
                 correct_predictions = 0
                 for t_index in range(len(df_test)):
                     test_data_point = df_test.iloc[t_index]
                     neighbors = getNeighbours(df_train, test_data_point, k)
                     predicted_class = getClassLabel(neighbors)
                     if predicted_class == test_data_point['species']:
                         correct_predictions += 1
                     #print('Predicted: ', predicted_class, ' Actual: ', test_data_point['species'])
```

```
            accuracy = round((correct_predictions/len(df_test)) * 100,3)
            test_result.append(accuracy)

        print(test_result)
        test_results.append(list(test_result))

    print(test_results)
    # Plotting to do
    # https://howtothink.readthedocs.io/en/latest/PvL_H.html
```

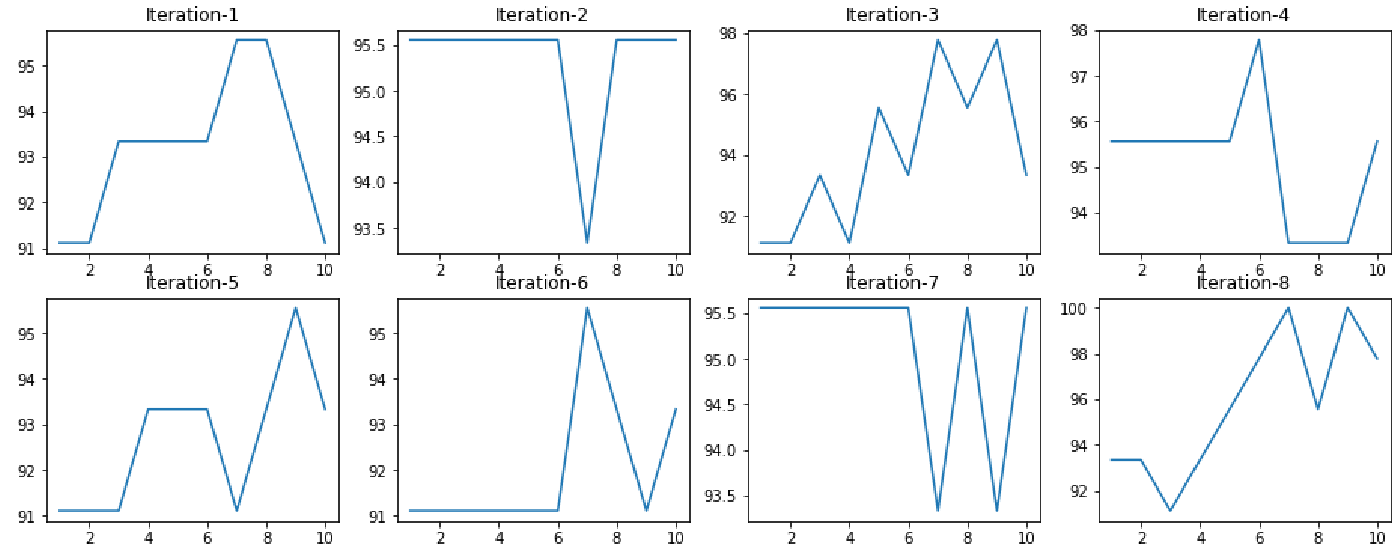
```
 Iteration :  1
[91.111, 91.111, 93.333, 93.333, 93.333, 93.333, 95.556, 95.556, 93.333, 91.111]

 Iteration :  2
[95.556, 95.556, 95.556, 95.556, 95.556, 95.556, 93.333, 95.556, 95.556, 95.556]

 Iteration :  3
[91.111, 91.111, 93.333, 91.111, 95.556, 93.333, 97.778, 95.556, 97.778, 93.333]

 Iteration :  4
[95.556, 95.556, 95.556, 95.556, 95.556, 97.778, 93.333, 93.333, 93.333, 95.556]

 Iteration :  5
[91.111, 91.111, 91.111, 93.333, 93.333, 93.333, 91.111, 93.333, 95.556, 93.333]

 Iteration :  6
[91.111, 91.111, 91.111, 91.111, 91.111, 91.111, 95.556, 93.333, 91.111, 93.333]

 Iteration :  7
[95.556, 95.556, 95.556, 95.556, 95.556, 95.556, 93.333, 95.556, 93.333, 95.556]

 Iteration :  8
[93.333, 93.333, 91.111, 93.333, 95.556, 97.778, 100.0, 95.556, 100.0, 97.778]
[[91.111, 91.111, 93.333, 93.333, 93.333, 93.333, 95.556, 95.556, 93.333, 91.111], [95.556, 95.556, 95.556, 95.556, 95.556, 95.556, 93.333, 95
CPU times: user 14min, sys: 7.93 s, total: 14min 8s
Wall time: 14min 5s
```

In [31]:
```
# Display various iteration results for bias/variance observation

k_val = [k for k in range(1,max_k)]
plt.figure(num=None, figsize=(8, 6), dpi=80, facecolor='w', edgecolor='k')
for test_case in range(max_repeat):
    plt.plot(k_val, test_results[test_case], label='Iteration_{0}'.format(test_case+1))
plt.legend()
```

Out[31]: <matplotlib.legend.Legend at 0x7f107aa4edd8>



In [32]:
```
# Display each iteration result as a seperate image for bias/variance observation

fig, axes = plt.subplots(int((max_repeat+1)/4),4)

fig.set_figwidth(16)
fig.set_figheight(6)

row_no = 0
col_no = 0

for test_case in range(max_repeat):
    axes[row_no, col_no].plot(k_val, test_results[test_case])
    axes[row_no, col_no].set_title('Iteration-{0}'.format(test_case+1))
    col_no += 1

    if ((col_no % 4) == 0):
        col_no = 0
        row_no += 1
```



3 Observation

- Training Data highly influences the prediction accuracy
  - if we rerun this test multiple times, you can see differences in accuracy for each test
  - High Sample Variability seen (Variance)
- Low Bias observered (most prediction matches with actual class)
  - Because of Iris Dataset itself very small and it has some real split-up based on its features, this low bias expected
- Cosine Similairy
  - almost no correct prediction is expected for this dataset
  - Since we are using ordinal values, the magnitude (that is we are using length, which is an ordinal measure) also need to be considered
  - but cosine similarity dont consider magnitude, it consideres only angle between vectors
  - so we are having almost incorrect predictions
- Cosine Dissimilarity
  - Yet to understand this observation
- On multiple trials, it can be observed that prediction performenece is very good
  - but still K that is if it is chosen based on above table means, it is a overfitting.
  - That is trying to find proper K in K-NN based on test data point. Making test data point indirectly as training data, because it is the deciding factor for K value.
    * This will not perform well with actual unseen data