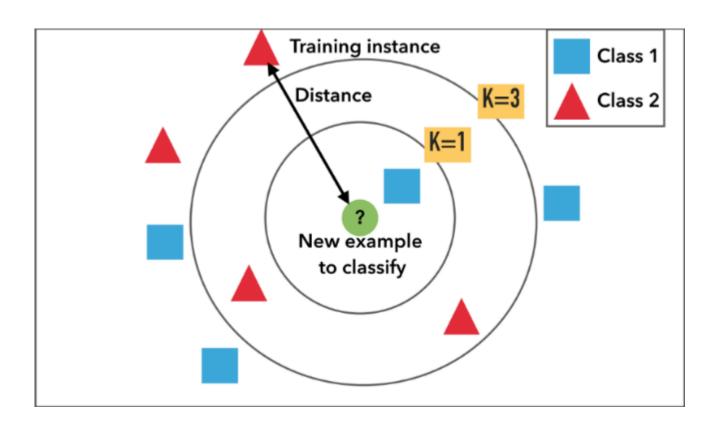
# Classification problem

In this notebook we will visualize the effect of hyperparameters on the classification process.

The algorithm used is "K Nearest Neighbors"

## K Nearest Neighbors explained



#### **Imports**

```
In [1]: import numpy as np
    import matplotlib.pyplot as plt
    from matplotlib.colors import ListedColormap
    from sklearn import neighbors, datasets
    from sklearn.neighbors import KNeighborsClassifier
    import numpy as np
    from sklearn import datasets
    from KNN_iris import KNN_plot
```

```
In [2]: # Loading the dataset
    iris = datasets.load_iris()
    iris_X = iris.data
    iris_y = iris.target

# Overlook on the dataset
    print "Number of features: ", iris_X.shape[1]
    print "Labels: ", np.unique(iris_y)
Number of features: 4
Labels: [0 1 2]
```

## Fitting the model

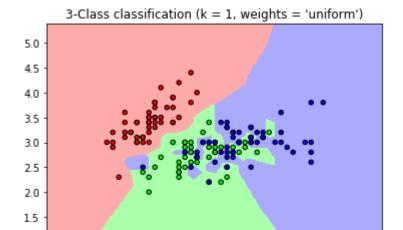
```
In [14]: # Split iris data in train and test data
    # A random permutation, to split the data randomly
    np.random.seed(0)
    indices = np.random.permutation(len(iris_X))
    iris_X_train = iris_X[indices[:-10]]
    iris_y_train = iris_y[indices[:-10]]
    iris_X_test = iris_X[indices[-10:]]
    iris_y_test = iris_y[indices[-10:]]

# Create and fit a nearest-neighbor classifier

def fit_test(n):
    knn = KNeighborsClassifier(n)
    knn.fit(iris_X_train, iris_y_train)
    print 'True Label: ', iris_y_test
    print 'Predicted Label: ', knn.predict(iris_X_test)
```

The number of neighbors K is our hyperparameter

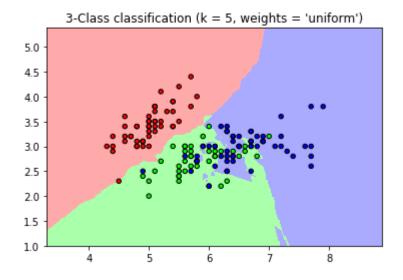
```
In [16]: n_neighbors = [1, 5, 50]
for i in n_neighbors:
    KNN_plot(i)
    fit_test(i)
```



True Label: [1 1 1 0 0 0 2 1 2 0]
Predicted Label: [1 2 1 0 0 0 2 1 2 0]

1.0

True Label:



[1 1 1 0 0 0 2 1 2 0]

3-Class classification (k = 50, weights = 'uniform')

5.0

4.5

4.0

3.5

3.0

2.5

2.0

1.5

1.0

True Label: [1 1 1 0 0 0 2 1 2 0]
Predicted Label: [1 1 1 0 0 0 2 1 2 0]

Predicted Label: [1 2 1 0 0 0 2 1 2 0]

#### Pros of KNN:

- 1) No assumptions about data useful, for example, for nonlinear data
- 2) Simple algorithm to explain and understand/interpret
- 3) Good with outlyers as we increase the number of neighbors

### Cons of KNN:

- 1) Computationally expensive because the algorithm stores all of the training dat a
- 2) High memory requirement
- 3) Data must be scaled!
- 4) Prediction stage might be slow with big N

NB: The visualization is done on the plane (x, y) where x is the first feature, and y the second features (X[:,0] and X[:,1]).

However, the algorithm KNN is calculating the distances using all the features. Any two other features could have been chosen.

In notebook KNN\_advanced, we will work with more hyperparameters and use different features.