In [1]:

```
import numpy as np
from sklearn import datasets, model_selection
import matplotlib.pyplot as plt
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline
```

Loading dataset

In [2]:

```
def load_dataset():
    f = open("01_homework_dataset.csv")
    f.readline()  # skip the header
    dataset = np.loadtxt(f, delimiter=",")
    #dataset = pd.read_csv('01_homework_dataset.csv')
    X, y = dataset[:,:3], dataset[:,3]
    return X, y
```

All needed functions

In [3]:

```
def euclidean_distance(x1, x2):
    return np.linalg.norm(np.subtract(x1,x2))
```

In [33]:

```
def get_neighbors_labels(X, y, x_new, k):
    euc_l = np.empty((0, 2), int)
    # getting an array [euclidean distance, label]
    for i in range(len(X)):
        euc_l = np.append(euc_l, [[euclidean_distance(X[i], x_new), y[i]]], axis=0)
    # sorting an array through the euclidean distance
    euc_l = euc_l[euc_l[:, 0].argsort()]
    return euc_l[0:k, :]
```

In [35]:

```
def get_response(neighbors, num_classes=3):
    m_dict = {'max': [0, 0]}
    """
    generating a dictionary where
    m_dict['max'] = [label, number of values]
    m_dict[label] = number of values
    """
    for i in neighbors[:,1]:
        if i in m_dict:
            m_dict[i] += 1
            if m_dict[i] > m_dict['max'][1]:
                m_dict['max'][0] = i
                m_dict['max'][1] = m_dict[i]
        else:
            m_dict[i] = 1
            if m_dict['max'][1] == 0:
                m_dict['max'][0] = i
                m_dict['max'][1] = 1
    # return of the label with maximum count
    return m_dict['max'][0]
```

In [73]:

```
def get_response_regression(neighbors, weight_flag):
    if not weight_flag:
        return np.sum(neighbors[:,1])/len(neighbors[:,1])
    else:
        sum_n = 0
        z = 0
        for i in neighbors:
            z += 1/i[0]
            sum_n += i[1]/i[0]
        return sum_n/z
```

We don't need test and train datasets here, so no need to split

In [74]:

```
X, y = load_dataset()
```

Answer for problem 4

In [75]:

```
def get_answer_4(X, y, x_new, k):
    # finding the closest neighbour
    return get_response(get_neighbors_labels(X, y, x_new, k))
k = 3
x1 = get_answer_4(X, y, [4.1, -0.1, 2.2], k)
x2 = get_answer_4(X, y, [6.1, 0.4, 1.3], k)
print('x1 = {0}'.format(x1))
print('x2 = {0}'.format(x2))
```

```
x1 = 0.0
x2 = 2.0
```

Answer for problem 5 (unweighted)

In [76]:

```
def get_answer_5(X, y, x_new, k):
    return get_response_regression(get_neighbors_labels(X, y, x_new, k),0)
k = 3
x1= get_answer_5(X, y, [4.1, -0.1, 2.2], k)
x2= get_answer_5(X, y, [6.1, 0.4, 1.3], k)
print('x1 = {0}'.format(x1))
print('x2 = {0}'.format(x2))
```

```
x1 = 1.0
x2 = 1.3333333333333333
```

Answer for problem 5 (weighted)

In [77]:

```
def get_answer_5(X, y, x_new, k):
    return get_response_regression(get_neighbors_labels(X, y, x_new, k),1)
k = 3
x1= get_answer_5(X, y, [4.1, -0.1, 2.2], k)
x2= get_answer_5(X, y, [6.1, 0.4, 1.3], k)
print('x1 = {0}'.format(x1))
print('x2 = {0}'.format(x2))
```

```
x1 = 0.5610164259744004
x2 = 1.3959245132894498
```

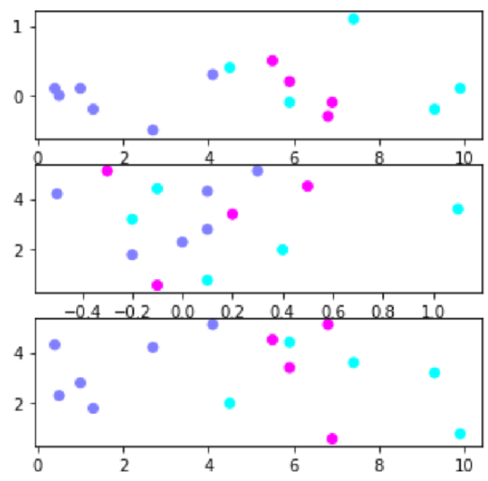
Analysis for problem 6

In [78]:

```
f, axes = plt.subplots(3,figsize=(5, 5))
axes[0].scatter(X[:,0],X[:,1], c=y, cmap=plt.cm.cool)
axes[1].scatter(X[:,1],X[:,2], c=y, cmap=plt.cm.cool)
axes[2].scatter(X[:,0],X[:,2], c=y, cmap=plt.cm.cool)
```

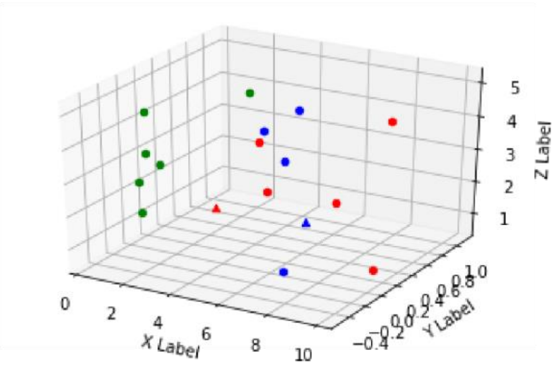
Out[78]:

```
<matplotlib.collections.PathCollection at 0x27d88f007f0>
```



In [17]:

```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
for i in range(len(X)):
    xs = X[i][0]
    ys = X[i][1]
    zs = X[i][2]
    if y[i] == 0:
        c = 'r'
    elif y[i] == 1:
        c = 'g'
    else:
        c = 'b'
    ax.scatter(xs, ys, zs, c=c, marker='o')
ax.scatter(4.1, -0.1, 2.2, c='r',marker='^')
ax.scatter(6.1, 0.4, 1.3, c='b',marker='^')
ax.set_xlabel('X Label')
ax.set_ylabel('Y Label')
ax.set_zlabel('Z Label')
plt.show()
```



As we can see in graphs, there can be 2 problems:

1) Using Euclidian distance in this case can cause a problem, because, for example, distribution of x_1 is not round shape, but different. Using Mahalanobis distance could work better in this case
2) Data is not standardize.
    a. I suppose, we could standardize it, but there is too little data to compute mean and variance.
    b. We don't know what is measure of data, and can't use it to standardize all of it.

I think, that this problems are not arise, when training a decision tree, because of the importance only of relative position of data (this one is more, than other), but not the amount of how close are they.