In [16]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
# SKLearn
import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn import datasets
```

In [33]:
```python
# Import data set
'''
features shape: (150, 2)
labels shape: (150, 1)
'''
iris = datasets.load_iris()
features = iris.data[:,:2]
labels = (iris.target != 0) * 1

x_train, x_test, y_train, y_test = train_test_split(features, labels, test_size=0.5)
x_training = x_train[np.logical_not(np.isnan(x_train))].reshape(75,2)
y_training = y_train[np.logical_not(np.isnan(y_train))].reshape(75, 1)
```

In [34]:
```python
# Sigmoid function. That maps any real number to a range of [0-1]
def sigmoid(z):
    return 1 / (1 + np.exp(-z))
```

In [35]:
```python
# In this cawse we use 'x' instead of 'x_trainig' because this functions
# could be used to predict the probability for new values (features)
def predict_probs(x, weights):
    return sigmoid(np.dot(x, weights))
```

In [36]:
```python
def predict(x, weights, threshold=0.5):
    return predict_probs(x, weights) >= threshold
```

In [37]:
```python
# Cost function
def cost_evaluation(hipotesis, y_training, weights, bias):
    number_of_training_rows = np.shape(y_training)[0]

    #print('Hipotesis: {}'.format(hipotesis))
    #print('1 - y_training: {}'.format((1 - y_training)))
    #print('(1 - hipotesis) + bias: {}'.format((1 - hipotesis)))
    #print('np.log((1 - hipotesis)): {}'.format(np.log((1 - hipotesis))))
    #print('bias: {}'.format(bias))
    #print('np.log((1 - hipotesis) + bias): {}'.format(np.log((1 - hipotesis))))

    #Take the error when label=1 (y=1)
    class1_cost = -y_training*np.log(hipotesis + bias)

    # Calculate the cost when the label=0 (y=0)
    class2_cost  = (1 - y_training)*np.log((1 - hipotesis) + bias)

     # Take the sum of both costs
    cost_contribution = class1_cost - class2_cost

    # Take the average cost
    cost = np.sum(cost_contribution) / number_of_training_rows

    return cost
```

In [38]:
```python
# Gradient descent
def gradient_descent(hipotesis, x_training, y_training, weights, learning_rate, bias):
    number_of_training_rows = np.shape(y_training)[0]

    #print('np.transpose(x_training) shape: {}'.format(np.transpose(x_training).shape))
    #print('hipotesis shape: {}'.format(hipotesis.shape))
    #print('y_training shape: {}'.format(y_training.shape))
    #print('hipotesis - y_training shape: {}'.format((hipotesis - y_training).shape))

    gradient = np.dot(np.transpose(x_training), (hipotesis - y_training)) / number_of_training_rows

    #print('gradient shape: {}'.format(gradient.shape))
    db = np.sum(hipotesis - y_training) / number_of_training_rows

    # Update weights
    weights -= learning_rate * gradient
    #bias -= (learning_rate * db)

    return weights
```

In [39]:
```python
def training(x_training, y_training, weights, learning_rate, iterations, bias):
    cost_history = []

    for i in range(iterations):
        z = np.dot(x_training, weights)
        #print('z shape: {}'.format(z.shape))
        hipotesis = sigmoid(z)

        # Gradient descent to update weights
        weights = gradient_descent(hipotesis, x_training, y_training, weights, learning_rate, bias)

        # Evaluate the cost with the new values of weights
        cost = cost_evaluation(hipotesis, y_training, weights, bias)
        cost_history.append(cost)

        # Log Progress
        if i % 1000 == 0:
            print("iterations: {} cost: {}".format(i,cost))

    return weights, cost_history
```

In [46]:
```python
# Call training
m,n = features.shape
weights = np.ones(n) # Inital colomn vector of theta
weights = weights.reshape(2,1)
learning_rate = 0.001
iterations = 50000
bias = 0.0001
print('x_training shape: {}'.format(x_training.shape))
print('weights shape: {}'.format(weights.shape))
weights, cost_history = training(x_training, y_training, weights, learning_rate, iterations, bias)
print('weights: {}'.format(weights))
#print('cost_history: {}'.format(cost_history))
```

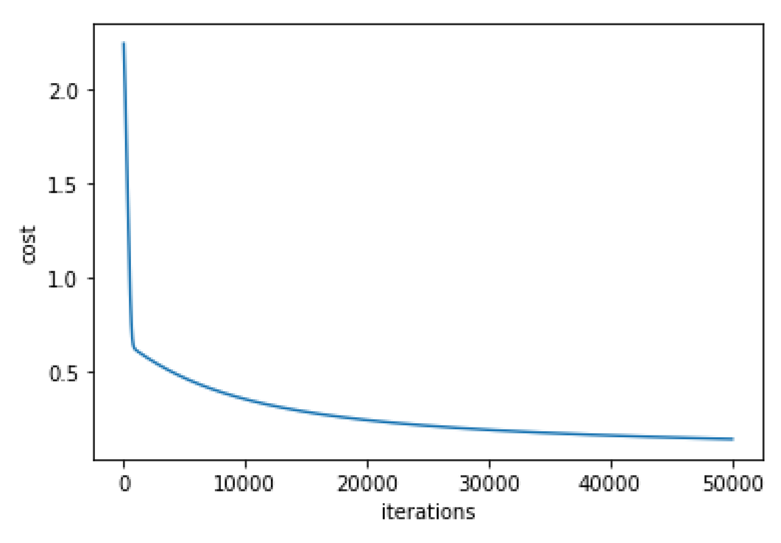
```
x_training shape: (75, 2)
weights shape: (2, 1)
iterations: 0 cost: 2.242876110984365
iterations: 1000 cost: 0.6179837133658947
iterations: 2000 cost: 0.5740295065116684
iterations: 3000 cost: 0.5350951804130778
iterations: 4000 cost: 0.5002592302806048
iterations: 5000 cost: 0.46913997369725213
iterations: 6000 cost: 0.44134918758866176
iterations: 7000 cost: 0.4165114328708399
iterations: 8000 cost: 0.39427663527537093
iterations: 9000 cost: 0.37432687456520064
iterations: 10000 cost: 0.35637883264615583
iterations: 11000 cost: 0.34018334066548456
iterations: 12000 cost: 0.3255232058044621
iterations: 13000 cost: 0.3122101747547511
iterations: 14000 cost: 0.3000815998162772
iterations: 15000 cost: 0.28899714959829303
iterations: 16000 cost: 0.27883575018816226
iterations: 17000 cost: 0.26949284168525633
iterations: 18000 cost: 0.260877973981684
iterations: 19000 cost: 0.2529127314895181
iterations: 20000 cost: 0.24552895934029303
iterations: 21000 cost: 0.2386672566404759
iterations: 22000 cost: 0.23227570123963096
iterations: 23000 cost: 0.22630877240224292
iterations: 24000 cost: 0.22072644112062567
iterations: 25000 cost: 0.21549340162003286
iterations: 26000 cost: 0.21057842137650543
iterations: 27000 cost: 0.20595379044042217
iterations: 28000 cost: 0.2015948539304713
iterations: 29000 cost: 0.19747961421245974
iterations: 30000 cost: 0.19358839152602567
iterations: 31000 cost: 0.18990353371025054
iterations: 32000 cost: 0.18640916725316864
iterations: 33000 cost: 0.183090983196653
iterations: 34000 cost: 0.17993605250969855
iterations: 35000 cost: 0.17693266643735336
iterations: 36000 cost: 0.1740701980716441
iterations: 37000 cost: 0.1713389820019763
iterations: 38000 cost: 0.16873020940832223
iterations: 39000 cost: 0.1662358363797345
iterations: 40000 cost: 0.16384850358879732
iterations: 41000 cost: 0.16156146574212416
iterations: 42000 cost: 0.15936852946835858
iterations: 43000 cost: 0.15726399850673578
iterations: 44000 cost: 0.15524262522806503
iterations: 45000 cost: 0.15329956766169717
iterations: 46000 cost: 0.15143035132122348
iterations: 47000 cost: 0.14963083522219886
iterations: 48000 cost: 0.1478971815701554
iterations: 49000 cost: 0.14622582866920358
weights: [[ 2.05135226]
 [-3.47709651]]
```

In [47]:
```python
# Prediction
prediction = predict(x_test, weights)
print(prediction)
```

```
[[ True]
 [False]
 [False]
 [ True]
 [False]
 [ True]
 [False]
 [ True]
 [ True]
 [ True]
 [False]
 [ True]
 [ True]
 [ True]
 [ True]
 [False]
 [False]
 [False]
 [False]
 [False]
 [False]
 [ True]
 [ True]
 [ True]
 [False]
 [False]
 [ True]
 [False]
 [ True]
 [False]
 [False]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [False]
 [ True]
 [False]
 [ True]
 [False]
 [ True]
 [False]
 [False]
 [ True]
 [False]
 [False]
 [ True]
 [ True]
 [ True]
 [False]
 [False]
 [ True]
 [False]
 [ True]
 [False]
 [ True]
 [False]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [ True]
 [False]
 [ True]
 [ True]
 [ True]]
```

In [48]:
```python
# Visualice the cost fuction for each iteration in the batch gradient descend algorithm
iterations_range = list(range(0,iterations))
plt.plot(iterations_range, cost_history, label='linear')  # Plot some data on the (implicit) axes.
plt.xlabel('iterations')
plt.ylabel('cost')
```

Out[48]: Text(0, 0.5, 'cost')



In [49]:
```python
# Evaluate the accuracy of the model
y_test_boolean = y_test >= 0.5

print("p: {}".format(prediction.ravel()))
print("t: {}".format(y_test_boolean))

print(accuracy_score(y_test_boolean, prediction))
```

```
p: [ True False False  True False  True False  True  True  True False  True
  True  True  True False False False False False False  True  True  True
 False False  True False  True False False  True  True  True  True  True
  True  True  True  True  True  True False  True False  True False  True
 False False  True False False  True  True  True False False  True False
  True False  True False  True  True  True  True  True  True  True False
  True  True  True]
t: [ True False False  True False  True False  True  True  True False  True
  True  True  True False False False False False False  True  True  True
 False False  True False  True False False  True  True  True  True  True
  True  True  True  True  True  True False  True False  True False  True
 False False  True False False  True  True  True False False  True False
  True False  True False  True  True  True  True  True  True  True False
  True  True  True]
1.0
```

In [50]:
```python
# With sklearn
lr_model = LogisticRegression(solver = 'lbfgs')

# Train model
lr_model.fit(x_training, y_training)

# Predict for
lr_preds = lr_model.predict(x_test)
#lr_preds = lr_preds.tolist()

lr_preds_boolean = lr_preds >= 0.5

print(lr_preds)

print(accuracy_score(y_test_boolean.ravel(), lr_preds_boolean.ravel()))

# Use score method to get accuracy of model
score = lr_model.score(x_training, y_training)
print(score)
```

```
[1 0 0 1 0 1 0 1 1 1 0 1 1 1 1 0 0 0 0 0 0 1 1 1 0 0 1 0 1 0 0 1 1 1 1 1 1
 1 1 1 1 1 0 1 0 1 0 1 0 0 1 0 0 1 1 1 0 0 1 0 1 0 1 0 1 1 1 1 1 1 1 0 1 1
 1]
1.0
1.0
C:\Users\osciv\anaconda3\lib\site-packages\sklearn\utils\validation.py:72: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples, ), for example using ravel
().
  return f(**kwargs)
```

In [ ]:

In [ ]: