In [45]:

```
import numpy as np
import matplotlib.pyplot as plt
import h5py
import scipy
from PIL import Image
from scipy import ndimage
from lr_utils import load_dataset

%matplotlib inline
```

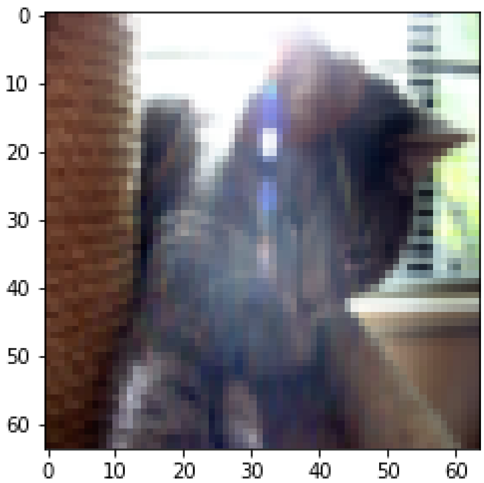
In [46]:

```
train_set_x_orig, train_set_y, test_set_x_orig, test_set_y, classes = load_dataset()
```

In [47]:

```
index = 42
plt.imshow(train_set_x_orig[index])
print ("y = " + str(train_set_y[:, index]) + ", it's a '" + classes[np.squeeze(train_se
t_y[:, index])].decode("utf-8") +  "' picture.")
```

```
y = [1], it's a 'cat' picture.
```



In [48]:

```
m_train = train_set_y.shape[1]
m_test = test_set_y.shape[1]
num_px = train_set_x_orig.shape[1]


print ("Number of training examples: m_train = " + str(m_train))
print ("Number of testing examples: m_test = " + str(m_test))
print ("Height/Width of each image: num_px = " + str(num_px))
print ("train_set_x shape: " + str(train_set_x_orig.shape))
print ("train_set_y shape: " + str(train_set_y.shape))
print ("test_set_x shape: " + str(test_set_x_orig.shape))
print ("test_set_y shape: " + str(test_set_y.shape))
```

```
Number of training examples: m_train = 209
Number of testing examples: m_test = 50
Height/Width of each image: num_px = 64
train_set_x shape: (209, 64, 64, 3)
train_set_y shape: (1, 209)
test_set_x shape: (50, 64, 64, 3)
test_set_y shape: (1, 50)
```

In [49]:

```
train_set_x_flatten = train_set_x_orig.reshape(train_set_x_orig.shape[0], -1).T
test_set_x_flatten = test_set_x_orig.reshape(test_set_x_orig.shape[0], -1).T

print ("train_set_x_flatten shape: " + str(train_set_x_flatten.shape))
print ("train_set_y shape: " + str(train_set_y.shape))
print ("test_set_x_flatten shape: " + str(test_set_x_flatten.shape))
print ("test_set_y shape: " + str(test_set_y.shape))
```

```
train_set_x_flatten shape: (12288, 209)
train_set_y shape: (1, 209)
test_set_x_flatten shape: (12288, 50)
test_set_y shape: (1, 50)
```

In [50]:

```
train_set_x = train_set_x_flatten/255.
test_set_x = test_set_x_flatten/255.
```

In [51]:

```
def sigmoid(z):

    s = 1 / (1 + np.exp(-z))

    return s
```

In [52]:

```
def initialize_with_zeros(dim):

    w = np.zeros(shape=(dim, 1))
    b = 0

    assert(w.shape == (dim, 1))
    assert(isinstance(b, float) or isinstance(b, int))

    return w, b
```

In [53]:

```
dim = 2
w, b = initialize_with_zeros(dim)
print ("w = " + str(w))
print ("b = " + str(b))
```

```
w = [[0.]
 [0.]]
b = 0
```

In [54]:

```
#propagate

def propagate(w, b, X, Y):

    m = X.shape[1]

    A = sigmoid(np.dot(w.T, X) + b)  # compute activation
    cost = (- 1 / m) * np.sum(Y * np.log(A) + (1 - Y) * (np.log(1 - A)))  # compute cos
t

    dw = (1 / m) * np.dot(X, (A - Y).T)
    db = (1 / m) * np.sum(A - Y)

    assert(dw.shape == w.shape)
    assert(db.dtype == float)
    cost = np.squeeze(cost)
    assert(cost.shape == ())

    grads = {"dw": dw,
             "db": db}

    return grads, cost
```

In [55]:

```
w, b, X, Y = np.array([[1], [2]]), 2, np.array([[1,2], [3,4]]), np.array([[1, 0]])
grads, cost = propagate(w, b, X, Y)
print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
print ("cost = " + str(cost))
```

```
dw = [[0.99993216]
 [1.99980262]]
db = 0.49993523062470574
cost = 6.000064773192205
```

In [56]:

```
# optimize

def optimize(w, b, X, Y, num_iterations, learning_rate, print_cost = False):
    costs = []

    for i in range(num_iterations):
        grads, cost = propagate(w, b, X, Y)

        dw = grads["dw"]
        db = grads["db"]


        w = w - learning_rate * dw  # need to broadcast
        b = b - learning_rate * db

        # Record the costs
        if i % 100 == 0:
            costs.append(cost)

        if print_cost and i % 100 == 0:
            print ("Cost after iteration %i: %f" % (i, cost))

    params = {"w": w,
              "b": b}

    grads = {"dw": dw,
             "db": db}

    return params, grads, costs
```

In [57]:

```
params, grads, costs = optimize(w, b, X, Y, num_iterations= 100, learning_rate = 0.009,
print_cost = False)

print ("w = " + str(params["w"]))
print ("b = " + str(params["b"]))
print ("dw = " + str(grads["dw"]))
print ("db = " + str(grads["db"]))
```

```
w = [[0.1124579 ]
 [0.23106775]]
b = 1.5593049248448891
dw = [[0.90158428]
 [1.76250842]]
db = 0.4304620716786828
```

In [58]:

```
#predict

def predict(w, b, X):

    m = X.shape[1]
    Y_prediction = np.zeros((1, m))
    w = w.reshape(X.shape[0], 1)

    A = sigmoid(np.dot(w.T, X) + b)

    for i in range(A.shape[1]):
        Y_prediction[0, i] = 1 if A[0, i] > 0.5 else 0
        ### END CODE HERE ###

    assert(Y_prediction.shape == (1, m))

    return Y_prediction
```

In [59]:

```
print("predictions = " + str(predict(w, b, X)))
```

```
predictions = [[1. 1.]]
```

In [60]:

```
#model

def model(X_train, Y_train, X_test, Y_test, num_iterations=2000, learning_rate=0.5, pri
nt_cost=False):

    w, b = initialize_with_zeros(X_train.shape[0])

    parameters, grads, costs = optimize(w, b, X_train, Y_train, num_iterations, learnin
g_rate, print_cost)

    w = parameters["w"]
    b = parameters["b"]

    Y_prediction_test = predict(w, b, X_test)
    Y_prediction_train = predict(w, b, X_train)

    print("train accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_train - Y_tra
in)) * 100))
    print("test accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_test - Y_test
)) * 100))


    d = {"costs": costs,
         "Y_prediction_test": Y_prediction_test,
         "Y_prediction_train" : Y_prediction_train,
         "w" : w,
         "b" : b,
         "learning_rate" : learning_rate,
         "num_iterations": num_iterations}

    return d
```

In [61]:

```
d = model(train_set_x, train_set_y, test_set_x, test_set_y, num_iterations = 2000, lear
ning_rate = 0.005, print_cost = True)
```

```
Cost after iteration 0: 0.693147
Cost after iteration 100: 0.584508
Cost after iteration 200: 0.466949
Cost after iteration 300: 0.376007
Cost after iteration 400: 0.331463
Cost after iteration 500: 0.303273
Cost after iteration 600: 0.279880
Cost after iteration 700: 0.260042
Cost after iteration 800: 0.242941
Cost after iteration 900: 0.228004
Cost after iteration 1000: 0.214820
Cost after iteration 1100: 0.203078
Cost after iteration 1200: 0.192544
Cost after iteration 1300: 0.183033
Cost after iteration 1400: 0.174399
Cost after iteration 1500: 0.166521
Cost after iteration 1600: 0.159305
Cost after iteration 1700: 0.152667
Cost after iteration 1800: 0.146542
Cost after iteration 1900: 0.140872
train accuracy: 99.04306220095694 %
test accuracy: 70.0 %
```