## Importing the libraries

In [3]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

## Loading the dataset

In [5]:

```
train_df = pd.read_csv('train.csv')
test_df = pd.read_csv('test.csv')
```

In [9]:

```
print("The size of training dataset is", train_df.shape)
print("The size of testing dataset is ", train_df.shape)
```

```
The size of training dataset is (891, 12)
The size of testing dataset is  (891, 12)
```

In [10]:

```
train_df
```

Out[10]:

| | PassengerId | Survived | Pclass | Name | Sex | Age | SibSp | Parch | Ticket | Fare |
|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 1 | 0 | 3 | Braund, Mr. Owen Harris | male | 22.0 | 1 | 0 | A/5 21171 | 7.2500 |
| **1** | 2 | 1 | 1 | Cumings, Mrs. John Bradley (Florence Briggs Th... | female | 38.0 | 1 | 0 | PC 17599 | 71.2833 |
| **2** | 3 | 1 | 3 | Heikkinen, Miss. Laina | female | 26.0 | 0 | 0 | STON/O2. 3101282 | 7.9250 |
| **3** | 4 | 1 | 1 | Futrelle, Mrs. Jacques Heath (Lily May Peel) | female | 35.0 | 1 | 0 | 113803 | 53.1000 |
| **4** | 5 | 0 | 3 | Allen, Mr. William Henry | male | 35.0 | 0 | 0 | 373450 | 8.0500 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **886** | 887 | 0 | 2 | Montvila, Rev. Juozas | male | 27.0 | 0 | 0 | 211536 | 13.0000 |
| **887** | 888 | 1 | 1 | Graham, Miss. Margaret Edith | female | 19.0 | 0 | 0 | 112053 | 30.0000 |
| **888** | 889 | 0 | 3 | Johnston, Miss. Catherine Helen "Carrie" | female | NaN | 1 | 2 | W./C. 6607 | 23.4500 |
| **889** | 890 | 1 | 1 | Behr, Mr. Karl Howell | male | 26.0 | 0 | 0 | 111369 | 30.0000 |
| **890** | 891 | 0 | 3 | Dooley, Mr. Patrick | male | 32.0 | 0 | 0 | 370376 | 7.7500 |

891 rows × 12 columns

In [3]:

```
Y_train = train_df['Survived']
Y_test_PassengerId = test_df['PassengerId'] # Save for submission

features = ['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked']
train_df = train_df[features]
test_df = test_df[features]
```

In [4]:

```
combined = [train_df, test_df]

for df in combined:
    # Filling missing values.
    df['Age'].fillna(df['Age'].mean(),inplace=True)
    df['Fare'].fillna(df['Fare'].mean(),inplace=True)
    df['Embarked'].fillna(value='S',inplace=True)

    # Converting categorical features to numeric
    df['Sex'] = df['Sex'].replace(['female','male'],[0,1]).astype(int)
    df['Embarked'] = df['Embarked'].replace(['S','Q','C'],[1,2,3]).astype(int)


    # Another way to convert categorical features to numeric
    #df['Sex'] = df['Sex'].map({'male': 0, 'female': 1 }).astype(int)
    #df['Embarked'] = df['Embarked'].map({'S': 0, 'C': 1, 'Q': 2}).astype(int)

    # Perform normalization
    df.loc[ df['Fare'] <= 7.91, 'Fare'] = 0
    df.loc[(df['Fare'] > 7.91) & (df['Fare'] <= 14.454), 'Fare'] = 1
    df.loc[(df['Fare'] > 14.454) & (df['Fare'] <= 31), 'Fare']   = 2
    df.loc[(df['Fare'] > 31) & (df['Fare'] <= 99), 'Fare']   = 3
    df.loc[(df['Fare'] > 99) & (df['Fare'] <= 250), 'Fare']   = 4
    df.loc[ df['Fare'] > 250, 'Fare'] = 5
    df['Fare'] = df['Fare'].astype(int)


# Make sure that train data does not contain NaN
assert not train_df.isnull().values.any()


# Make sure that test data does not contain NaN
assert not test_df.isnull().values.any()
```

In [5]:

```
train_df.head()
```

Out[5]:

| | Pclass | Sex | Age | SibSp | Parch | Fare | Embarked |
|---|---|---|---|---|---|---|---|
| **0** | 3 | 1 | 22.0 | 1 | 0 | 0 | 1 |
| **1** | 1 | 0 | 38.0 | 1 | 0 | 3 | 3 |
| **2** | 3 | 0 | 26.0 | 0 | 0 | 1 | 1 |
| **3** | 1 | 0 | 35.0 | 1 | 0 | 3 | 1 |
| **4** | 3 | 1 | 35.0 | 0 | 0 | 1 | 1 |

In [6]:

```
test_df.head()
```

Out[6]:

| | Pclass | Sex | Age | SibSp | Parch | Fare | Embarked |
|---|---|---|---|---|---|---|---|
| **0** | 3 | 1 | 34.5 | 0 | 0 | 0 | 2 |
| **1** | 3 | 0 | 47.0 | 1 | 0 | 0 | 1 |
| **2** | 2 | 1 | 62.0 | 0 | 0 | 1 | 2 |
| **3** | 3 | 1 | 27.0 | 0 | 0 | 1 | 1 |
| **4** | 3 | 0 | 22.0 | 1 | 1 | 1 | 1 |

## Defining Sigmoid function

In [7]:

```
def sigmoid(z):
    return 1 / (1 + np.exp(-z))
```

In [8]:

```
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
```

```
    """
    This function creates a vector of zeros of shape (dim, 1) for w and initializes b
     to 0.

    Argument:
    dim -- size of the w vector we want (or number of parameters in this case)

    Returns:
    w -- initialized vector of shape (dim, 1)
    b -- initialized scalar (corresponds to the bias)
    """
```

## Defining the cost and gradint functions

In [10]:

```
def propagate(w, b, X, Y):
    m = X.shape[1]

    # FORWARD PROPAGATION (FROM X TO COST)
    A = sigmoid(np.dot(w.T, X) + b)                                              # com
    cost = (- 1 / m) * np.sum(Y * np.log(A) + (1 - Y) * np.log(1 - A))        # compute c

    # BACKWARD PROPAGATION (TO FIND GRAD)
    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
```

""" Arguments: w -- weights, a numpy array of size (num_px * num_px * 3, 1) b -- bias, a scalar X -- data of size (num_px * num_px * 3, number of examples) Y -- true "label" vector (containing 0 if non-cat, 1 if cat) of size (1, number of examples)

```
Return :
cost -- negative log-likelihood cost for logistic regression
dw -- gradient of the loss with respect to w, thus same shape as w
db -- gradient of the loss with respect to b, thus same shape as b
```

"""

In [13]:

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

    for i in range(num_iterations):


        # Cost and gradient calculation (≈ 1-4 lines of code)
        grads, cost = propagate(w, b, X, Y)

        # Retrieve derivatives from grads
        dw = grads["dw"]
        db = grads["db"]

        # update rule (≈ 2 lines of code)
        w = w - learning_rate * dw
        b = b - learning_rate * db

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

        # Print the cost every 100 training iterations
        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 [15]:

```
def predict(w, b, X):
    m = X.shape[1]
    Y_prediction = np.zeros((1,m))
    w = w.reshape(X.shape[0], 1)

    # Compute vector "A" predicting the probabilities of a cat being present in the picture
    A = sigmoid(np.dot(w.T, X) + b)
    for i in range(A.shape[1]):

        # Convert probabilities A[0,i] to actual predictions p[0,i]
        Y_prediction[0, i] = 1 if A[0, i] >= 0.5 else 0

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

    return Y_prediction
```

## Defining the models

In [17]:

```
def model(X_train, Y_train, X_test, num_iterations = 2000, learning_rate = 0.5, print_cost
    w, b = initialize_with_zeros(X_train.shape[0])

    # Gradient descent (≈ 1 line of code)
    parameters, grads, costs = optimize(w, b, X_train, Y_train, num_iterations, learning_ra

    # Retrieve parameters w and b from dictionary "parameters"
    w = parameters["w"]
    b = parameters["b"]

    # Predict test/train set examples (≈ 2 lines of code)
    Y_prediction_train = predict(w, b, X_train)
    Y_prediction_test = predict(w, b, X_test)

    # Print train/test Errors
    print("train accuracy: {} %".format(100 - np.mean(np.abs(Y_prediction_train - Y_train))



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

    return d
```

In [18]:

```
X_train = np.array(train_df).T
Y_train = np.array(Y_train)
Y_train = Y_train.reshape(Y_train.shape[0], 1).T
X_test = np.array(test_df).T

assert X_train.shape[1] == Y_train.shape[1]
assert X_train.shape[0] == X_test.shape[0]
X_train.shape, Y_train.shape, X_test.shape
```

Out[18]:

```
((7, 891), (1, 891), (7, 418))
```

## Training the model

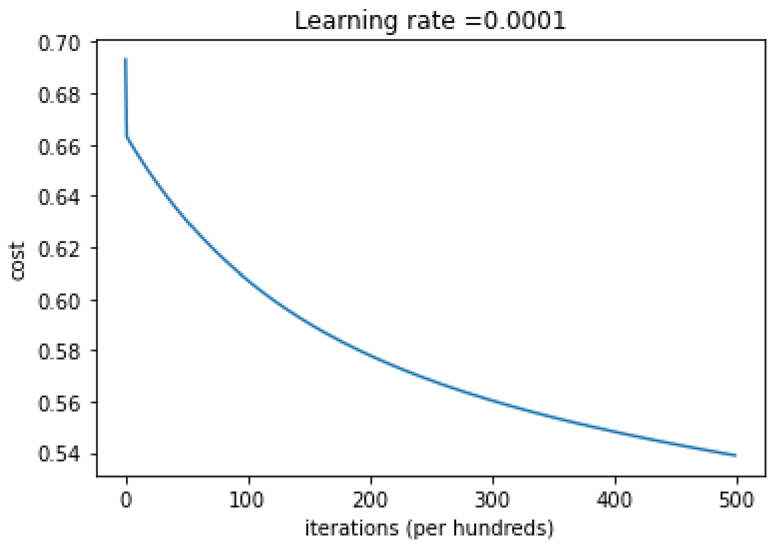
In [19]:

```
d = model(X_train, Y_train, X_test, num_iterations = 50000, learning_rate = 0.0001, print_c
```

```
train accuracy: 72.39057239057239 %
```

In [20]:

```
costs = np.squeeze(d['costs'])
plt.plot(costs)
plt.ylabel('cost')
plt.xlabel('iterations (per hundreds)')
plt.title("Learning rate =" + str(d["learning_rate"]))
plt.show()
```




In [21]:

```
submission = pd.DataFrame({
        "PassengerId": Y_test_PassengerId,
        "Survived": d['Y_prediction_test'].T.flatten().astype(int)
    })
submission.to_csv('submission.csv', index=False)
```

## Final thoughts:

- There is a lot that could be done to improve the score, like feature extraction, normalization, regularization, hyperparameter tuning, etc.
- Tuned scikit-learn algorithms like Random Forest or Decision Tree would perform slightly better, and some would be able to reach above 80%.
- For me the main goal was to implement Logistic Regression from scratch, and make it work!

In [ ]:

```

```