In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_csv('diabetes2.csv')
df.head()
```

Out[2]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	A
0	6	148	72	35	0	33.6	0.627	
1	1	85	66	29	0	26.6	0.351	
2	8	183	64	0	0	23.3	0.672	
3	1	89	66	23	94	28.1	0.167	
4	0	137	40	35	168	43.1	2.288	

In [3]:
```
df.shape
```

Out[3]: (768, 9)

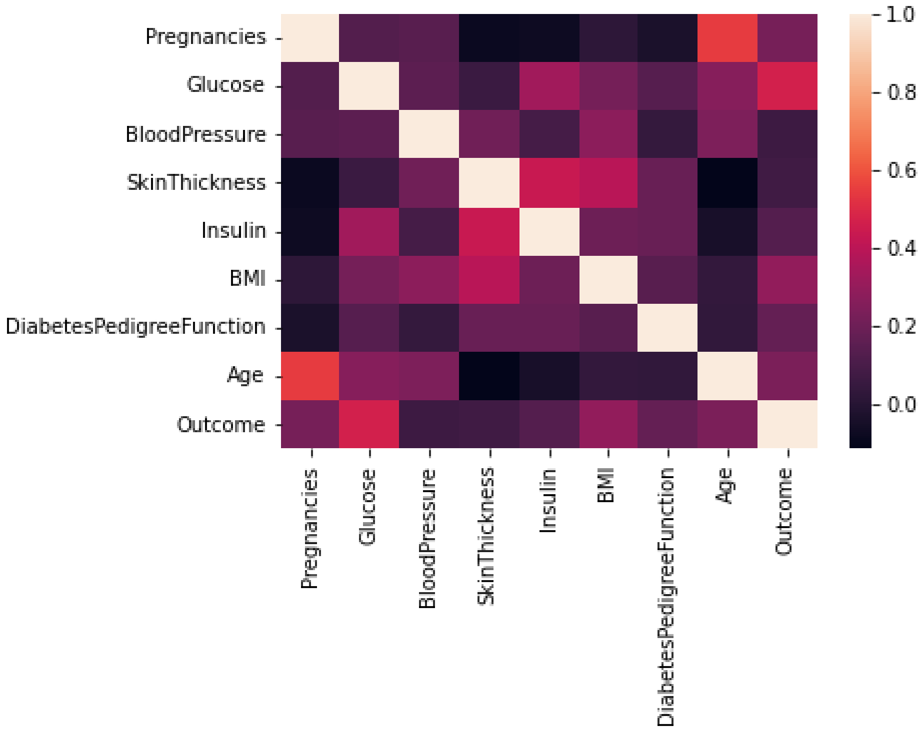
In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype  
---  ------                    --------------  -----  
 0   Pregnancies               768 non-null    int64  
 1   Glucose                   768 non-null    int64  
 2   BloodPressure             768 non-null    int64  
 3   SkinThickness             768 non-null    int64  
 4   Insulin                   768 non-null    int64  
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64  
 8   Outcome                   768 non-null    int64  
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

There are no null values in the data, so we dont need to remove any rows

In [5]:
```
sns.heatmap(df.corr())
```

Out[5]: <AxesSubplot:>



We can see that the data is not highly correlated, so there is no need to drop any columns

Standardising the input data using StandardScaler

In [6]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
df[df.columns[:-1]] = scaler.fit_transform(df[df.columns[:-1]])
df.head()
```

Out[6]:

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFu
0	0.639947	0.848324	0.149641	0.907270	-0.692891	0.204013	0.4
1	-0.844885	-1.123396	-0.160546	0.530902	-0.692891	-0.684422	-0.3
2	1.233880	1.943724	-0.263941	-1.288212	-0.692891	-1.103255	0.6
3	-0.844885	-0.998208	-0.160546	0.154533	0.123302	-0.494043	-0.9
4	-1.141852	0.504055	-1.504687	0.907270	0.765836	1.409746	5.4

Splitting data into train validation and test sets with seed 0

In [7]:
```
train = df.sample(frac=0.7, random_state=0)
val = df.drop(train.index).sample(frac=0.666, random_state=0)
test = df.drop(np.concatenate((train.index, val.index)))

print('Training set size:', train.shape[0])
print('Validation set size:', val.shape[0])
print('Testing set size:', test.shape[0])
```

```
Training set size: 538
Validation set size: 153
Testing set size: 77
```

Splitting data into input and output

In [8]:
```
X_train = train.iloc[:, :-1]
y_train = train.iloc[:, -1]
X_val = val.iloc[:, :-1]
y_val = val.iloc[:, -1]
X_test = test.iloc[:, :-1]
y_test = test.iloc[:, -1]
```

Part 1

Performing Logistic regression

In [9]:
```
def sigmoid(x):
    return 1.0 / (1 + np.exp(-x))

class LogisticRegression():
    def __init__(self, alpha, iters):
        self.alpha = alpha
        self.iters = iters

    def bgd(self, x, y, resume):
        # number of training samples and number of features
        m, n = x.shape
        # initialising weights and bias
        if(not resume):
            self.w = np.zeros(n)
            self.b = 0

        self.losses = []
        # iterating until error is negligible or max number of iterations is reac
        for i in range(self.iters):
            self.update(x, y, 'bgd')
            hx = sigmoid(x.dot(self.w) + self.b)
            self.losses.append(loss(hx, y))
            if(resume):
                if(i>2):
                    if(self.losses[-1]>self.losses[-2]):
                        print('early stopping')
                        break

    def sgd(self, x, y, resume):
        # number of training samples and number of features
        m, n = x.shape
        # initialising weights and bias
        if(not resume):
            self.w = np.zeros(n)
            self.b = 0

        self.losses = []
        # iterating until error is negligible or max number of iterations is reac
        for i in range(self.iters):
            for j in range(0, m):
                self.update(x.iloc[j], y.iloc[j], 'sgd')
            hx = sigmoid(x.dot(self.w) + self.b)
            self.losses.append(loss(hx, y))
            if(resume):
                if(i>2):
                    if(self.losses[-1]>self.losses[-2]):
                        print('early stopping')
                        break

    def update(self, x, y, opt):
        x = np.array(x)
        y = np.array(y)
        m = len(x)
        hx = sigmoid(x.dot(self.w) + self.b)
        # gradients for weights and bias
        dw = ( (x.T).dot(hx - y) ) * (1/m)
```

```
        db = ( np.sum(hx - y) ) * (1/m)

        # updating the weights
        self.w = self.w - self.alpha * dw
        self.b = self.b - self.alpha * db

    def predict(self, x):
        hx = sigmoid(x.dot(self.w) + self.b)
        y_pred = np.where(hx > 0.5, 1, 0)
        return y_pred
    # class ends here

def loss(y_pred, y):
    # adding small value so log foes not become 0
    epsilon = 1e-10
    # calculates loss for the given predictions
    loss = -np.mean(y*np.log(y_pred + epsilon) + (1-y)*np.log(1-y_pred + epsilon)
    return loss
```

A

BGD loss vs iterations

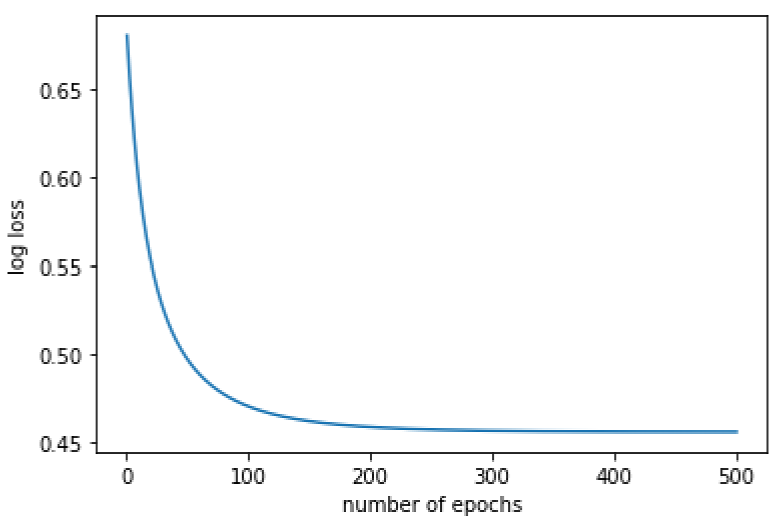
On training set

In [10]:

```
# lr = 0.1, iters = 500
model = LogisticRegression(0.1, 500)
model.bgd(X_train, y_train, False)
```

In [11]:

```
plt.plot(np.arange(1, model.iters+1), model.losses)
plt.xlabel('number of epochs')
plt.ylabel('log loss')
plt.show()
```



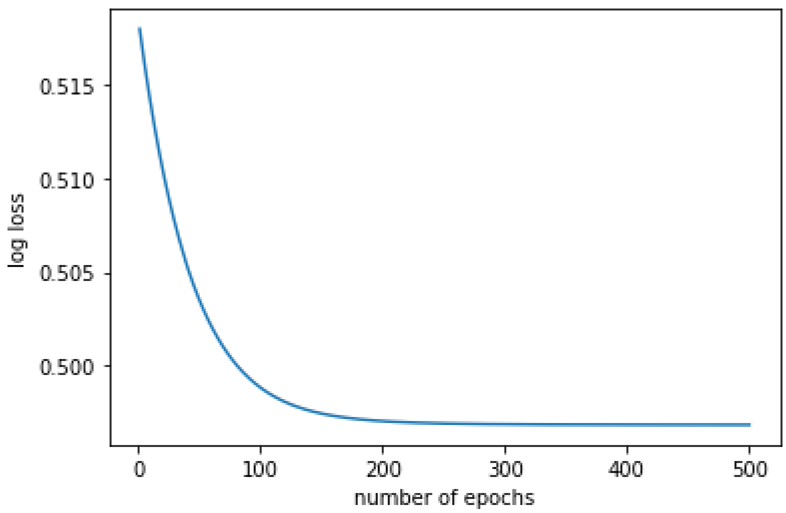
In [12]:
```
accuracy = np.sum(model.predict(X_train)==y_train) / len(y_train)
print('Our model correctly predicts outcome', accuracy*100, '% of the time on the
```

```
Our model correctly predicts outcome 79.182156133829 % of the time on the train
ing set
```

On validation set

In [13]:
```
# lr = 0.1, iters = 500
model.bgd(X_val, y_val, True)
```

In [14]:
```
plt.plot(np.arange(1, model.iters+1), model.losses)
plt.xlabel('number of epochs')
plt.ylabel('log loss')
plt.show()
```



In [15]:
```
accuracy = np.sum(model.predict(X_train)==y_train) / len(y_train)
print('Our model correctly predicts outcome', accuracy*100, '% of the time on the
```

```
Our model correctly predicts outcome 77.88104089219331 % of the time on the val
idation set
```

On both the sets it takes around 200 epochs for our model to converge

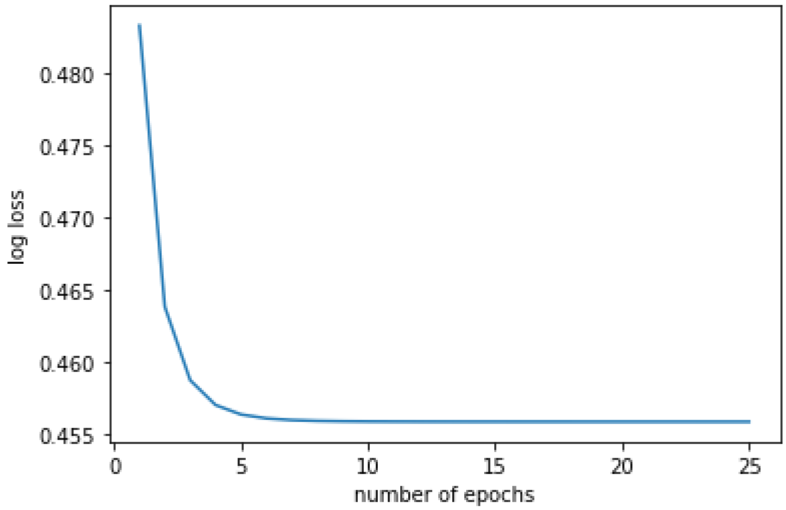
The accuracy is lower and final loss is higher for validation set as the number of samples is lower in validation set

SGD loss vs iterations

On training set

In [16]:
```
# lr = 0.1, iters = 25
model = LogisticRegression(0.1, 25)
model.sgd(X_train, y_train, False)
```

In [17]:
```
plt.plot(np.arange(1, model.iters+1), model.losses)
plt.xlabel('number of epochs')
plt.ylabel('log loss')
plt.show()
```



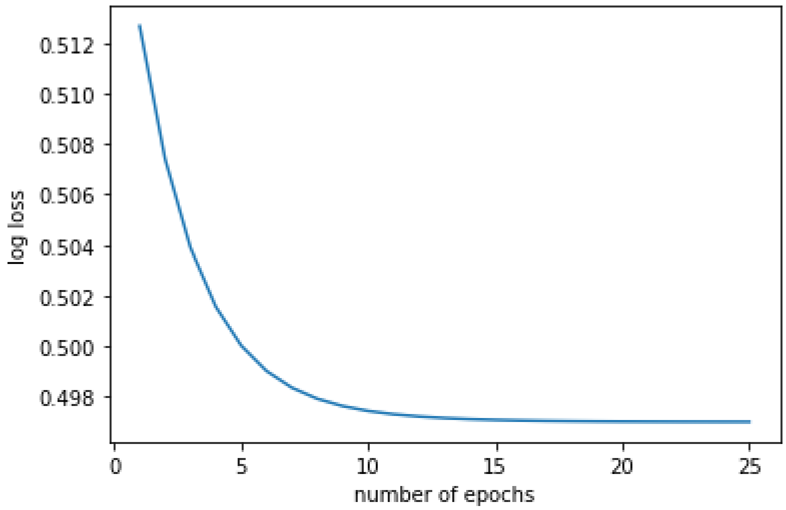
In [18]:
```
accuracy = np.sum(model.predict(X_train)==y_train) / len(y_train)
print('Our model correctly predicts outcome', accuracy*100, '% of the time on the
```

```
Our model correctly predicts outcome 78.62453531598513 % of the time on the tra
ining set
```

On validation set

In [19]:
```
# lr = 0.1, iters = 25
model.sgd(X_val, y_val, True)
```

In [20]:
```
plt.plot(np.arange(1, model.iters+1), model.losses)
plt.xlabel('number of epochs')
plt.ylabel('log loss')
plt.show()
```



In [21]:
```
accuracy = np.sum(model.predict(X_train)==y_train) / len(y_train)
print('Our model correctly predicts outcome', accuracy*100, '% of the time on the
```

```
Our model correctly predicts outcome 77.69516728624535 % of the time on the val
idation set
```

On both the sets it takes around 10 epochs for our model to converge

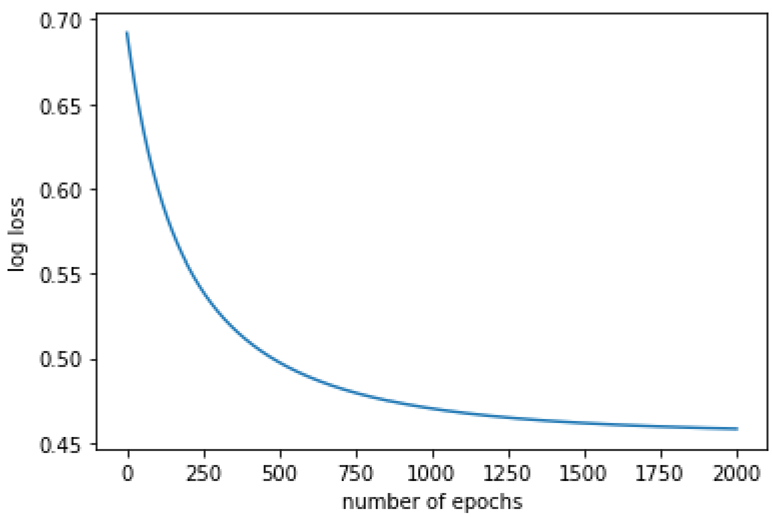
SGD converges in much lesser number of epochs than BGD since the weights are updated with each input point

B

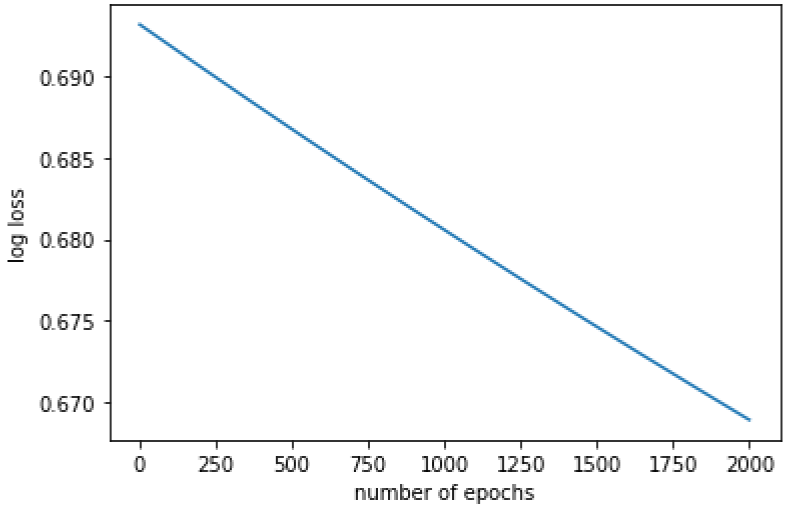
BGD

In [22]:
```
def graph(model):
    plt.plot(np.arange(1, model.iters+1), model.losses)
    plt.xlabel('number of epochs')
    plt.ylabel('log loss')
    plt.show()

def accuracy(model):
    accuracy = np.sum(model.predict(X_test)==y_test) / len(y_test)
    print('Our model correctly predicts outcome', accuracy*100, '% of the time or

# iters = 2000
lrs = [0.01, 0.0001, 10]
for lr in lrs:
    model = LogisticRegression(lr, 2000)
    model.bgd(X_train, y_train, False)
    print('\n\nLearning rate =', lr)
    graph(model)
    accuracy(model)
```

```
Learning rate = 0.01
```

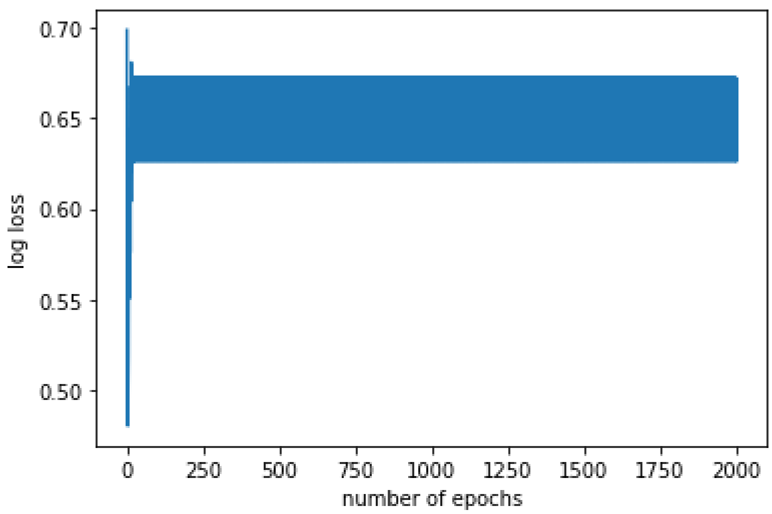



```
Our model correctly predicts outcome 72.72727272727273 % of the time on the tes
ting set


Learning rate = 0.0001
```




```
Our model correctly predicts outcome 75.32467532467533 % of the time on the tes
ting set
```

```
Learning rate = 10
```




```
Our model correctly predicts outcome 67.53246753246754 % of the time on the tes
ting set
```

0.01 learning rate is slower to converge than the original 0.1 taken by us, but it does reach convergence after a few thousand iterations

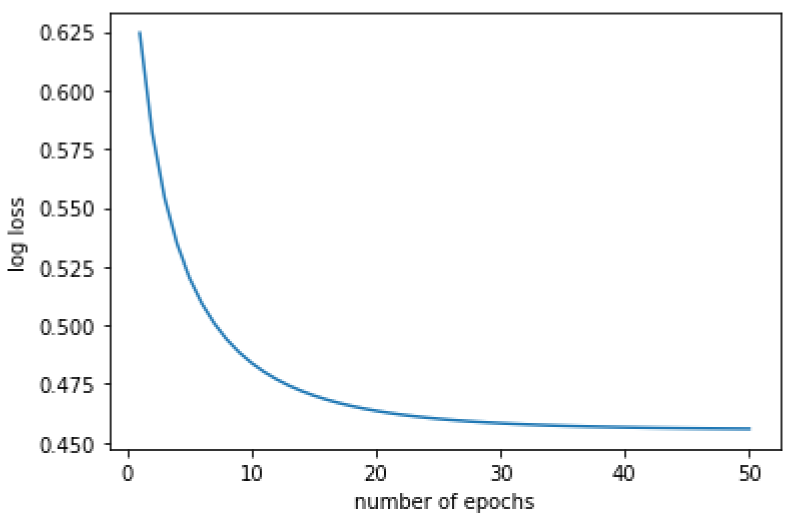
0.0001 is too low for the learning rate, it will take an unfeasibly large number of iterations to converge.

10 is too high, after some iterations the loss starts bouncing between 2 high loss values and does not reduce any further, it cannot reduce the loss to an acceptable level

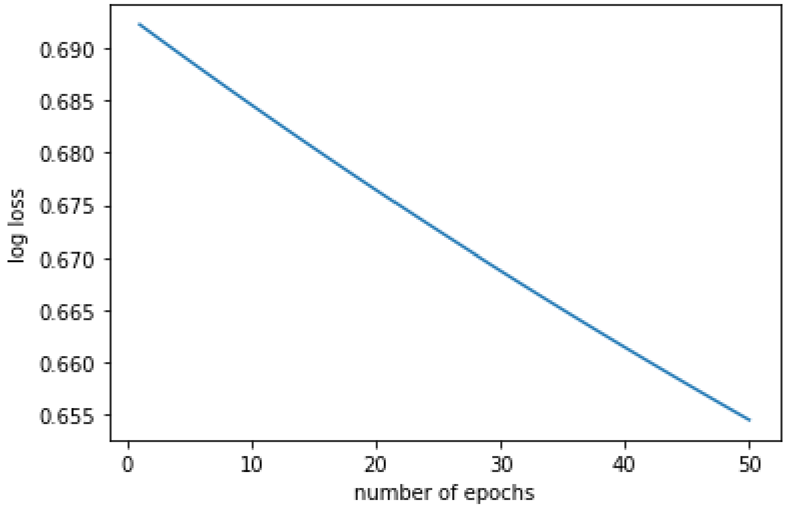
SGD

In [23]:
```
def graph(model):
    plt.plot(np.arange(1, model.iters+1), model.losses)
    plt.xlabel('number of epochs')
    plt.ylabel('log loss')
    plt.show()

def accuracy(model):
    accuracy = np.sum(model.predict(X_test)==y_test) / len(y_test)
    print('Our model correctly predicts outcome', accuracy*100, '% of the time or

# iters = 50
lrs = [0.01, 0.0001, 10]
for lr in lrs:
    model = LogisticRegression(lr, 50)
    model.sgd(X_train, y_train, False)
    print('\n\nLearning rate =', lr)
    graph(model)
    accuracy(model)
```

```
Learning rate = 0.01
```

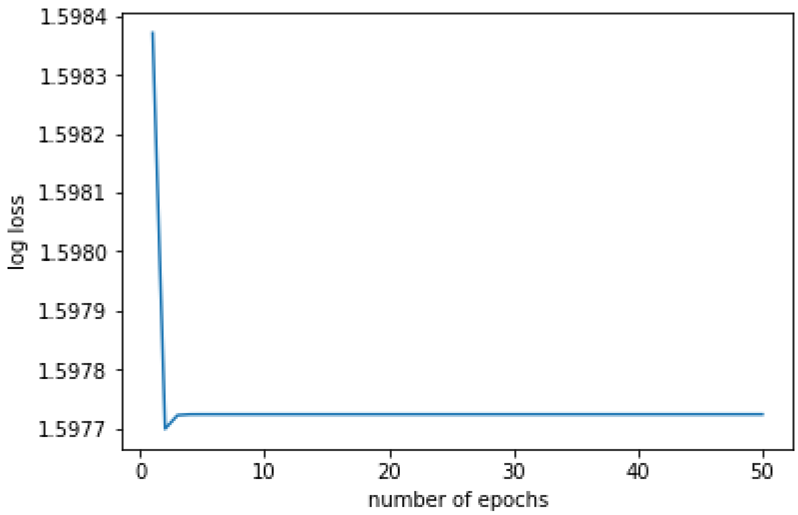



```
Our model correctly predicts outcome 72.72727272727273 % of the time on the tes
ting set


Learning rate = 0.0001
```




```
Our model correctly predicts outcome 75.32467532467533 % of the time on the tes
ting set
```

```
Learning rate = 10
```




```
Our model correctly predicts outcome 71.42857142857143 % of the time on the tes
ting set
```

0.01 learning rate is slower to converge than the original 0.1 taken by us, but it does reach convergence after about 30 iterations

0.0001 is too low for the learning rate, it will take an infeasibly large number of iterations to converge.

10 is too high, after some iterations the loss starts bouncing between 2 high loss values and does not reduce any further, it cannot reduce the loss to an acceptable level

C

In [24]:
```
def confusionMatrix(y, yh):
    # n is number of classes
    y = np.array(y)
    yh = np.array(yh)
    n = len(np.unique(y))
    mat = np.zeros((n, n))
    for i in range(len(y)):
        mat[y[i]][yh[i]] += 1
    return mat
```

BGD

In [25]:
```
# lr = 0.05, iters = 500
model = LogisticRegression(0.05, 500)
model.bgd(X_train, y_train, False)
```

In [26]:
```
cmat = confusionMatrix(np.array(y_test), model.predict(X_test))
print('Confusion matrix:\n', cmat)
```

```
Confusion matrix:
 [[42. 11.]
 [10. 14.]]
```

In [27]:
```
accuracy = (cmat[0][0] + cmat[1][1]) / np.sum(cmat)
precision = (cmat[1][1]) / (cmat[1][1] + cmat[0][1])
recall = (cmat[1][1]) / (cmat[1][1] + cmat[1][0])
f1score = 2* (precision * recall) / (precision + recall)

print('Accuracy:', accuracy)
print('Precision:', precision)
print('Recall:', recall)
print('F1score:', f1score)
```

```
Accuracy: 0.7272727272727273
Precision: 0.56
Recall: 0.5833333333333334
F1score: 0.5714285714285714
```

SGD

In [28]:
```
# lr = 0.05, iters = 25
model = LogisticRegression(0.05, 25)
model.sgd(X_train, y_train, False)
```

In [29]:
```
cmat = confusionMatrix(np.array(y_test), model.predict(X_test))
print('Confusion matrix:\n', cmat)
```

```
Confusion matrix:
 [[42. 11.]
 [10. 14.]]
```

In [30]:
```
accuracy = (cmat[0][0] + cmat[1][1]) / np.sum(cmat)
precision = (cmat[1][1]) / (cmat[1][1] + cmat[0][1])
recall = (cmat[1][1]) / (cmat[1][1] + cmat[1][0])
f1score = 2* (precision * recall) / (precision + recall)

print('Accuracy:', accuracy)
print('Precision:', precision)
print('Recall:', recall)
print('F1score:', f1score)
```

```
Accuracy: 0.7272727272727273
Precision: 0.56
Recall: 0.5833333333333334
F1score: 0.5714285714285714
```

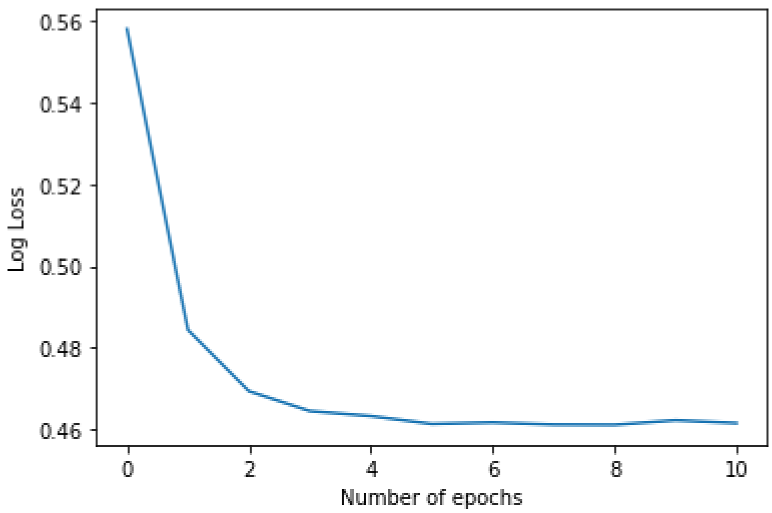
Part 2

0.01 is chosen as the learning rate, with maximum 50 iterations

In [31]:
```
from sklearn.linear_model import SGDClassifier
from io import StringIO
import sys
```

A

In [32]:
```
old_stdout = sys.stdout
sys.stdout = mystdout = StringIO()
model = SGDClassifier(learning_rate='constant', eta0=0.01, loss='log', max_iter=5
model.fit(X_train, y_train)
sys.stdout = old_stdout
loss_history = mystdout.getvalue()
loss_list = []
for line in loss_history.split('\n'):
    if(len(line.split("loss: ")) == 1):
        continue
    loss_list.append(float(line.split("loss: ")[-1]))
plt.figure()
plt.plot(np.arange(len(loss_list)), loss_list)
plt.xlabel("Number of epochs")
plt.ylabel("Log Loss")
plt.show()
plt.close()
```



SGDClassifier and our model both have the same kind of plot, and the final loss value is also similar for both

B

In [33]:
```
print('SGDClassifier converged in', model.n_iter_, 'iterations')
```

```
SGDClassifier converged in 11 iterations
```

sklearn SGDClassifer converges in around 10 epochs while our algorithm took more than 25 epochs, this may be because the sklearn model may use some extra optimisations that we have not

C

In [34]:
```
cmat = confusionMatrix(y_test, model.predict(X_test))
accuracy = (cmat[0][0] + cmat[1][1]) / np.sum(cmat)
precision = (cmat[1][1]) / (cmat[1][1] + cmat[0][1])
recall = (cmat[1][1]) / (cmat[1][1] + cmat[1][0])
f1score = 2* (precision * recall) / (precision + recall)

print('Accuracy:', accuracy)
print('Precision:', precision)
print('Recall:', recall)
print('F1score:', f1score)
```

```
Accuracy: 0.7272727272727273
Precision: 0.56
Recall: 0.5833333333333334
F1score: 0.5714285714285714
```

Confusion matrix for both the SGDClassifier and our model is the same, so both perform similarly in terms of accuracy, precision, recall and f1score

In [ ]:
```
```