**1. Initialization techniques**

The usual initialization technique is to generate Gaussian or uniform random numbers and multiply it by a small value like 0.01. Two techniques which are used to speed up convergence is the [He](https://www.cv-foundation.org/openaccess/content_iccv_2015/papers/He_Delving_Deep_into_ICCV_2015_paper.pdf) initialization or [Xavier](http://proceedings.mlr.press/v9/glorot10a/glorot10a.pdf). These initialization techniques enable gradient descent to converge faster.

**1.1 a Default initialization – Python**

This technique just initializes the weights to small random values based on Gaussian or uniform distribution

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import sklearn.linear\_model

import pandas as pd

import sklearn

import sklearn.datasets

exec(open("DLfunctions61.py").read())

#Load the data

train\_X, train\_Y, test\_X, test\_Y = load\_dataset()

# Set the layers dimensions

layersDimensions = [2,7,1]

# Train a deep learning network with random initialization

parameters = L\_Layer\_DeepModel(train\_X, train\_Y, layersDimensions, hiddenActivationFunc='relu', outputActivationFunc="sigmoid",learningRate = 0.6, num\_iterations = 9000, initType="default", print\_cost = True,figure="fig1.png")

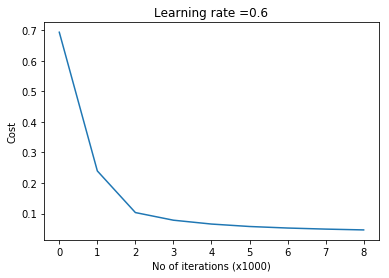
# Clear the plot

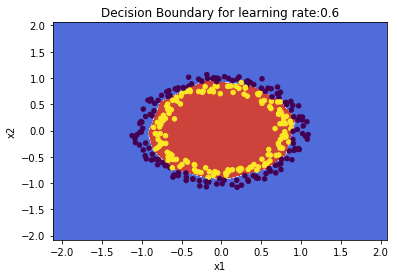
plt.clf()

plt.close()

# Plot the decision boundary

plot\_decision\_boundary(lambda x: predict(parameters, x.T), train\_X, train\_Y,str(0.6),figure1="fig2.png")





**1.1 b He initialization – Python**

‘He’ initialization attributed to [He et al](https://www.cv-foundation.org/openaccess/content_iccv_2015/papers/He_Delving_Deep_into_ICCV_2015_paper.pdf), multiplies the random weights by  
\sqrt{\frac{2}{dimension\ of\ previous\ layer}}

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import sklearn.linear\_model

import pandas as pd

import sklearn

import sklearn.datasets

exec(open("DLfunctions61.py").read())

#Load the data

train\_X, train\_Y, test\_X, test\_Y = load\_dataset()

# Set the layers dimensions

layersDimensions = [2,7,1]

# Train a deep learning network with He initialization

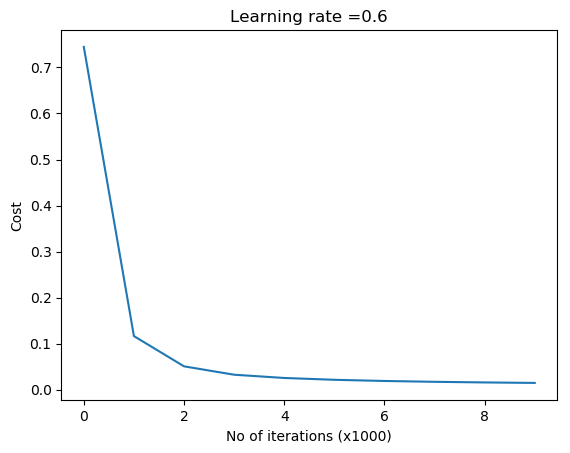
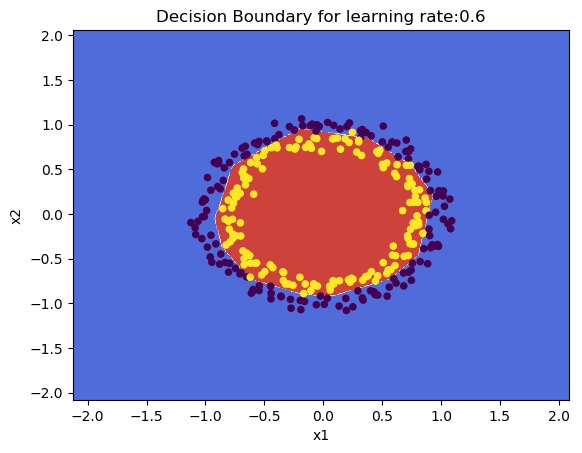
parameters = L\_Layer\_DeepModel(train\_X, train\_Y, layersDimensions, hiddenActivationFunc='relu', outputActivationFunc="sigmoid", learningRate =0.6, num\_iterations = 10000,initType="He",print\_cost = True, figure="fig3.png")

plt.clf()

plt.close()

# Plot the decision boundary

plot\_decision\_boundary(lambda x: predict(parameters, x.T), train\_X, train\_Y,str(0.6),figure1="fig4.png")

**1.1 c Xavier initialization – Python**

[Xavier](http://proceedings.mlr.press/v9/glorot10a/glorot10a.pdf) initialization multiply the random weights by  
\sqrt{\frac{1}{dimension\ of\ previous\ layer}}

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import sklearn.linear\_model

import pandas as pd

import sklearn

import sklearn.datasets

exec(open("DLfunctions61.py").read())

#Load the data

train\_X, train\_Y, test\_X, test\_Y = load\_dataset()

# Set the layers dimensions

layersDimensions = [2,7,1]

# Train a L layer Deep Learning network

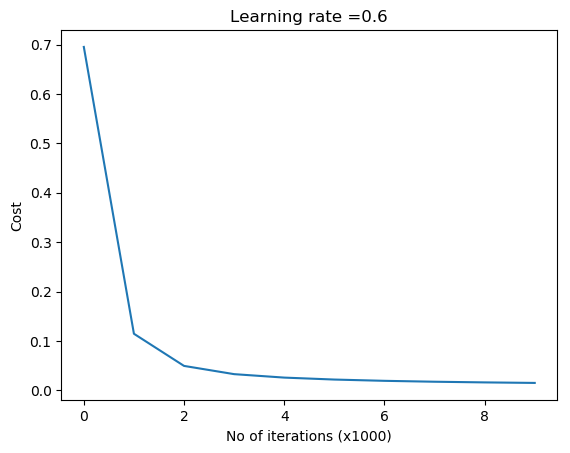
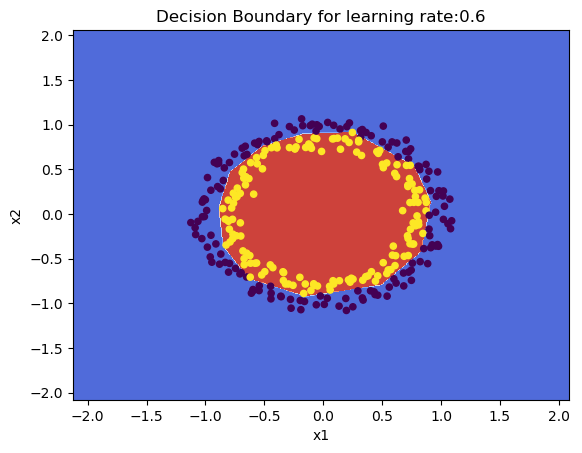
parameters = L\_Layer\_DeepModel(train\_X, train\_Y, layersDimensions, hiddenActivationFunc='relu', outputActivationFunc="sigmoid",

learningRate = 0.6,num\_iterations = 10000, initType="Xavier",print\_cost = True,

figure="fig5.png")

# Plot the decision boundary

plot\_decision\_boundary(lambda x: predict(parameters, x.T), train\_X, train\_Y,str(0.6),figure1="fig6.png")

**1.2a Default initialization – R**

source("DLfunctions61.R")

#Load the data

z <- as.matrix(read.csv("circles.csv",header=FALSE))

x <- z[,1:2]

y <- z[,3]

X <- t(x)

Y <- t(y)

#Set the layer dimensions

layersDimensions = c(2,11,1)

# Train a deep learning network

retvals = L\_Layer\_DeepModel(X, Y, layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

numIterations = 8000,

initType="default",

print\_cost = True)

#Plot the cost vs iterations

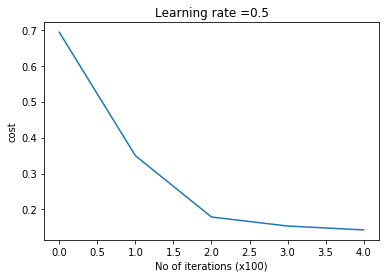
iterations <- seq(0,8000,1000)

costs=retvals$costs

df=data.frame(iterations,costs)

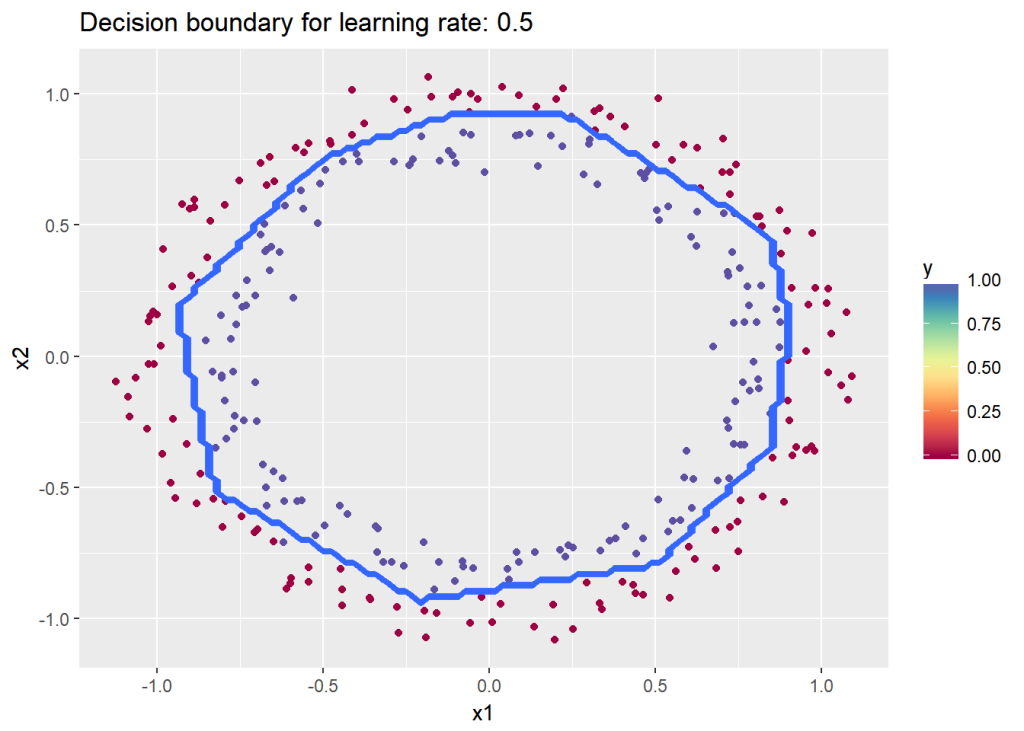
ggplot(df,aes(x=iterations,y=costs)) + geom\_point() + geom\_line(color="blue") +

ggtitle("Costs vs iterations") + xlab("No of iterations") + ylab("Cost")



# Plot the decision boundary

plotDecisionBoundary(z,retvals,hiddenActivationFunc="relu",lr=0.5)



**1.2b He initialization – R**

The code for ‘He’ initilaization in R is included below

# He Initialization model for L layers

# Input : List of units in each layer

# Returns: Initial weights and biases matrices for all layers

# He initilization multiplies the random numbers with sqrt(2/layerDimensions[previouslayer])

HeInitializeDeepModel <- function(layerDimensions){

set.seed(2)

# Initialize empty list

layerParams <- list()

# Note the Weight matrix at layer 'l' is a matrix of size (l,l-1)

# The Bias is a vectors of size (l,1)

# Loop through the layer dimension from 1.. L

# Indices in R start from 1

for(l in 2:length(layersDimensions)){

# Initialize a matrix of small random numbers of size l x l-1

# Create random numbers of size l x l-1

w=rnorm(layersDimensions[l]\*layersDimensions[l-1])

# Create a weight matrix of size l x l-1 with this initial weights and

# Add to list W1,W2... WL

# He initialization - Divide by sqrt(2/layerDimensions[previous layer])

layerParams[[paste('W',l-1,sep="")]] = matrix(w,nrow=layersDimensions[l],

ncol=layersDimensions[l-1])\*sqrt(2/layersDimensions[l-1])

layerParams[[paste('b',l-1,sep="")]] = matrix(rep(0,layersDimensions[l]),

nrow=layersDimensions[l],ncol=1)

}

return(layerParams)

}

The code in R below uses He initialization to learn the data

source("DLfunctions61.R")

# Load the data

z <- as.matrix(read.csv("circles.csv",header=FALSE))

x <- z[,1:2]

y <- z[,3]

X <- t(x)

Y <- t(y)

# Set the layer dimensions

layersDimensions = c(2,11,1)

# Train a deep learning network

retvals = L\_Layer\_DeepModel(X, Y, layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

numIterations = 9000,

initType="He",

print\_cost = True)

#Plot the cost vs iterations

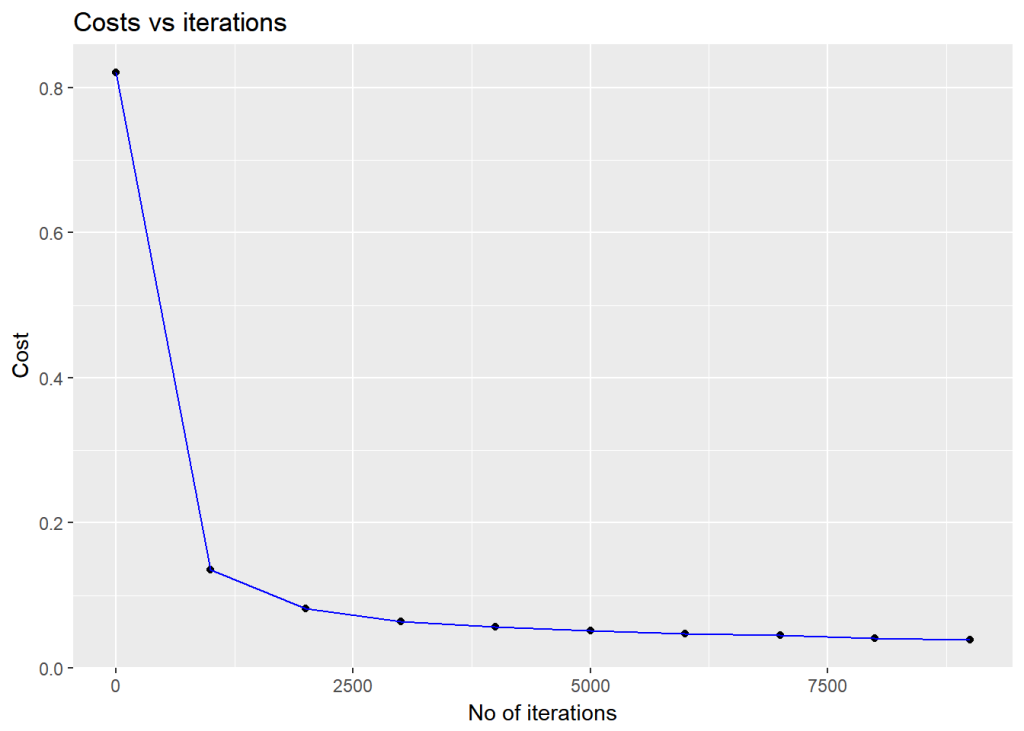
iterations <- seq(0,9000,1000)

costs=retvals$costs

df=data.frame(iterations,costs)

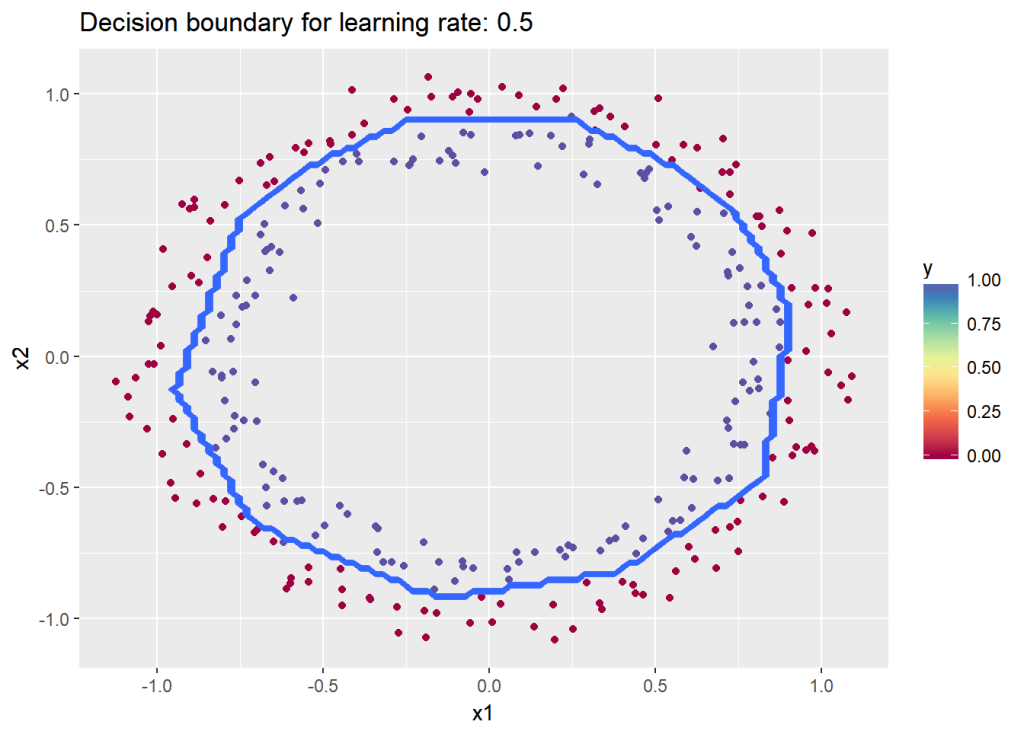
ggplot(df,aes(x=iterations,y=costs)) + geom\_point() + geom\_line(color="blue") +

ggtitle("Costs vs iterations") + xlab("No of iterations") + ylab("Cost")



# Plot the decision boundary

plotDecisionBoundary(z,retvals,hiddenActivationFunc="relu",0.5,lr=0.5)



**1.2c Xavier initialization – R**

## Xav initialization

# Set the layer dimensions

layersDimensions = c(2,11,1)

# Train a deep learning network

retvals = L\_Layer\_DeepModel(X, Y, layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

numIterations = 9000,

initType="Xav",

print\_cost = True)

#Plot the cost vs iterations

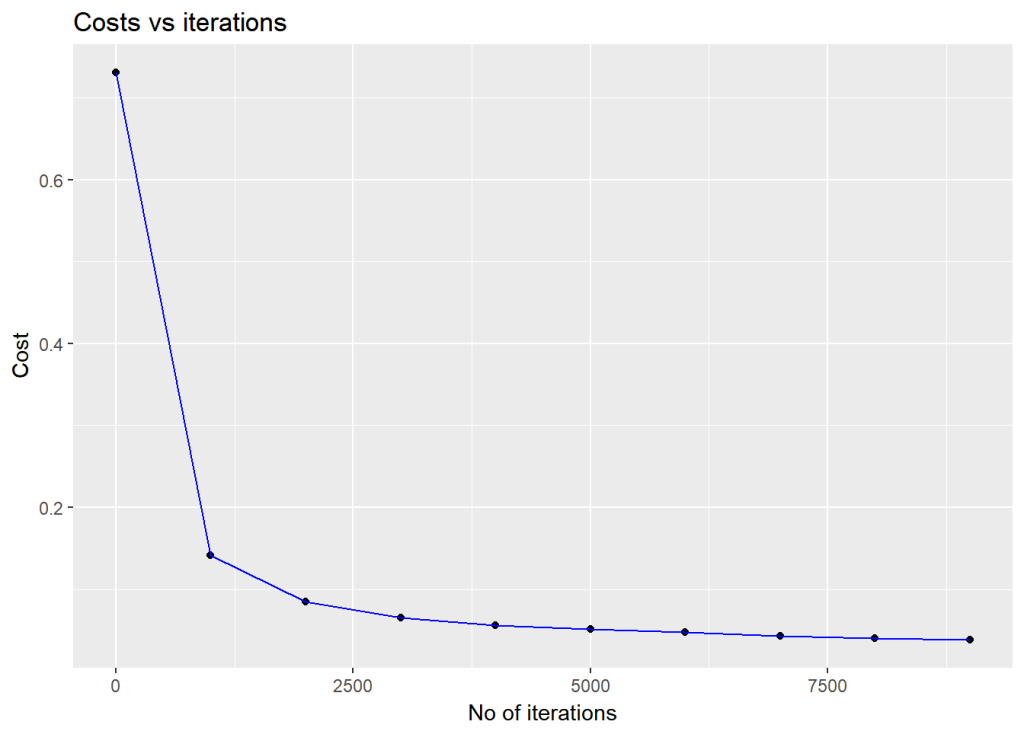
iterations <- seq(0,9000,1000)

costs=retvals$costs

df=data.frame(iterations,costs)

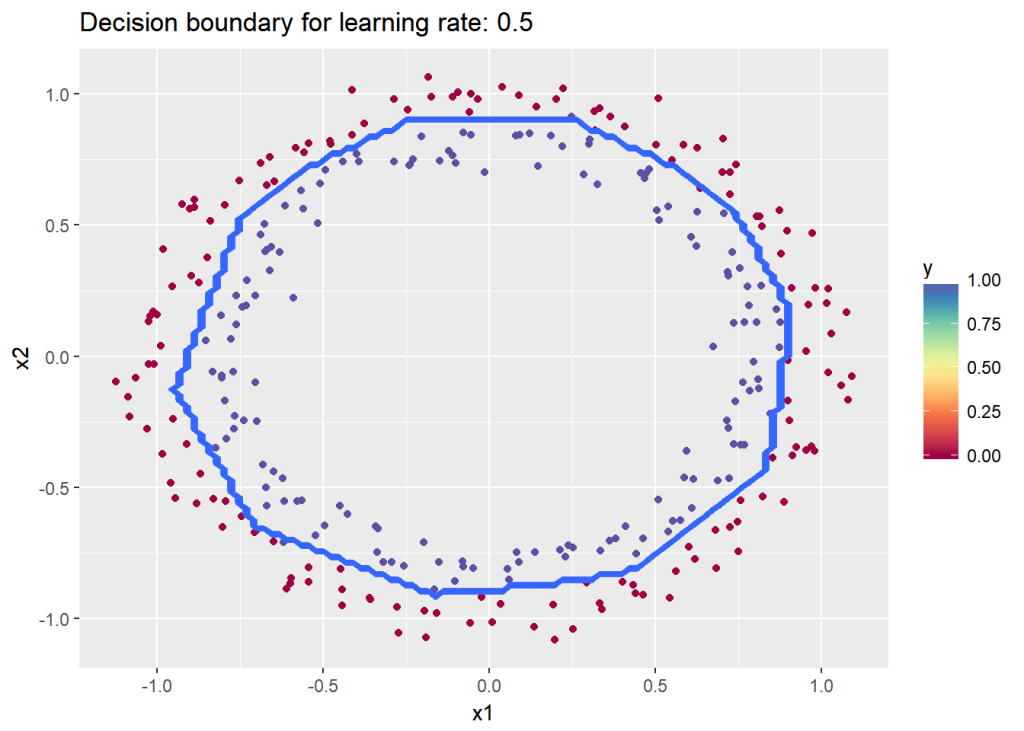
ggplot(df,aes(x=iterations,y=costs)) + geom\_point() + geom\_line(color="blue") +

ggtitle("Costs vs iterations") + xlab("No of iterations") + ylab("Cost")



# Plot the decision boundary

plotDecisionBoundary(z,retvals,hiddenActivationFunc="relu",0.5)



**1.3a Default initialization – Octave**

source("DL61functions.m")

# Read the data

data=csvread("circles.csv");

X=data(:,1:2);

Y=data(:,3);

# Set the layer dimensions

layersDimensions = [2 11 1]; #tanh=-0.5(ok), #relu=0.1 best!

# Train a deep learning network

[weights biases costs]=L\_Layer\_DeepModel(X', Y', layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

lambd=0,

keep\_prob=1,

numIterations = 10000,

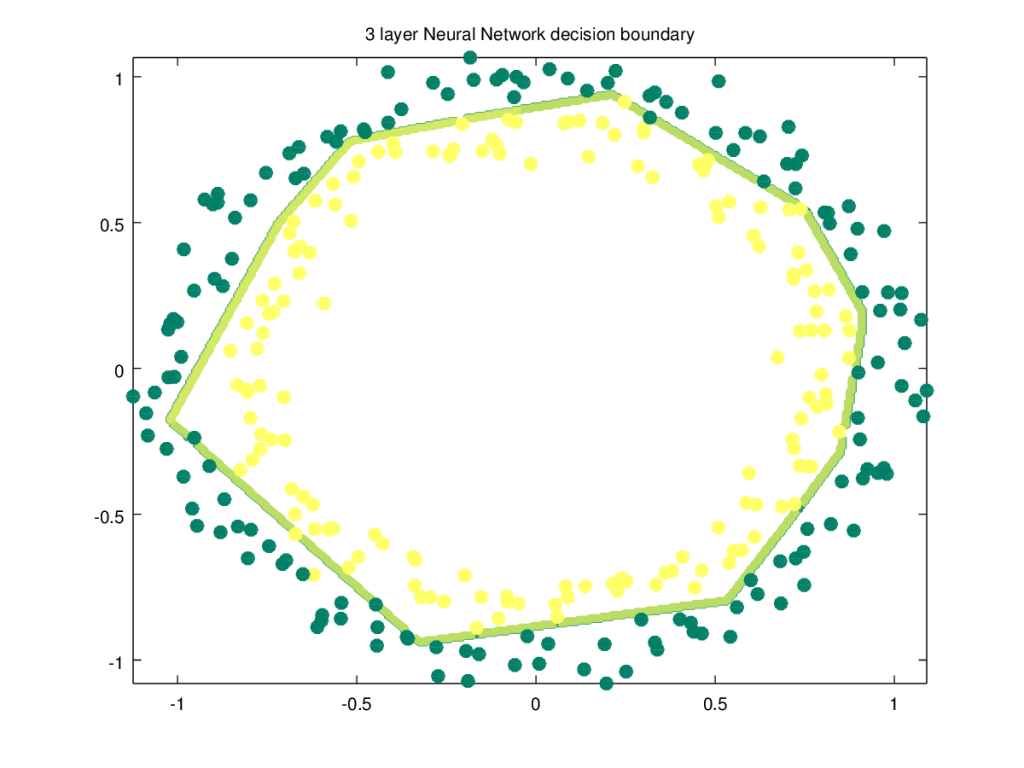
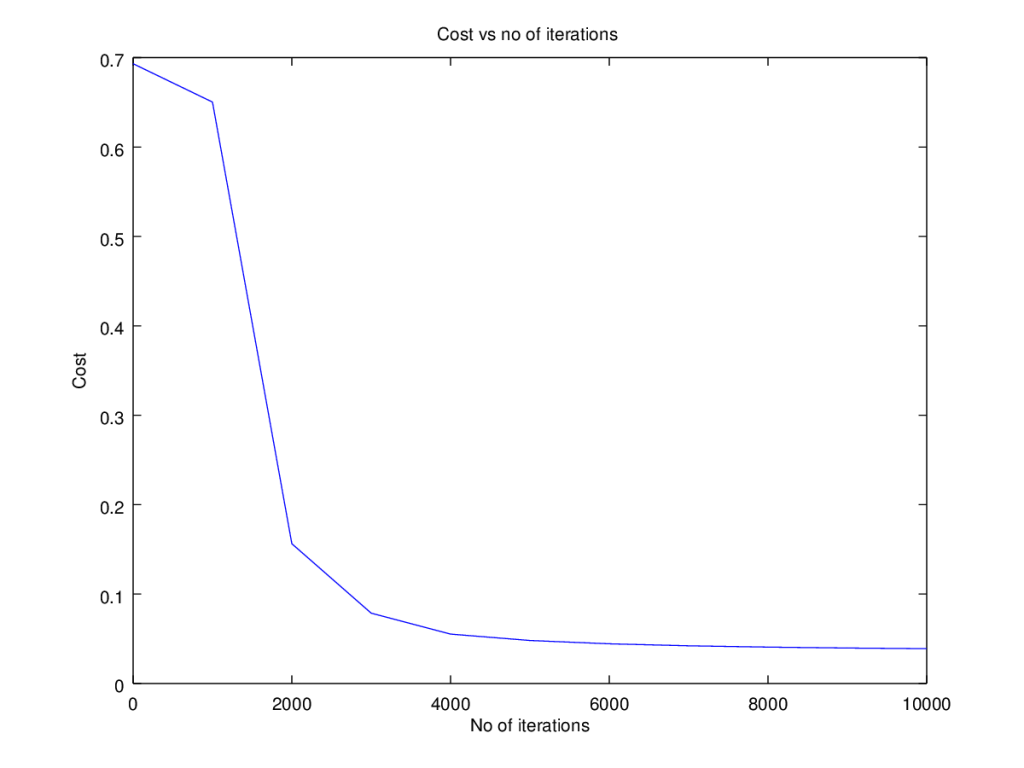
initType="default");

# Plot cost vs iterations

plotCostVsIterations(10000,costs)

#Plot decision boundary

plotDecisionBoundary(data,weights, biases,keep\_prob=1, hiddenActivationFunc="relu")

****

**1.3b He initialization – Octave**

source("DL61functions.m")

#Load data

data=csvread("circles.csv");

X=data(:,1:2);

Y=data(:,3);

# Set the layer dimensions

layersDimensions = [2 11 1]; #tanh=-0.5(ok), #relu=0.1 best!

# Train a deep learning network

[weights biases costs]=L\_Layer\_DeepModel(X', Y', layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

lambd=0,

keep\_prob=1,

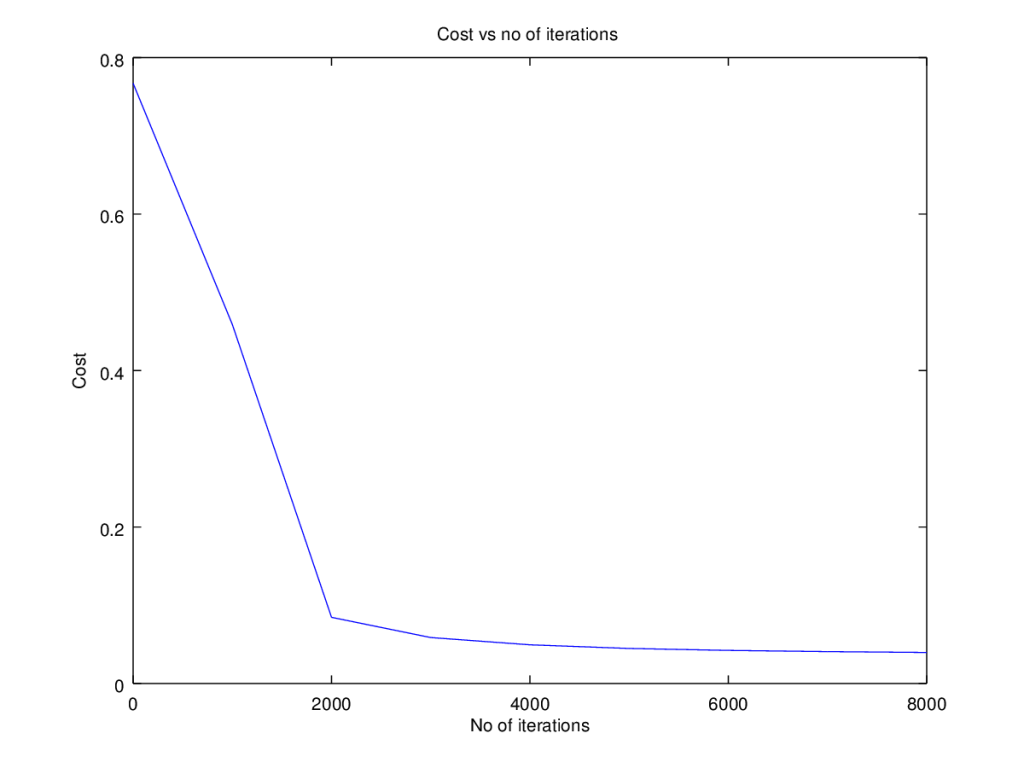
numIterations = 8000,

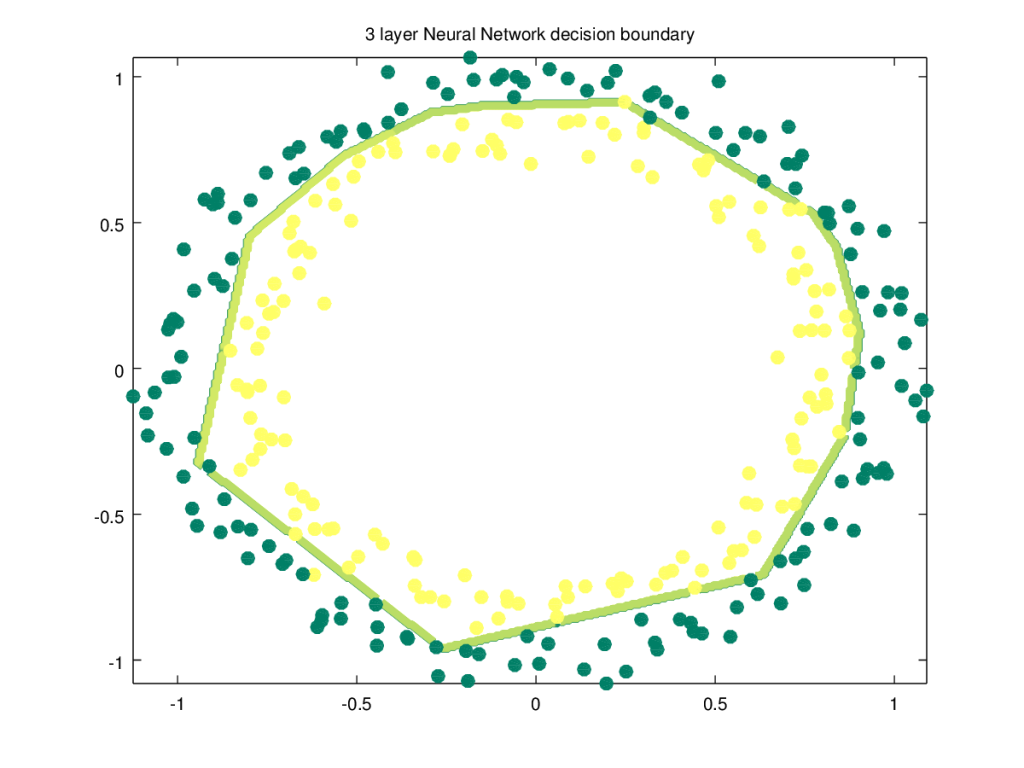
initType="He");

plotCostVsIterations(8000,costs)

#Plot decision boundary

plotDecisionBoundary(data,weights, biases,keep\_prob=1,hiddenActivationFunc="relu")





**1.3c Xavier initialization – Octave**

The code snippet for Xavier initialization in Octave is shown below

source("DL61functions.m")

# Xavier Initialization for L layers

# Input : List of units in each layer

# Returns: Initial weights and biases matrices for all layers

function [W b] = XavInitializeDeepModel(layerDimensions)

rand ("seed", 3);

# note the Weight matrix at layer 'l' is a matrix of size (l,l-1)

# The Bias is a vectors of size (l,1)

# Loop through the layer dimension from 1.. L

# Create cell arrays for Weights and biases

for l =2:size(layerDimensions)(2)

W{l-1} = rand(layerDimensions(l),layerDimensions(l-1))\* sqrt(1/layerDimensions(l-1)); # Multiply by .01

b{l-1} = zeros(layerDimensions(l),1);

endfor

end

The Octave code below uses Xavier initialization

source("DL61functions.m")

#Load data

data=csvread("circles.csv");

X=data(:,1:2);

Y=data(:,3);

#Set layer dimensions

layersDimensions = [2 11 1]; #tanh=-0.5(ok), #relu=0.1 best!

# Train a deep learning network

[weights biases costs]=L\_Layer\_DeepModel(X', Y', layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

lambd=0,

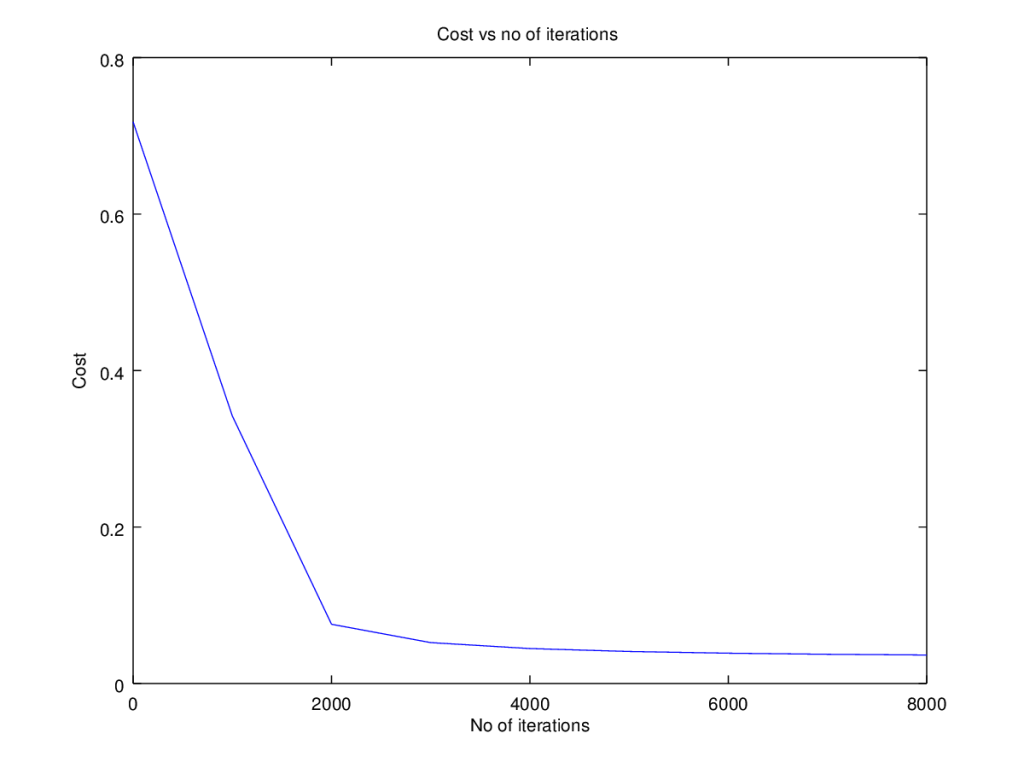
keep\_prob=1,

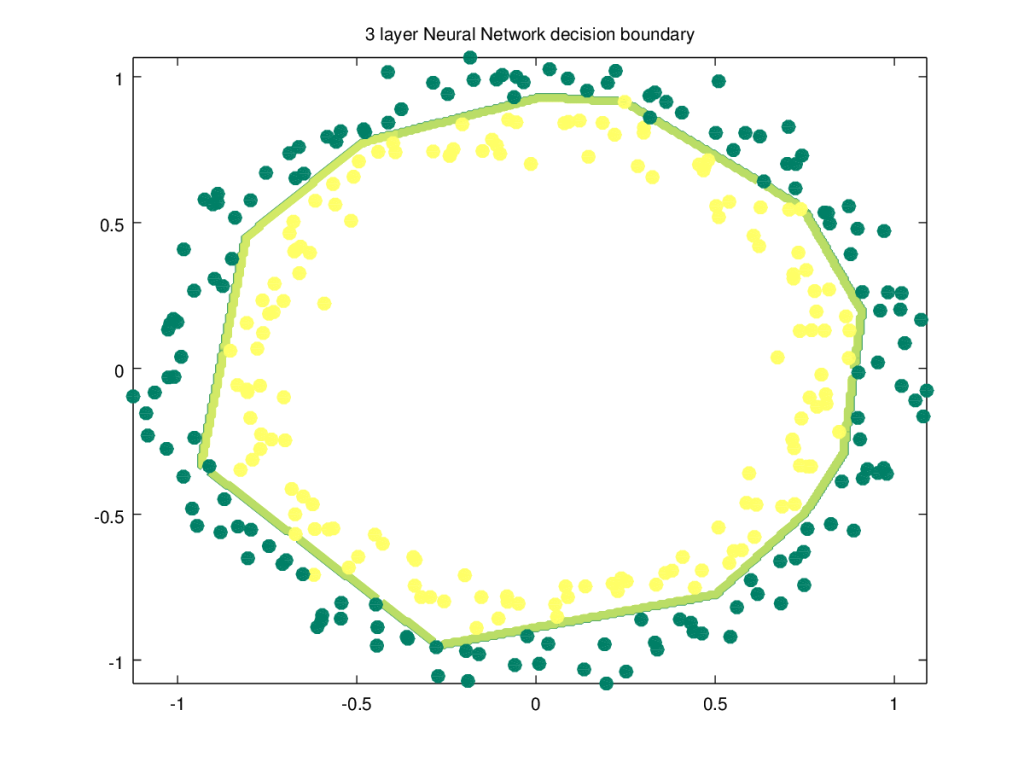
numIterations = 8000,

initType="Xav");

plotCostVsIterations(8000,costs)

plotDecisionBoundary(data,weights, biases,keep\_prob=1,hiddenActivationFunc="relu")





**2.1a Regularization : Circles data – Python**

The cross entropy cost for Logistic classification is given as J = \frac{1}{m}\sum_{i=1}^{m}y^{i}log((a^{L})^{(i)}) - (1-y^{i})log((a^{L})^{(i)})The regularized L2 cost is given by J = \frac{1}{m}\sum_{i=1}^{m}y^{i}log((a^{L})^{(i)}) - (1-y^{i})log((a^{L})^{(i)}) + \frac{\lambda}{2m}\sum \sum \sum W_{kj}^{l}

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import sklearn.linear\_model

import pandas as pd

import sklearn

import sklearn.datasets

exec(open("DLfunctions61.py").read())

#Load the data

train\_X, train\_Y, test\_X, test\_Y = load\_dataset()

# Set the layers dimensions

layersDimensions = [2,7,1]

# Train a deep learning network

parameters = L\_Layer\_DeepModel(train\_X, train\_Y, layersDimensions, hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",learningRate = 0.6, lambd=0.1, num\_iterations = 9000,

initType="default", print\_cost = True,figure="fig7.png")

# Clear the plot

plt.clf()

plt.close()

# Plot the decision boundary

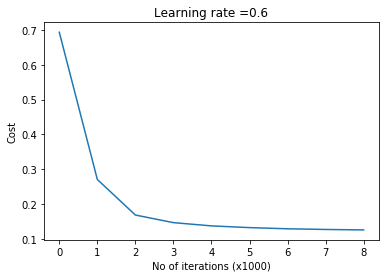
plot\_decision\_boundary(lambda x: predict(parameters, x.T), train\_X, train\_Y,str(0.6),figure1="fig8.png")

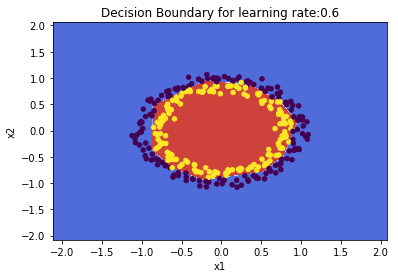
plt.clf()

plt.close()

#Plot the decision boundary

plot\_decision\_boundary(lambda x: predict(parameters, x.T,keep\_prob=0.9), train\_X, train\_Y,str(2.2),"fig8.png",)





**2.1 b Regularization: Spiral data  – Python**

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import sklearn.linear\_model

import pandas as pd

import sklearn

import sklearn.datasets

exec(open("DLfunctions61.py").read())

N = 100 # number of points per class

D = 2 # dimensionality

K = 3 # number of classes

X = np.zeros((N\*K,D)) # data matrix (each row = single example)

y = np.zeros(N\*K, dtype='uint8') # class labels

for j in range(K):

ix = range(N\*j,N\*(j+1))

r = np.linspace(0.0,1,N) # radius

t = np.linspace(j\*4,(j+1)\*4,N) + np.random.randn(N)\*0.2 # theta

X[ix] = np.c\_[r\*np.sin(t), r\*np.cos(t)]

y[ix] = j

# Plot the data

plt.scatter(X[:, 0], X[:, 1], c=y, s=40, cmap=plt.cm.Spectral)

plt.clf()

plt.close()

#Set layer dimensions

layersDimensions = [2,100,3]

y1=y.reshape(-1,1).T

# Train a deep learning network

parameters = L\_Layer\_DeepModel(X.T, y1, layersDimensions, hiddenActivationFunc='relu', outputActivationFunc="softmax",

learningRate = 1,lambd=1e-3, num\_iterations = 5000, print\_cost = True,figure="fig9.png")

plt.clf()

plt.close()

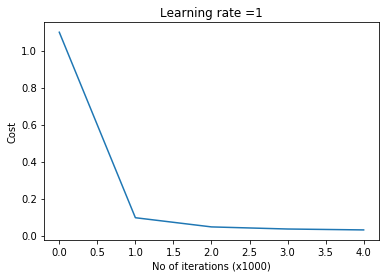
W1=parameters['W1']

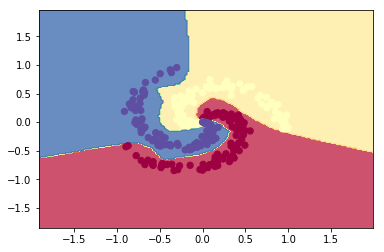
b1=parameters['b1']

W2=parameters['W2']

b2=parameters['b2']

plot\_decision\_boundary1(X, y1,W1,b1,W2,b2,figure2="fig10.png")





**2.2a Regularization: Circles data  – R**

source("DLfunctions61.R")

#Load data

df=read.csv("circles.csv",header=FALSE)

z <- as.matrix(read.csv("circles.csv",header=FALSE))

x <- z[,1:2]

y <- z[,3]

X <- t(x)

Y <- t(y)

#Set layer dimensions

layersDimensions = c(2,11,1)

# Train a deep learning network

retvals = L\_Layer\_DeepModel(X, Y, layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

lambd=0.1,

numIterations = 9000,

initType="default",

print\_cost = True)

#Plot the cost vs iterations

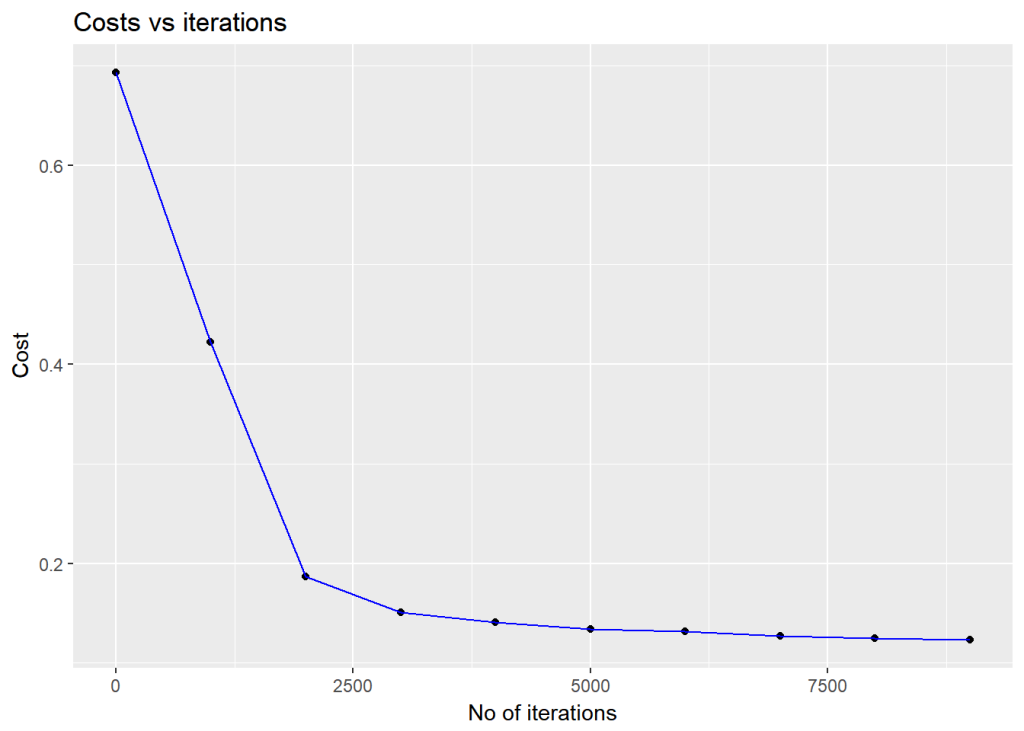
iterations <- seq(0,9000,1000)

costs=retvals$costs

df=data.frame(iterations,costs)

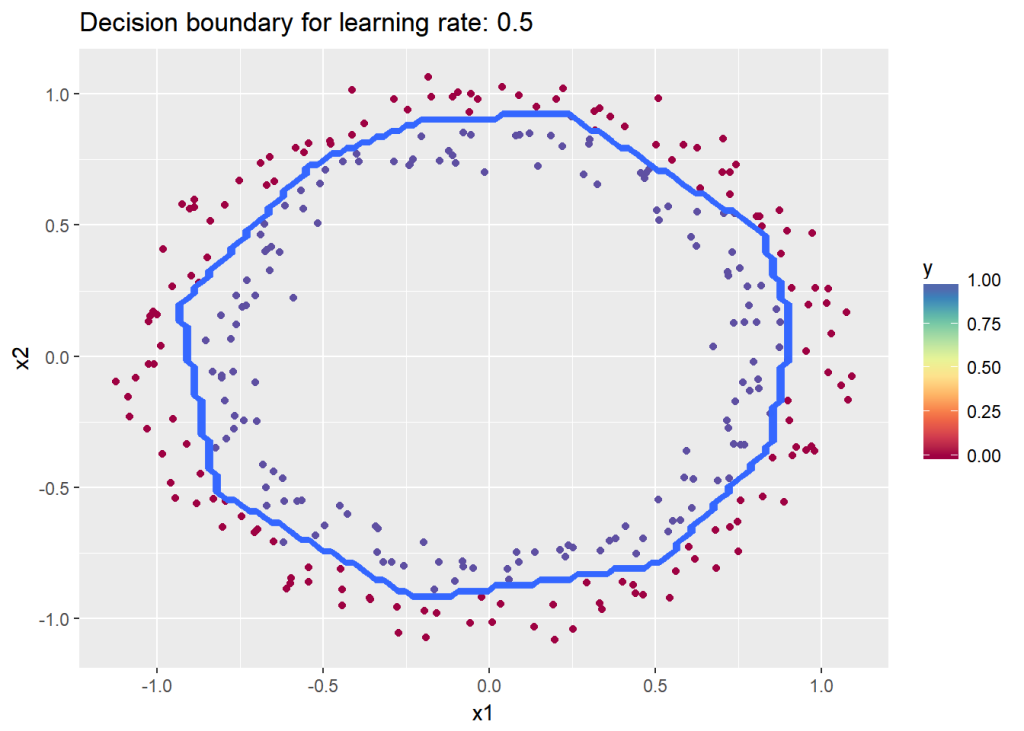
ggplot(df,aes(x=iterations,y=costs)) + geom\_point() + geom\_line(color="blue") +

ggtitle("Costs vs iterations") + xlab("No of iterations") + ylab("Cost")



# Plot the decision boundary

plotDecisionBoundary(z,retvals,hiddenActivationFunc="relu",0.5)



**2.2b Regularization:Spiral data – R**

# Read the spiral dataset

#Load the data

source("DLfunctions61.R")

Z <- as.matrix(read.csv("spiral.csv",header=FALSE))

# Setup the data

X <- Z[,1:2]

y <- Z[,3]

X <- t(X)

Y <- t(y)

layersDimensions = c(2, 100, 3)

# Train a deep learning network

retvals = L\_Layer\_DeepModel(X, Y, layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="softmax",

learningRate = 0.5,

lambd=0.01,

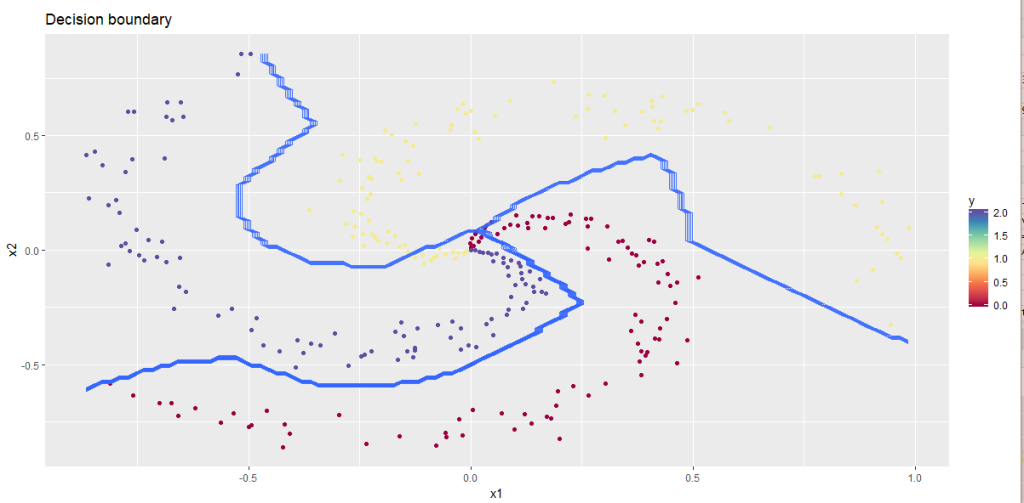
numIterations = 9000,

print\_cost = True)

print\_cost = True)

parameters<-retvals$parameters

plotDecisionBoundary1(Z,parameters)

  
**2.3a Regularization: Circles data – Octave**

source("DL61functions.m")

#Load data

data=csvread("circles.csv");

X=data(:,1:2);

Y=data(:,3);

layersDimensions = [2 11 1]; #tanh=-0.5(ok), #relu=0.1 best!

# Train a deep learning network

[weights biases costs]=L\_Layer\_DeepModel(X', Y', layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

lambd=0.2,

keep\_prob=1,

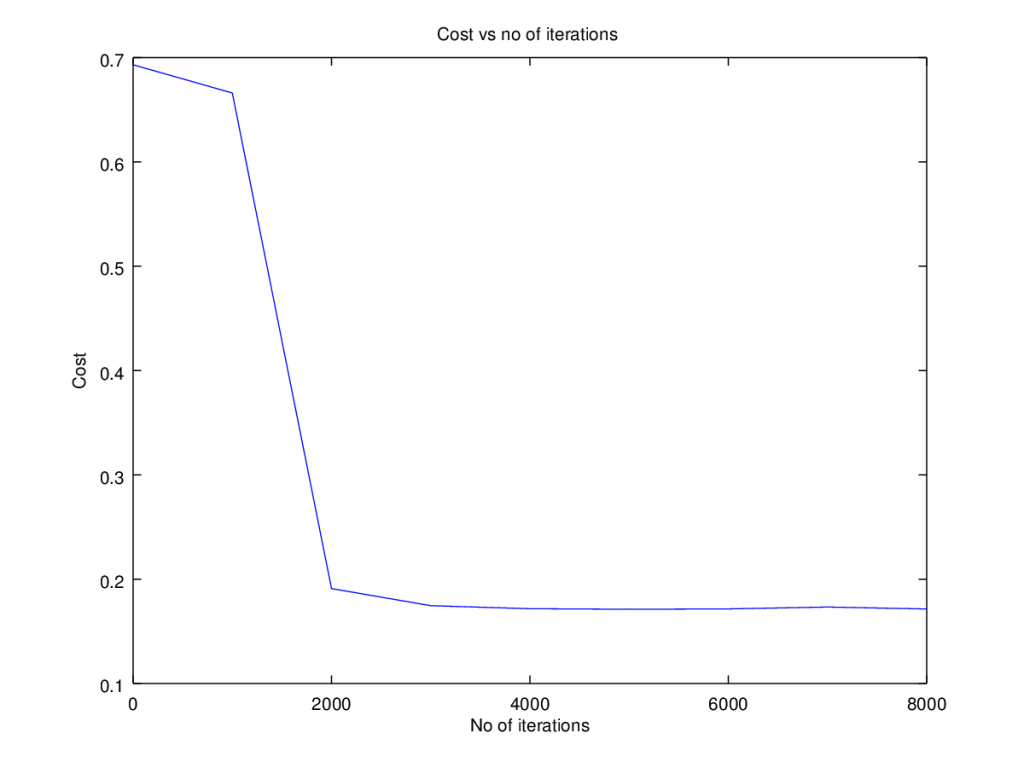
numIterations = 8000,

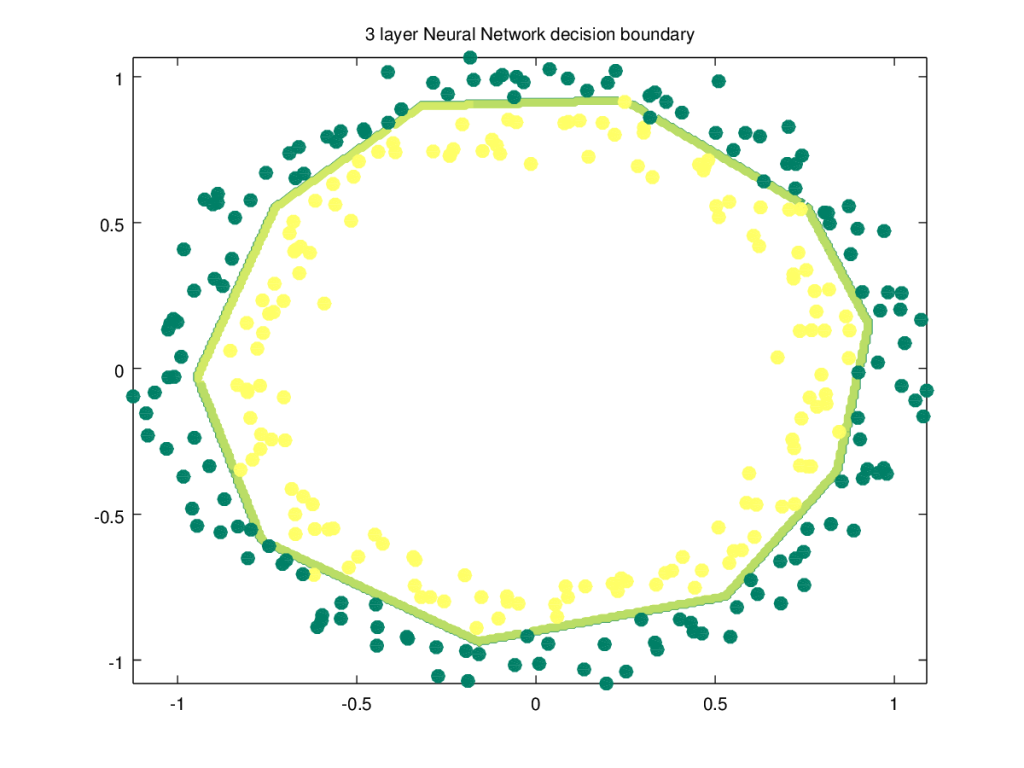
initType="default");

plotCostVsIterations(8000,costs)

#Plot decision boundary

plotDecisionBoundary(data,weights, biases,keep\_prob=1,hiddenActivationFunc="relu")





**2.3b Regularization:Spiral data  2 – Octave**

source("DL61functions.m")

data=csvread("spiral.csv");

# Setup the data

X=data(:,1:2);

Y=data(:,3);

layersDimensions = [2 100 3]

# Train a deep learning network

[weights biases costs]=L\_Layer\_DeepModel(X', Y', layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="softmax",

learningRate = 0.6,

lambd=0.2,

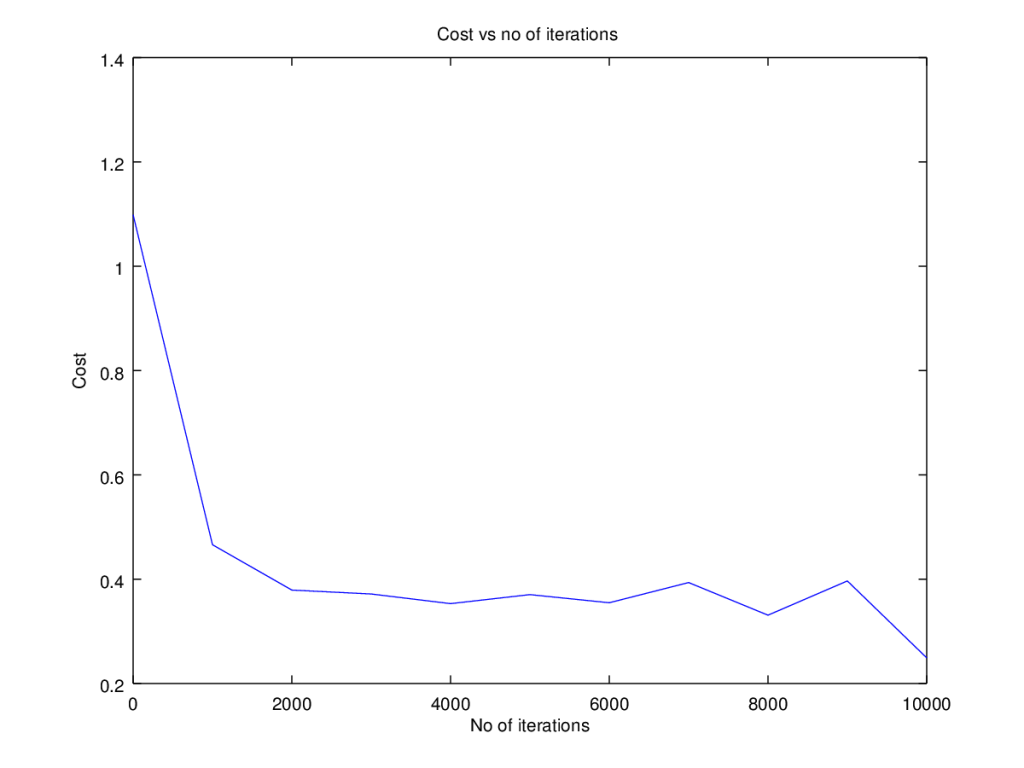
keep\_prob=1,

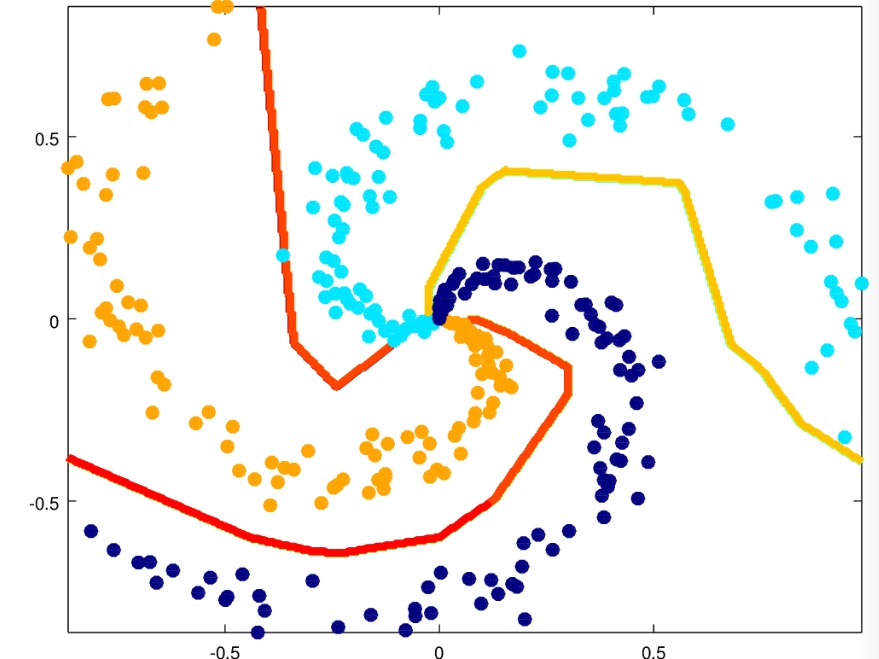
numIterations = 10000);

plotCostVsIterations(10000,costs)

#Plot decision boundary

plotDecisionBoundary1(data,weights, biases,keep\_prob=1,hiddenActivationFunc="relu")





**3.1 a Dropout: Circles data – Python**

The ‘dropout’ regularization technique was used with great effectiveness, to prevent overfitting  by Alex Krizhevsky, Ilya Sutskever and Prof Geoffrey E. Hinton in the [Imagenet classification with Deep Convolutional Neural Networks](https://www.nvidia.cn/content/tesla/pdf/machine-learning/imagenet-classification-with-deep-convolutional-nn.pdf)

The technique of dropout works by dropping a random set of activation units in each hidden layer, based on a ‘keep\_prob’ criteria in the forward propagation cycle. Here is the code for Octave. A ‘dropoutMat’ is created for each layer which specifies which units to drop **Note**: The same ‘dropoutMat has to be used which computing the gradients in the backward propagation cycle. Hence the dropout matrices are stored in a cell array.

 for l =1:L-1

...

D=rand(size(A)(1),size(A)(2));

D = (D < keep\_prob) ;

# Zero out some hidden units

A= A .\* D;

# Divide by keep\_prob to keep the expected value of A the same

A = A ./ keep\_prob;

# Store D in a dropoutMat cell array

dropoutMat{l}=D;

...

endfor

In the backward propagation cycle we have

for l =(L-1):-1:1

...

D = dropoutMat{l};

# Zero out the dAl based on same dropout matrix

dAl= dAl .\* D;

# Divide by keep\_prob to maintain the expected value

dAl = dAl ./ keep\_prob;

...

endfor

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import sklearn.linear\_model

import pandas as pd

import sklearn

import sklearn.datasets

exec(open("DLfunctions61.py").read())

#Load the data

train\_X, train\_Y, test\_X, test\_Y = load\_dataset()

# Set the layers dimensions

layersDimensions = [2,7,1]

# Train a deep learning network

parameters = L\_Layer\_DeepModel(train\_X, train\_Y, layersDimensions, hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",learningRate = 0.6, keep\_prob=0.7, num\_iterations = 9000,

initType="default", print\_cost = True,figure="fig11.png")

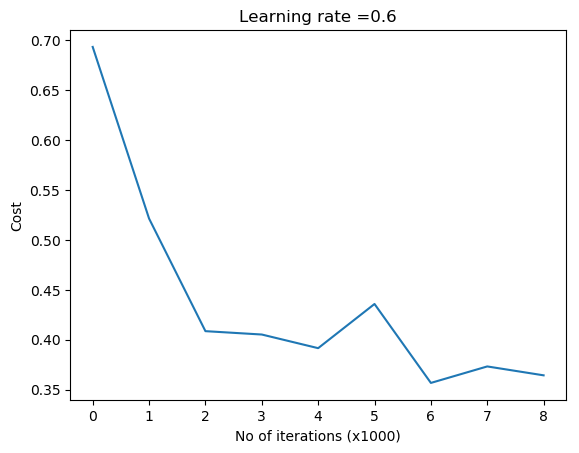
# Clear the plot

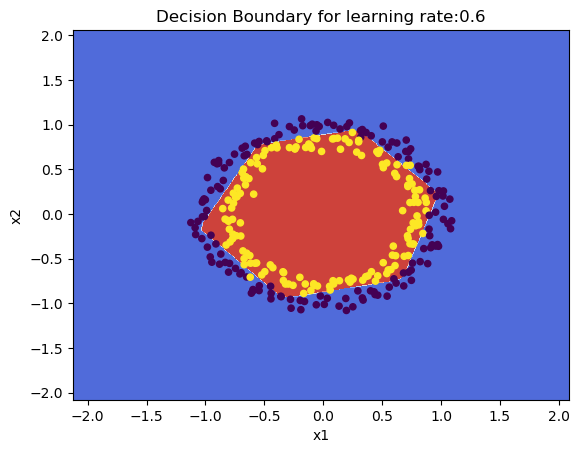
plt.clf()

plt.close()

# Plot the decision boundary

plot\_decision\_boundary(lambda x: predict(parameters, x.T,keep\_prob=0.7), train\_X, train\_Y,str(0.6),figure1="fig12.png")





**3.1b Dropout: Spiral data – Python**

import numpy as np

import matplotlib

import matplotlib.pyplot as plt

import sklearn.linear\_model

import pandas as pd

import sklearn

import sklearn.datasets

exec(open("DLfunctions61.py").read())

# Create an input data set - Taken from CS231n Convolutional Neural networks,

# http://cs231n.github.io/neural-networks-case-study/

N = 100 # number of points per class

D = 2 # dimensionality

K = 3 # number of classes

X = np.zeros((N\*K,D)) # data matrix (each row = single example)

y = np.zeros(N\*K, dtype='uint8') # class labels

for j in range(K):

ix = range(N\*j,N\*(j+1))

r = np.linspace(0.0,1,N) # radius

t = np.linspace(j\*4,(j+1)\*4,N) + np.random.randn(N)\*0.2 # theta

X[ix] = np.c\_[r\*np.sin(t), r\*np.cos(t)]

y[ix] = j

# Plot the data

plt.scatter(X[:, 0], X[:, 1], c=y, s=40, cmap=plt.cm.Spectral)

plt.clf()

plt.close()

layersDimensions = [2,100,3]

y1=y.reshape(-1,1).T

# Train a deep learning network

parameters = L\_Layer\_DeepModel(X.T, y1, layersDimensions, hiddenActivationFunc='relu', outputActivationFunc="softmax",

learningRate = 1,keep\_prob=0.9, num\_iterations = 5000, print\_cost = True,figure="fig13.png")

plt.clf()

plt.close()

W1=parameters['W1']

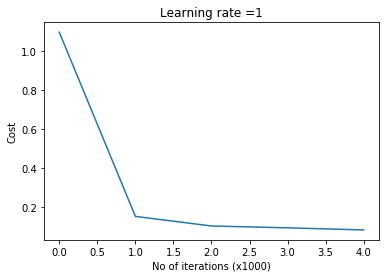
b1=parameters['b1']

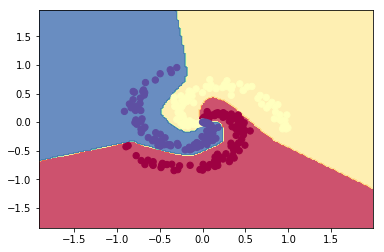
W2=parameters['W2']

b2=parameters['b2']

#Plot decision boundary

plot\_decision\_boundary1(X, y1,W1,b1,W2,b2,figure2="fig14.png")





**3.2a Dropout: Circles data – R**

source("DLfunctions61.R")

#Load data

df=read.csv("circles.csv",header=FALSE)

z <- as.matrix(read.csv("circles.csv",header=FALSE))

x <- z[,1:2]

y <- z[,3]

X <- t(x)

Y <- t(y)

layersDimensions = c(2,11,1)

# Train a deep learning network

retvals = L\_Layer\_DeepModel(X, Y, layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

keep\_prob=0.8,

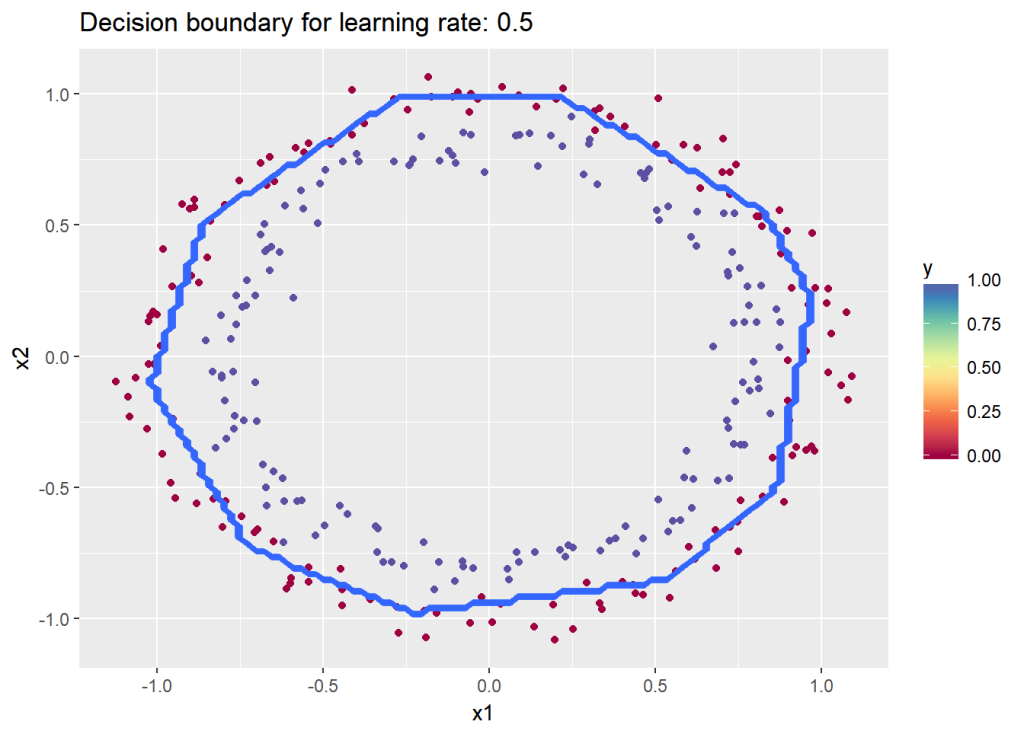
numIterations = 9000,

initType="default",

print\_cost = True)

# Plot the decision boundary

plotDecisionBoundary(z,retvals,keep\_prob=0.6, hiddenActivationFunc="relu",0.5)



**3.2b Dropout: Spiral data – R**

# Read the spiral dataset

source("DLfunctions61.R")

# Load data

Z <- as.matrix(read.csv("spiral.csv",header=FALSE))

# Setup the data

X <- Z[,1:2]

y <- Z[,3]

X <- t(X)

Y <- t(y)

# Train a deep learning network

retvals = L\_Layer\_DeepModel(X, Y, layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="softmax",

learningRate = 0.1,

keep\_prob=0.90,

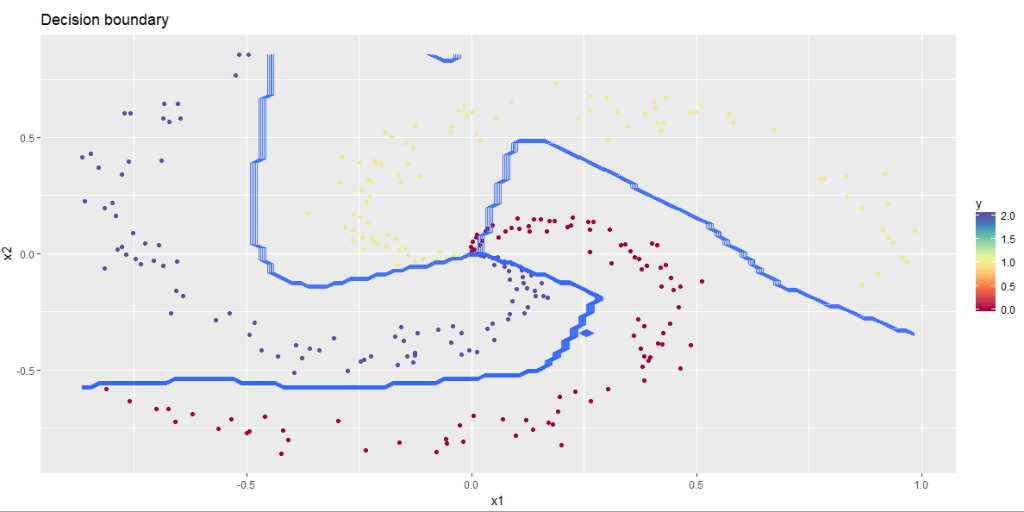
numIterations = 9000,

print\_cost = True)

parameters<-retvals$parameters

#Plot decision boundary

plotDecisionBoundary1(Z,parameters)



**3.3a Dropout: Circles data – Octave**

data=csvread("circles.csv");

X=data(:,1:2);

Y=data(:,3);

layersDimensions = [2 11 1]; #tanh=-0.5(ok), #relu=0.1 best!

# Train a deep learning network

[weights biases costs]=L\_Layer\_DeepModel(X', Y', layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="sigmoid",

learningRate = 0.5,

lambd=0,

keep\_prob=0.8,

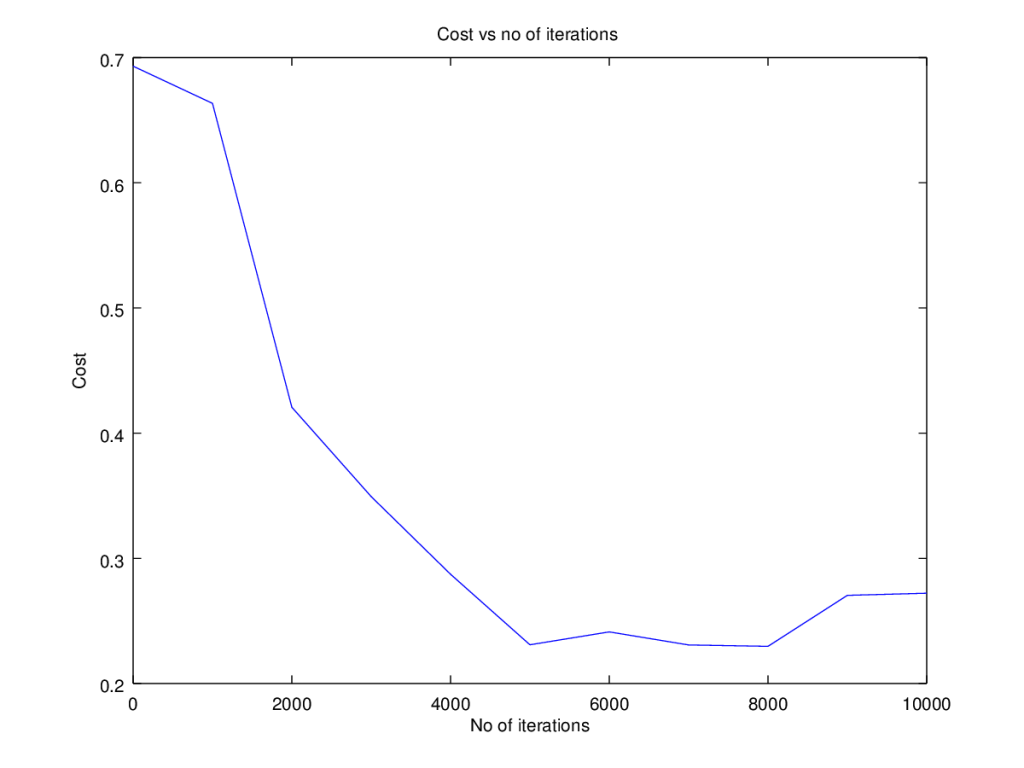
numIterations = 10000,

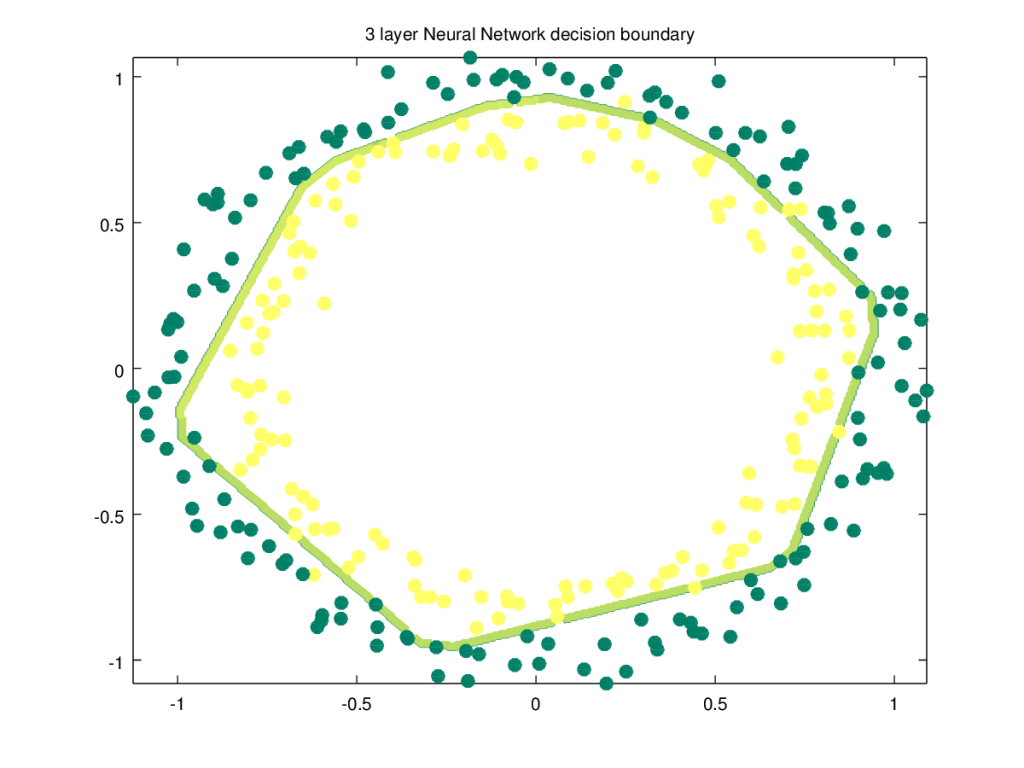
initType="default");

plotCostVsIterations(10000,costs)

#Plot decision boundary

plotDecisionBoundary1(data,weights, biases,keep\_prob=1, hiddenActivationFunc="relu")





**3.3b Dropout  Spiral data – Octave**

source("DL61functions.m")

data=csvread("spiral.csv");

# Setup the data

X=data(:,1:2);

Y=data(:,3);

layersDimensions = [numFeats numHidden numOutput];

# Train a deep learning network

[weights biases costs]=L\_Layer\_DeepModel(X', Y', layersDimensions,

hiddenActivationFunc='relu',

outputActivationFunc="softmax",

learningRate = 0.1,

lambd=0,

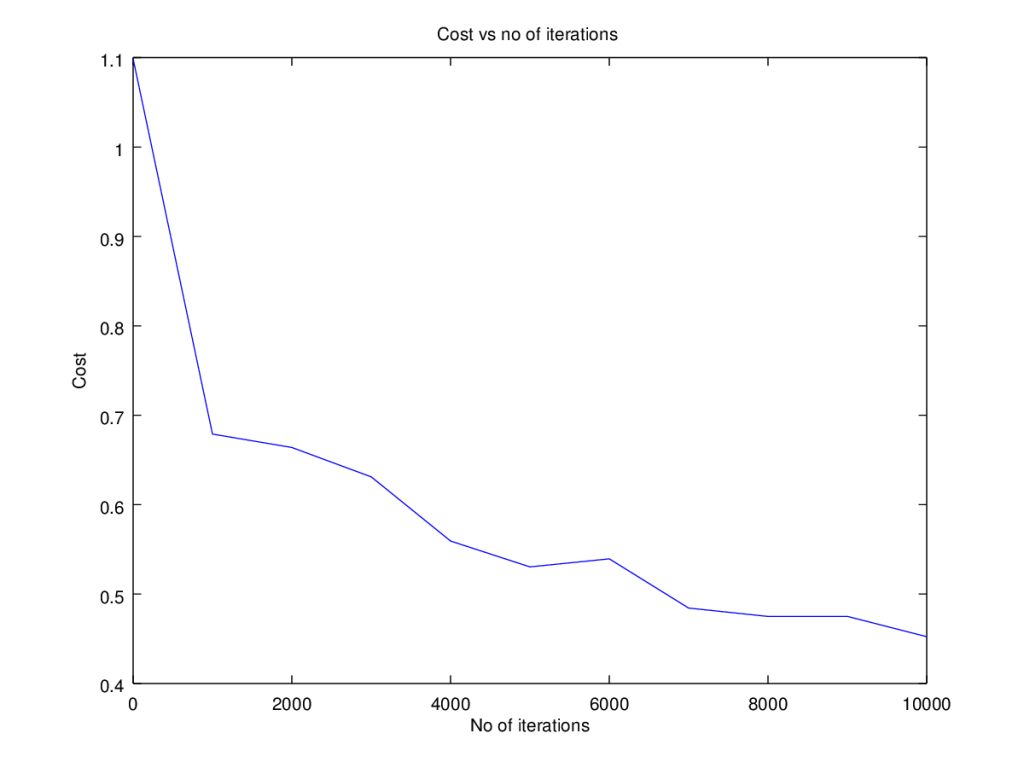
keep\_prob=0.8,

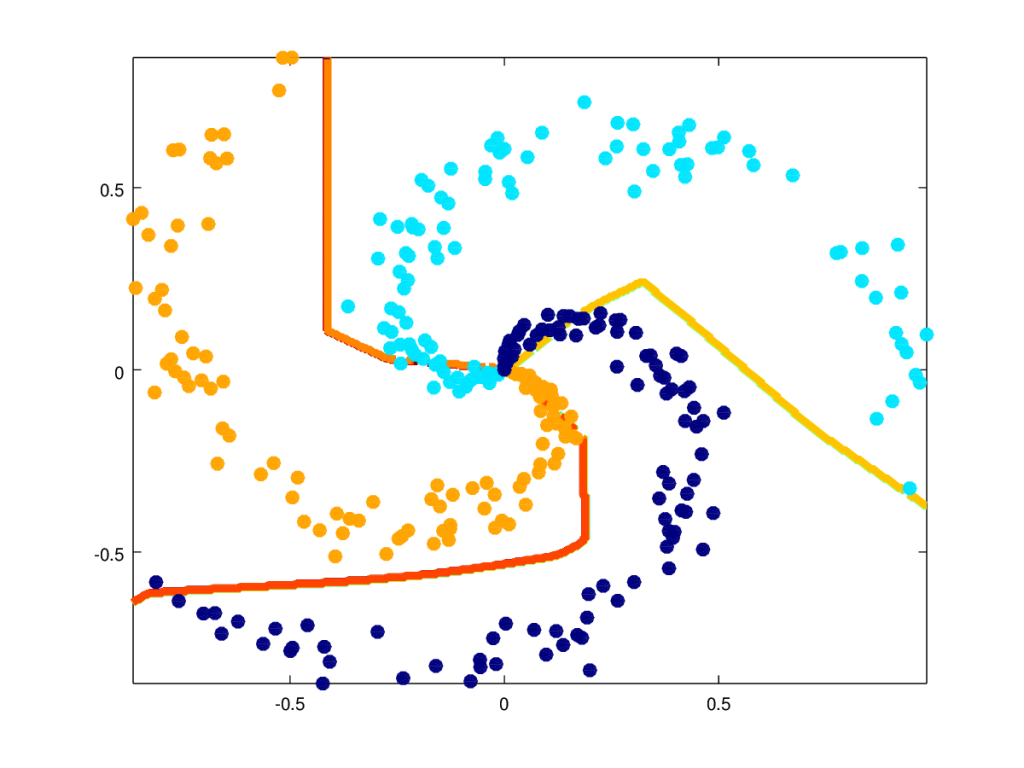
numIterations = 10000);

plotCostVsIterations(10000,costs)

#Plot decision boundary

plotDecisionBoundary1(data,weights, biases,keep\_prob=1, hiddenActivationFunc="relu")





**Conclusion**  
This post further enhances my earlier L-Layer generic implementation of a Deep Learning network to include options for initialization techniques, L2 regularization or dropout regularization