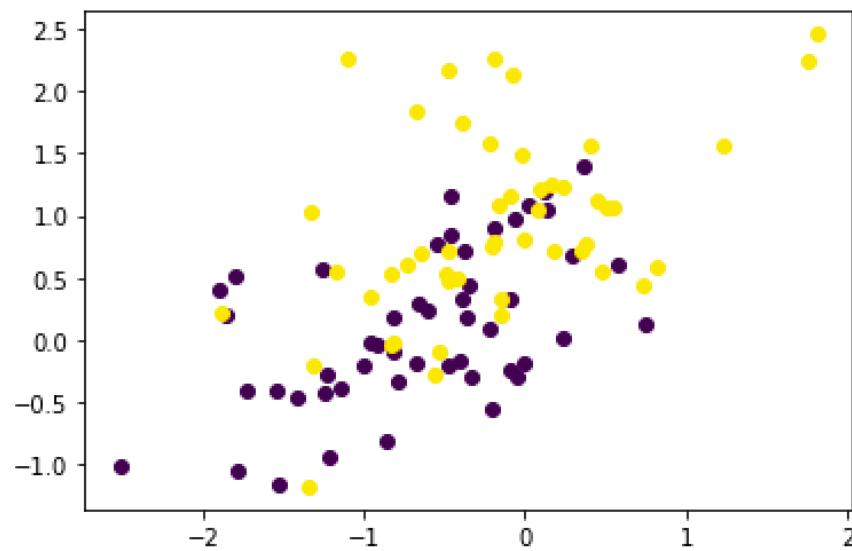
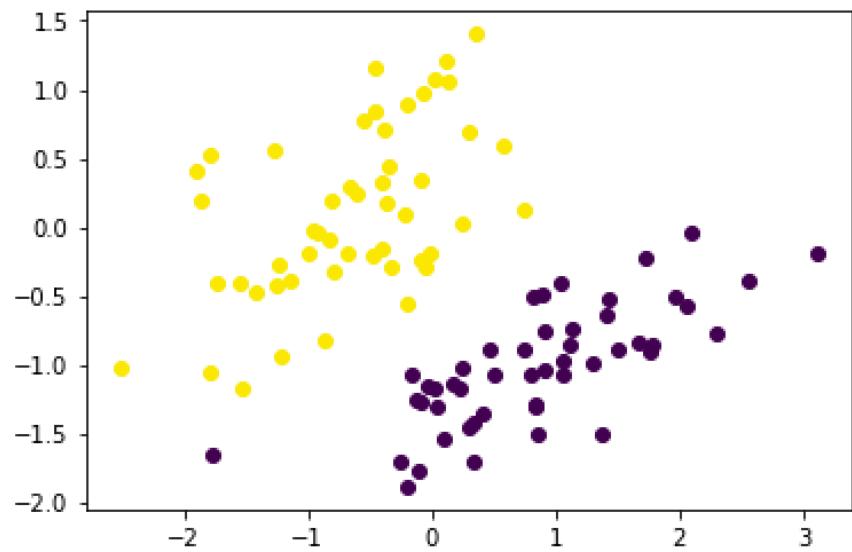


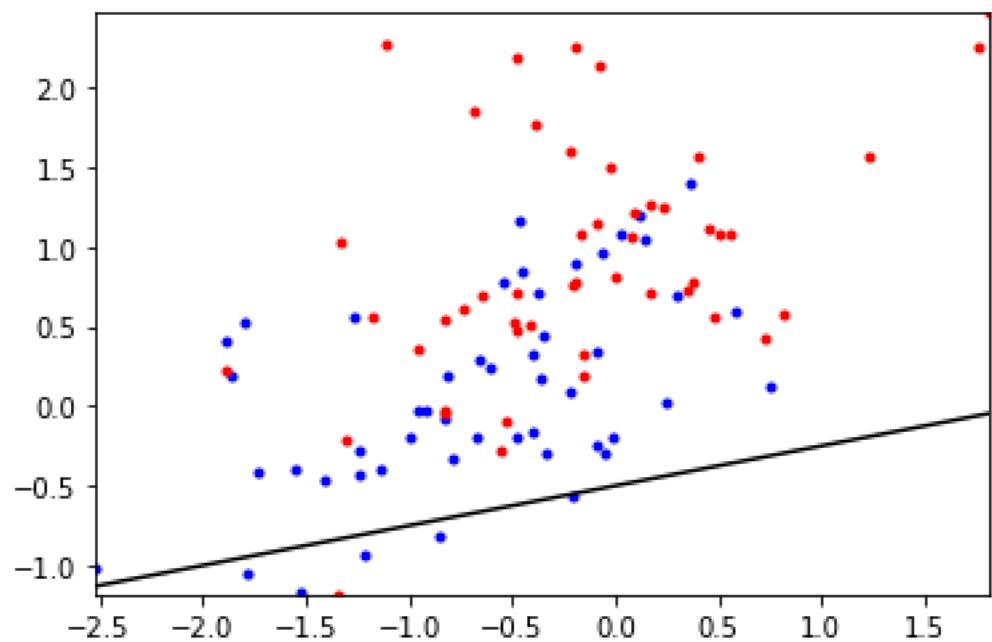
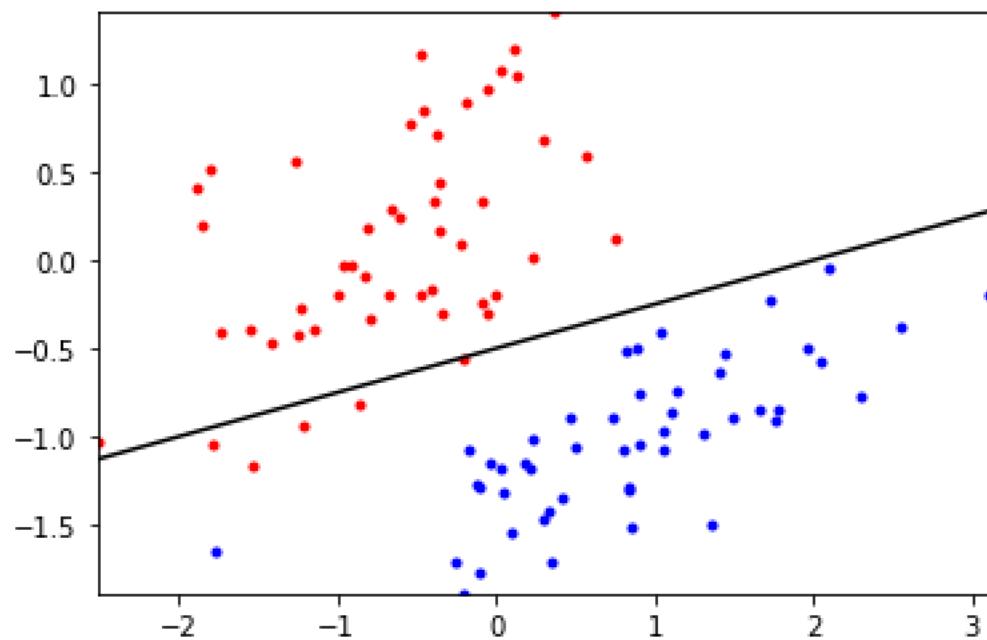
Mohamed Kharaev
43121144

CS 178 HW 3

Part 1



Part 2

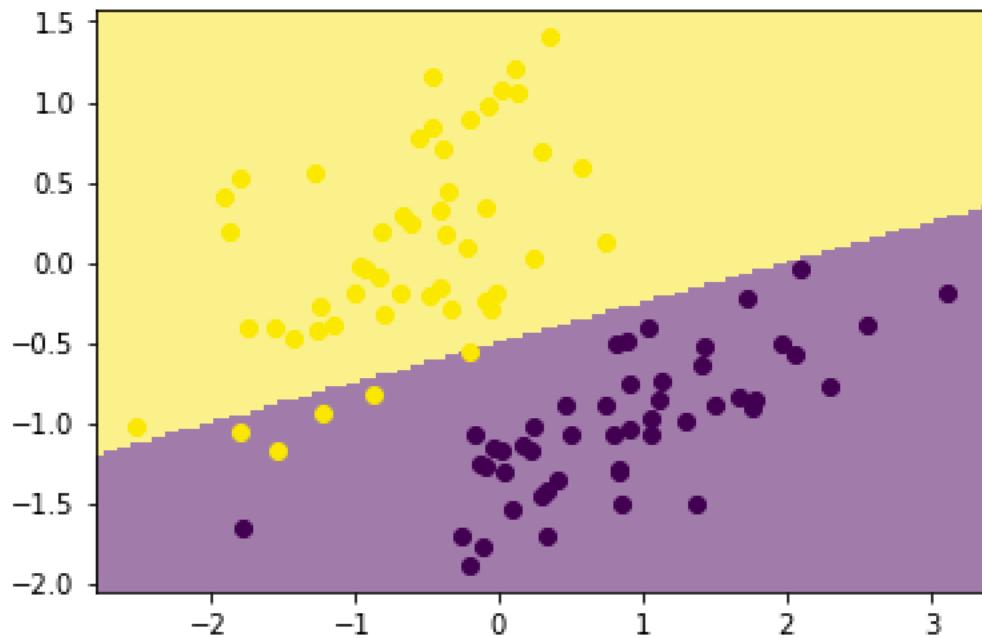


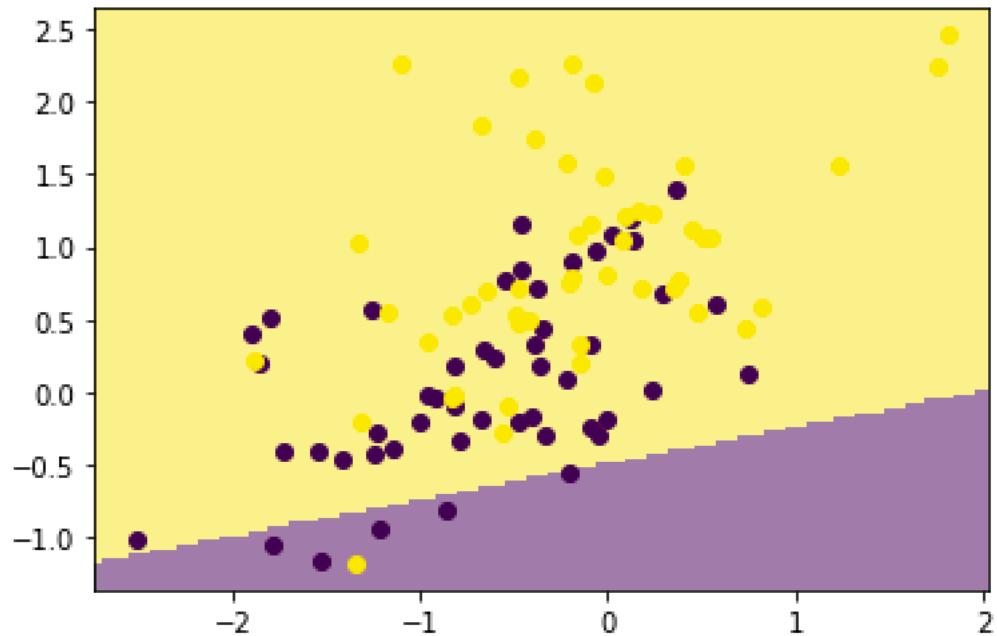
Part 3
ERROR: 0.050505050505050504

ERROR: 0.464646464646464

```
def predict(self, X):
    """ Return the predicted class of each data point in X"""
    ## TODO: compute linear response r[i] = theta0 + theta1 X[i,1] + theta2 X[i,2] + ... for each i
    ## TODO: if z[i] > 0, predict class 1: Yhat[i] = self.classes[1]
    ## else predict class 0: Yhat[i] = self.classes[0]
    Yhat = []
    for i in range(len(X)):
        if (self.theta[0] + (self.theta[1] * X[i][0]) + (self.theta[2] * X[i][1])) > 0:
            Yhat.append(self.classes[1])
        else:
            Yhat.append(self.classes[0])
    return np.array(Yhat)
```

Part 4





Part 5

CS 178 HW 3

$$\begin{aligned}
 J(\theta) &= -y^{(i)} \ln(\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) - (1-y^{(i)}) \ln(1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \\
 J_i(\theta) &= -y^{(i)} \ln(\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) - (1-y^{(i)}) \ln(1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \\
 \frac{\partial J}{\partial \theta_0} &= -y^{(i)} \times \frac{1}{\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)} \times \sigma'(x_0\theta_0 + x_1\theta_1 + x_2\theta_2) \\
 &\quad \times (1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \times x_0 \\
 &= -y^{(i)} \times (1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \times x_0 \\
 &= (1-y^{(i)}) \times \frac{1}{1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)} \times (1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \\
 &\quad \times (1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \times x_0 \\
 &= (1-y^{(i)}) \times (1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \times x_0 \\
 -y^{(i)} \times (1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \times x_0 &+ (1-y^{(i)}) \times (\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2)) \times x_0 \\
 \frac{\partial J}{\partial \theta_0} &= x_0 \times ((1-y^{(i)})\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2) - (y^{(i)})(1-\sigma(x_0\theta_0 + x_1\theta_1 + x_2\theta_2))) \\
 \frac{\partial J}{\partial \theta_1} &= x_1 \times \\
 \frac{\partial J}{\partial \theta_2} &= x_2 \times
 \end{aligned}$$

```

def train(self, X, Y, initStep=1.0, stopTol=1e-4, stopEpochs=5000, plot=None):
    """ Train the logistic regression using stochastic gradient descent """
    M,N = X.shape;          # initialize the model if necessary!
    self.classes = np.unique(Y); # Y may have two classes, any values
    XX = np.hstack((np.ones((M,1)),X)) # XX is X, but with an extra column of ones
    YY = ml.toIndex(Y,self.classes); # YY is Y, but with canonical values 0 or 1
    if len(self.theta)!=N+1: self.theta=np.random.rand(N+1);
    # init loop variables:
    epoch=0; done=False; Jnll=[]; J01=[];
    while not done:
        stepsize = initStep*2.0/(2.0+epoch); epoch+=1; # update stepsize
        # Do an SGD pass through the entire data set:
        Jsur = 0
        for i in np.random.permutation(M):
            ri = (self.theta[0] * XX[i,0]) + (self.theta[1] * XX[i, 1]) + (self.theta[2] * XX[i, 2]);      # TODO: compute linear response r(x)
            gradi = np.array([
                XX[i,0] * ((1 - YY[i]) * (self.sigmoid(ri)) - (YY[i]) * (1 - self.sigmoid(ri))),
                XX[i,1] * ((1 - YY[i]) * (self.sigmoid(ri)) - (YY[i]) * (1 - self.sigmoid(ri))),
                XX[i,2] * ((1 - YY[i]) * (self.sigmoid(ri)) - (YY[i]) * (1 - self.sigmoid(ri)))));           # TODO: compute gradient of NLL loss
            self.theta -= stepsize * gradi; # take a gradient step
            if (YY[i] == 1):
                Jsur = np.add(Jsur, np.log10(self.sigmoid(ri)))
            else:
                Jsur = np.add(Jsur, 1 - np.log10(1 - self.sigmoid(ri)))

        J01.append( self.err(X,Y) ) # evaluate the current error rate
        ## TODO: compute surrogate loss (logistic negative log-likelihood)
        ## Jsur = sum_i [ (log si) if yi==1 else (log(1-si)) ]
        Jsur = Jsur / M
        Jnll.append(Jsur) # TODO evaluate the current NLL loss
        plt.figure(1); plt.plot(Jnll,'b-',J01,'r-'); plt.draw(); # plot losses
        if N==2: plt.figure(2); self.plotBoundary(X,Y); plt.draw(); # & predictor if 2D
        plt.pause(.01); # let OS draw the plot

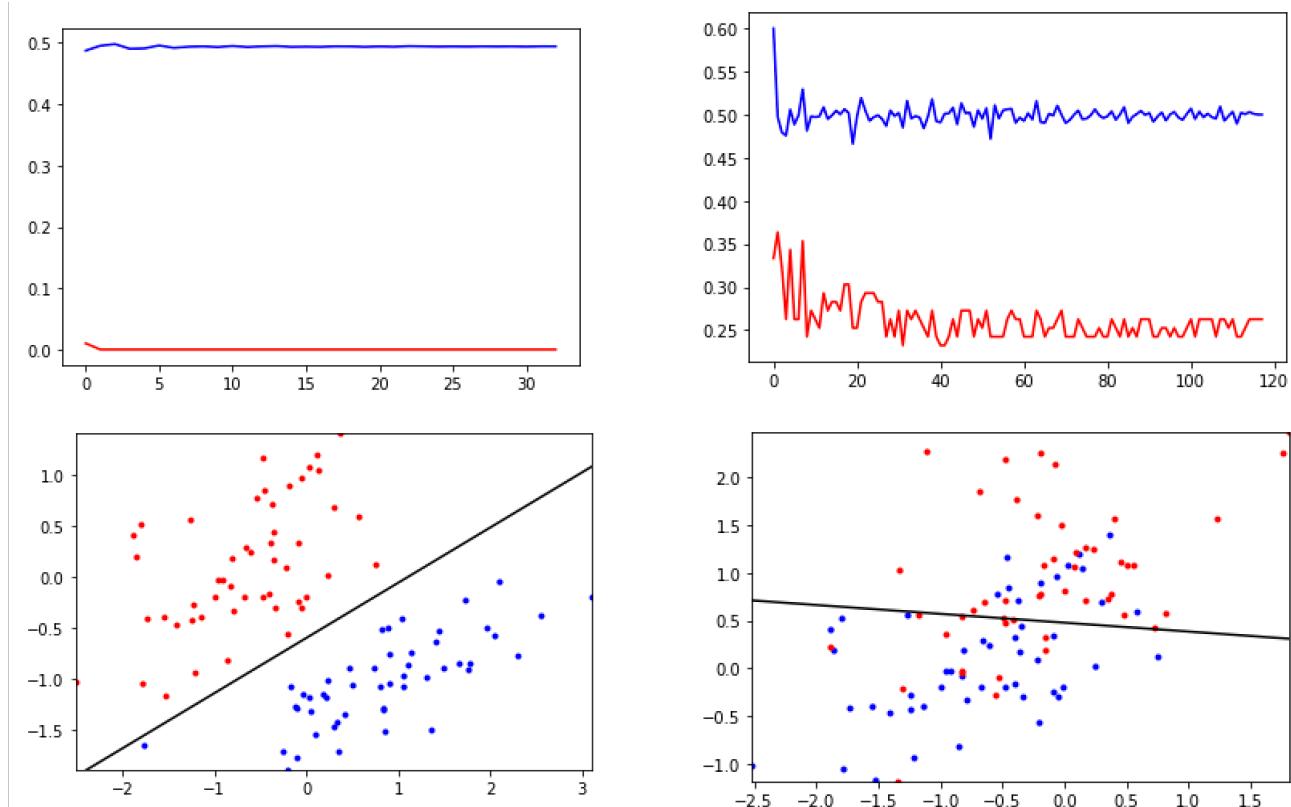
        ## For debugging: you may want to print current parameters & losses
        # print self.theta, '=>', Jnll[-1], ' / ', J01[-1]
        # raw_input() # pause for keystroke

        # TODO check stopping criteria: exit if exceeded # of epochs ( > stopEpochs )
        # or if Jnll not changing between epochs ( < stopTol )
        if epoch > stopEpochs:
            done = True
        if len(Jnll) > 2:
            if abs(Jnll[-1] - Jnll[-2]) < stopTol:
                done = True

    def sigmoid(self, r):
        return ((1 + math.exp(-1 * r)) ** -1);

```

Part 6



PROBLEM 2

-A-

1. Yes, having an 'a' value of 0 and any positive 'b' value will make $T[z] = 1$ for any $x_1 > 0$
2. Yes, positive values for 'a', 'b', and 'c' will always make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$
3. Yes, having any positive value for 'c' will make $T[z] = 1$ for any x_1 and x_2 , because $(x_1 - a)^2$ and $(x_2 - b)^2$ will always be ≥ 0 . The sum will be positive
4. Yes, having positive values for 'a', 'b', 'c', and 'd' will make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$

-B-

1. Yes, having an 'a' value of 0 and any positive 'b' value will make $T[z] = 1$ for any $x_1 > 0$
2. Yes, positive values for 'a', 'b', and 'c' will always make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$
3. Yes, having any positive value for 'c' will make $T[z] = 1$ for any x_1 and x_2 , because $(x_1 - a)^2$ and $(x_2 - b)^2$ will always be ≥ 0 . The sum will be positive
4. Yes, having positive values for 'a', 'b', 'c', and 'd' will make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$

-C-

1. Yes, having an 'a' value of 0 and any positive 'b' value will make $T[z] = 1$ for any $x_1 > 0$
2. Yes, positive values for 'a', 'b', and 'c' will always make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$
3. Yes, having any positive value for 'c' will make $T[z] = 1$ for any x_1 and x_2 , because $(x_1 - a)^2$ and $(x_2 - b)^2$ will always be ≥ 0 . The sum will be positive
4. Yes, having positive values for 'a', 'b', 'c', and 'd' will make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$

-D-

1. Yes, having an 'a' value of 0 and any positive 'b' value will make $T[z] = 1$ for any $x_1 > 0$
2. Yes, positive values for 'a', 'b', and 'c' will always make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$
3. Yes, having any positive value for 'c' will make $T[z] = 1$ for any x_1 and x_2 , because $(x_1 - a)^2$ and $(x_2 - b)^2$ will always be ≥ 0 . The sum will be positive
4. Yes, having positive values for 'a', 'b', 'c', and 'd' will make $T[z] = 1$ for any $x_1 > 0 \& x_2 > 0$

I worked by myself