CS189–FALL 2015 — Homework 3 Write up

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Problem 1. solution

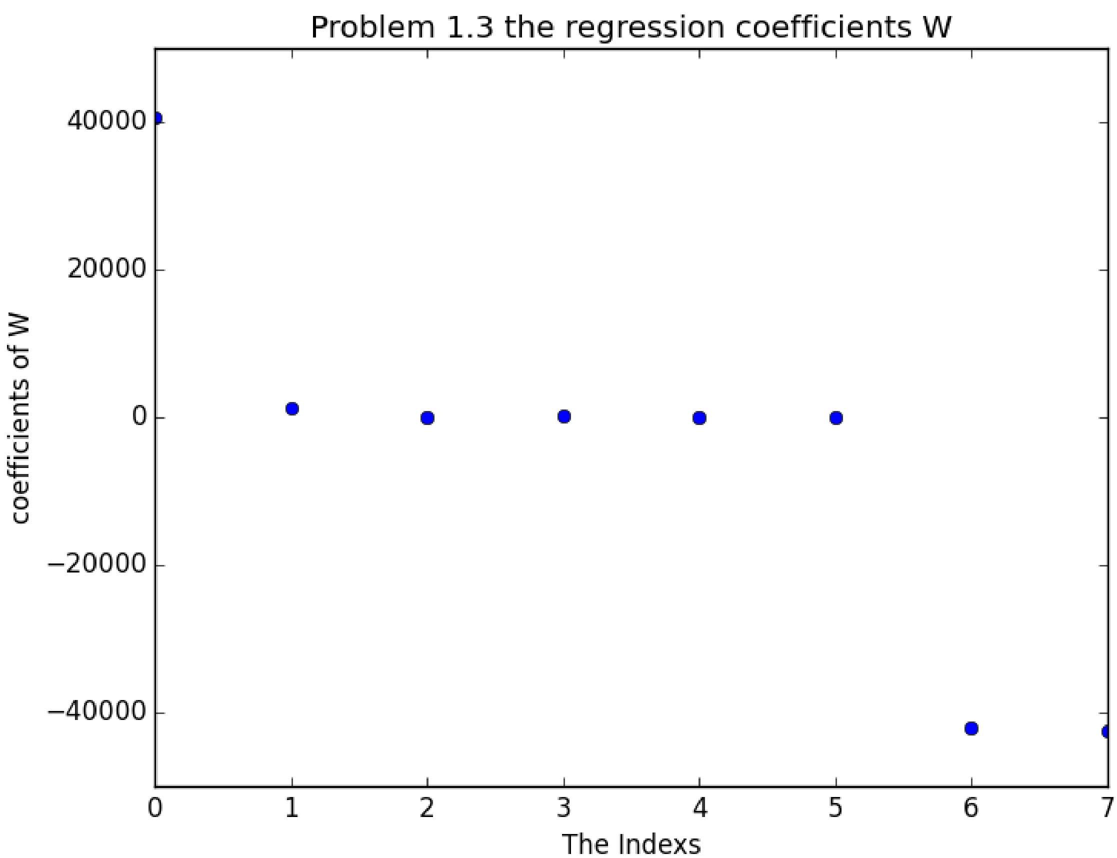
1 . See problem1.py file

2 . The residual sum of squares(RSS) is 5.79495380e+12

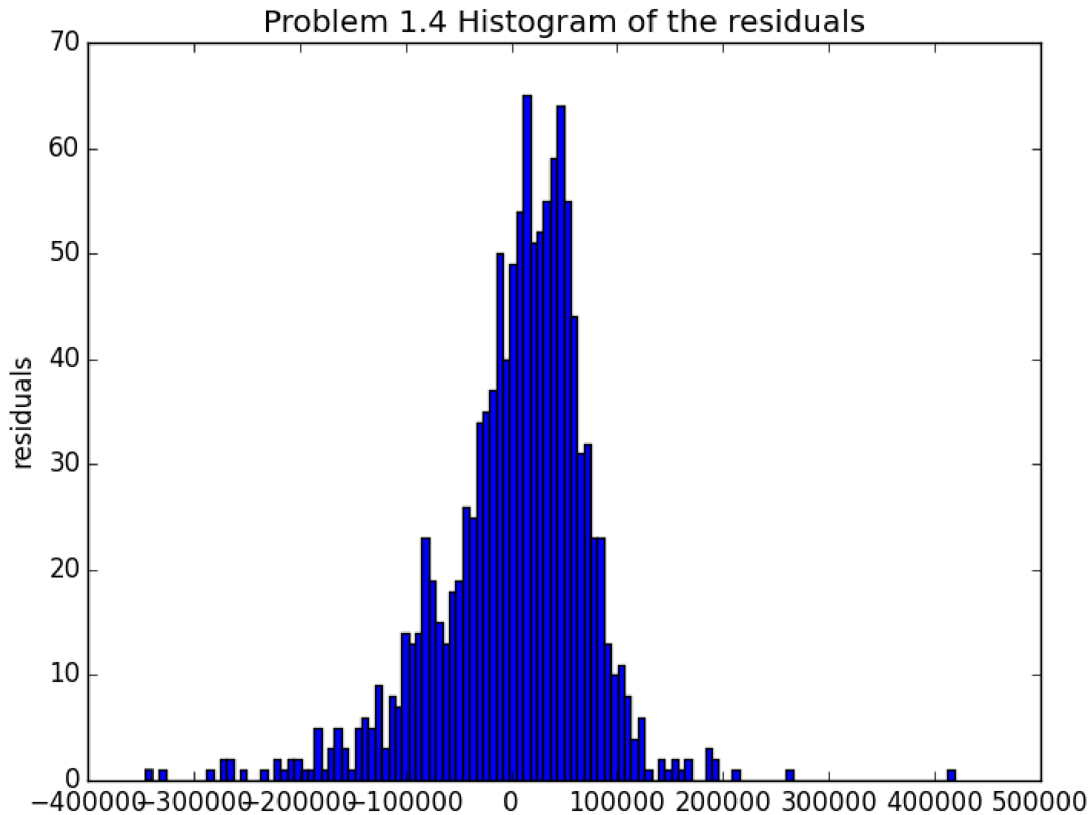
The predicted value is -56562.8275451 to 710798.838694. The range is 767361.66624.

It doesn't make sense. All the exact home values are positive in real. Our predicted value has negative value which do not make sense.

3 .



4 . It is almost normal distribution.



Problem 2. solution

Problem 2.

1. $R[w] = \sum_{i=1}^{n} \log(1+e^{-z^i}) = \log(1+e^{-z^1}) + \cdots + \log(1+e^{-z^n})$

$$\frac{\partial R[w]}{\partial w} = \frac{-1}{1+e^{z^1}} \cdot y^1 \cdot x^1 + \cdots + \frac{-1}{1+e^{z^n}} \cdot y^n \cdot x^n \quad ; \text{since } \frac{\partial z^i}{\partial w} = y^i x^i$$

$$= [x^1 \ x^2 \ \cdots \ x^n] \begin{bmatrix} y_1 & & 0 \\ & y_2 & \\ 0 & & \ddots \ y_n \end{bmatrix} \begin{bmatrix} \frac{1}{1+e^{z_1}} \\ \vdots \\ \frac{1}{1+e^{z_n}} \end{bmatrix}$$

; and $\frac{\partial (\log(1+e^{-z^i}))}{\partial w} = -\frac{e^{-z^i}}{1+e^{-z^i}} \cdot \frac{\partial z^i}{\partial w} = \frac{-1}{1+e^{z^i}} \cdot y^i x^i$

$$= -X^T \cdot \text{diag}(y) \cdot \frac{1}{1+e^{z}} \quad \text{where } z = \text{diag}(y) \cdot X \cdot w$$

With Let $Q = \text{diag}(y) X$

$Q^T = X^T \cdot \text{diag}(y)^T = X^T \cdot \text{diag}(y)$.

Thus, $\frac{\partial R[w]}{\partial w} = -Q^T \left(\frac{1}{1+e^{Qw}}\right)$

2. $\frac{\partial R[w]}{\partial w_i} = \sum_{k=1}^{n} -\frac{y^k \cdot x_i^k}{1+e^{z^k}}$

$$\frac{\partial}{\partial w_j}\left(\frac{\partial R[w]}{\partial w_i}\right) = \frac{\partial}{\partial w_j}\left(\sum_{k=1}^{n} -\frac{y^k \cdot x_i^k}{1+e^{z^k}}\right)$$

$$= \sum_{k=1}^{n} \frac{e^{z^k}}{(1+e^{z^k})^2} \cdot y^k \cdot x_i^k \cdot y^k \cdot x_j^k$$

In the Hessian matrix H. each entry $h_{ij} = \frac{\partial^2 (R[w])}{\partial w_i w_j}$

And $X^T \Lambda X$ will have $\sum_{k=1}^{n} x_i^k x_j^k$ in each ijth entry. (for diagonal matrix Λ.)

Thus, $H = X^T \cdot \text{diag}(y) \cdot \text{diag}(e^{z}) \cdot \text{diag}\left(\frac{1}{(1+e^{z})^2}\right) \text{diag}(y) \cdot X$

$$= Q^T \cdot \text{diag}(e^{z}) \cdot \text{diag}\left(\frac{1}{(1+e^{z})^2}\right) \cdot Q$$

$$= Q^T \cdot \text{diag}(e^{Qw}) \ \text{diag}\left(\frac{1}{(1+e^{Qw})^2}\right) \cdot Q$$

3 .

By using code in problem1.py

We can get:

$\mu^{[0]}$ is [0.95257413 0.73105858 0.73105858 0.26894142]

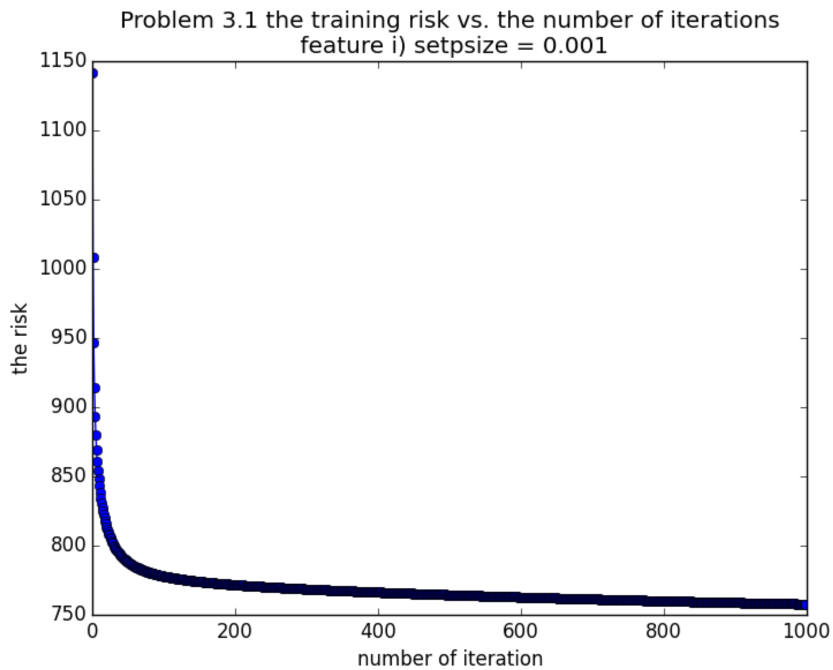
$\omega^{(1)}$ is [-2. 0.94910188 -0.68363271]

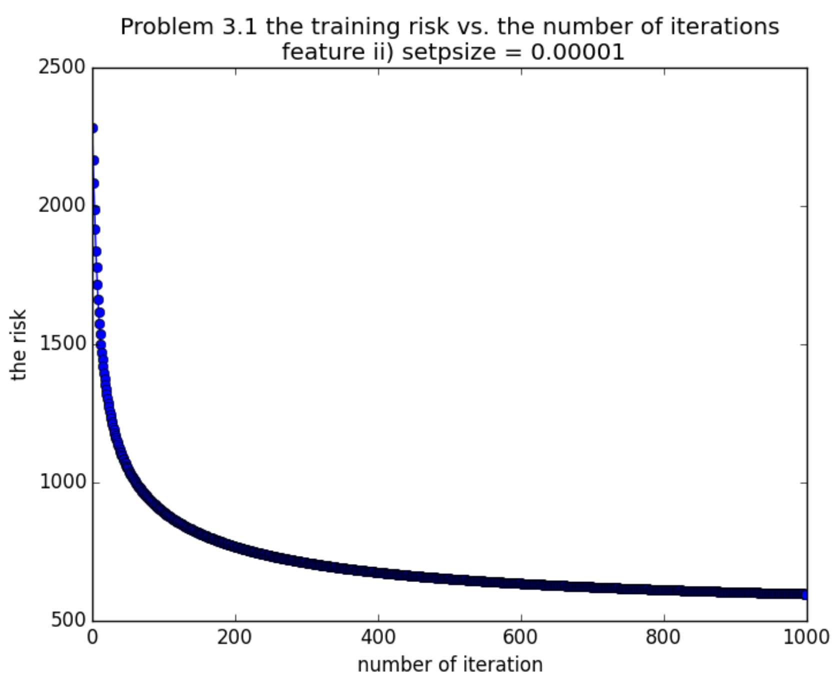
$\mu^{[1]}$ is [0.89693957 0.54082713 0.56598026 0.15000896]

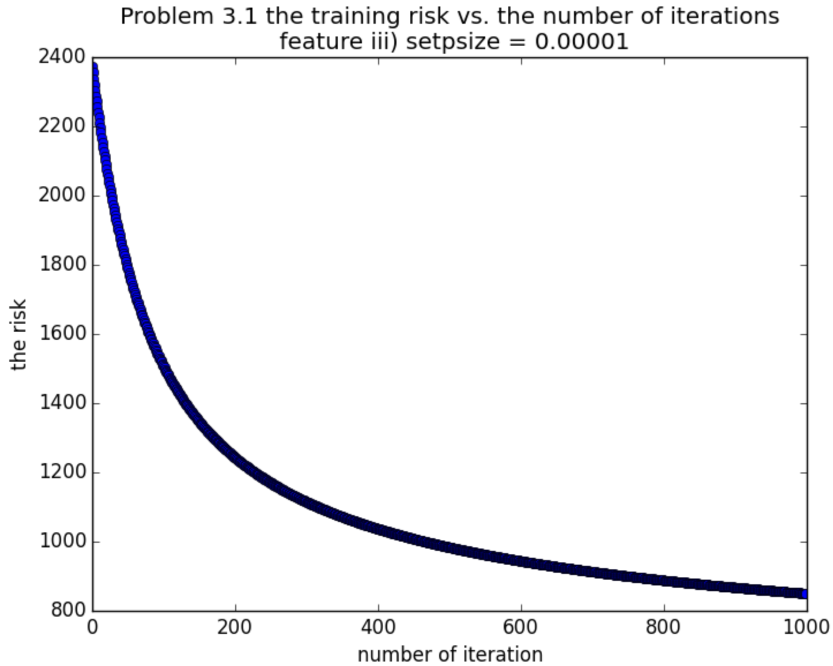
$\omega^{(2)}$ is [-1.69083609 1.91981257 -0.83738862]

Problem 3. solution

1 .







2 .

Problem 3.2.

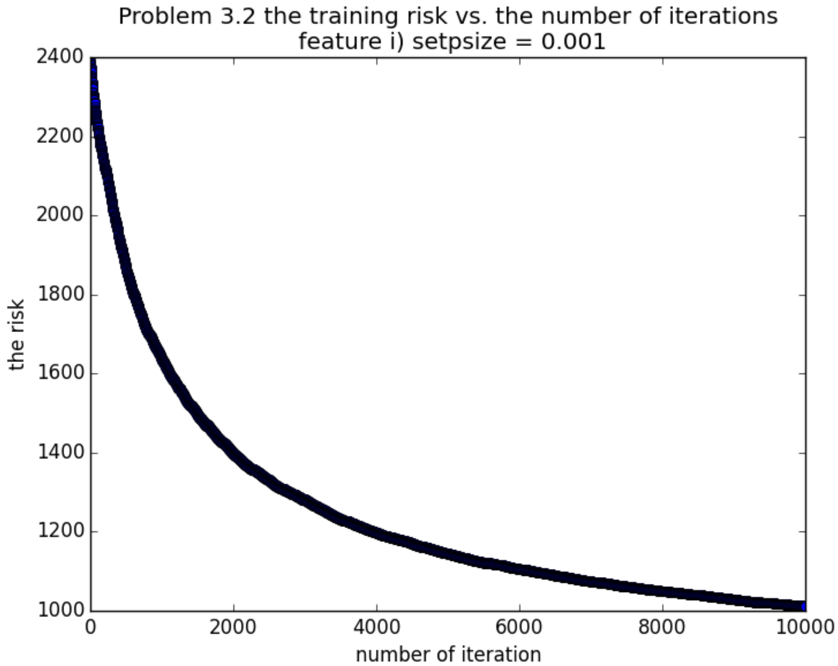
$$\Delta W = -\eta \frac{\partial L}{\partial W} = -\eta \frac{\partial L}{\partial z^i}\cdot\frac{\partial z^i}{\partial W}$$ for given x^i point

$$= -\eta \frac{-e^{-z^i}}{1+e^{-z^i}}\cdot y^i\cdot x^i$$

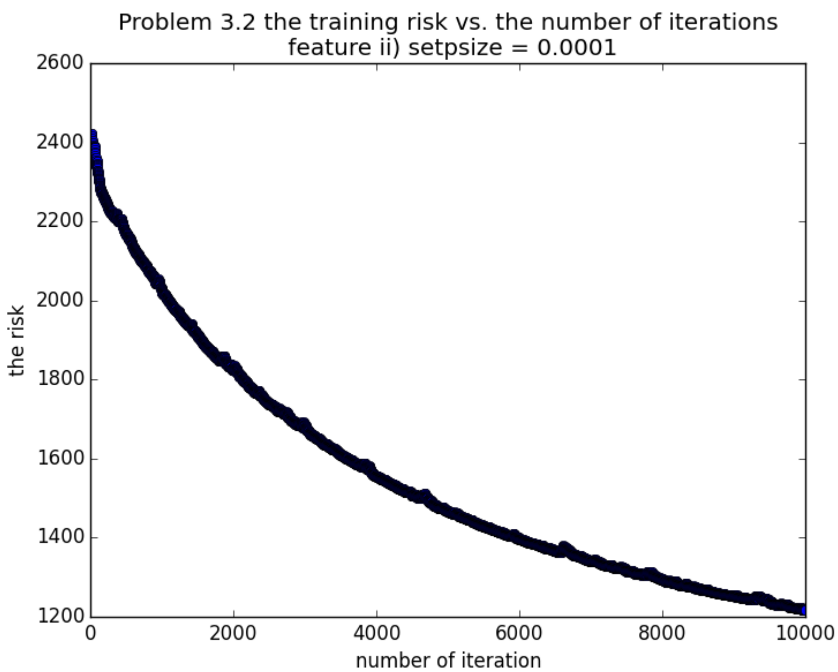
$$= \eta\cdot\frac{1}{1+e^{z^i}}\cdot y^i\cdot x^i$$

Thus $W := W + \Delta W = W + \eta\frac{1}{1+e^{z^i}}\cdot y^i\cdot x^i$

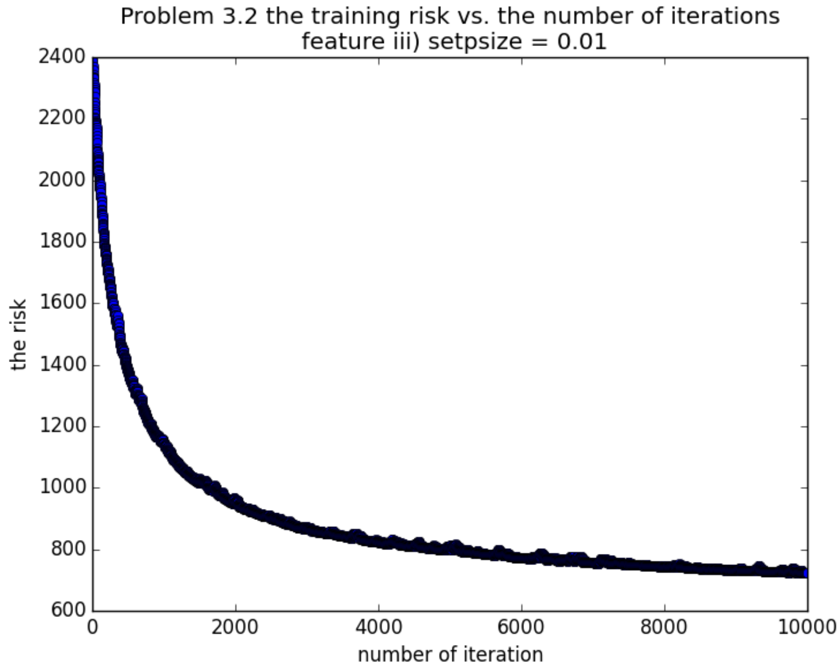
Compare to the plots from (1), with the same iteration, batch gradient descent method is better on reducing the training risk. Also, in the stochastic gradient descent, when we get a bad data point, the training risk even raise.



Problem 3.2 the training risk vs. the number of iterations
feature i) setpsize = 0.001
the risk
number of iteration
2400
2200
2000
1800
1600
1400
1200
1000
0
2000
4000
6000
8000
10000

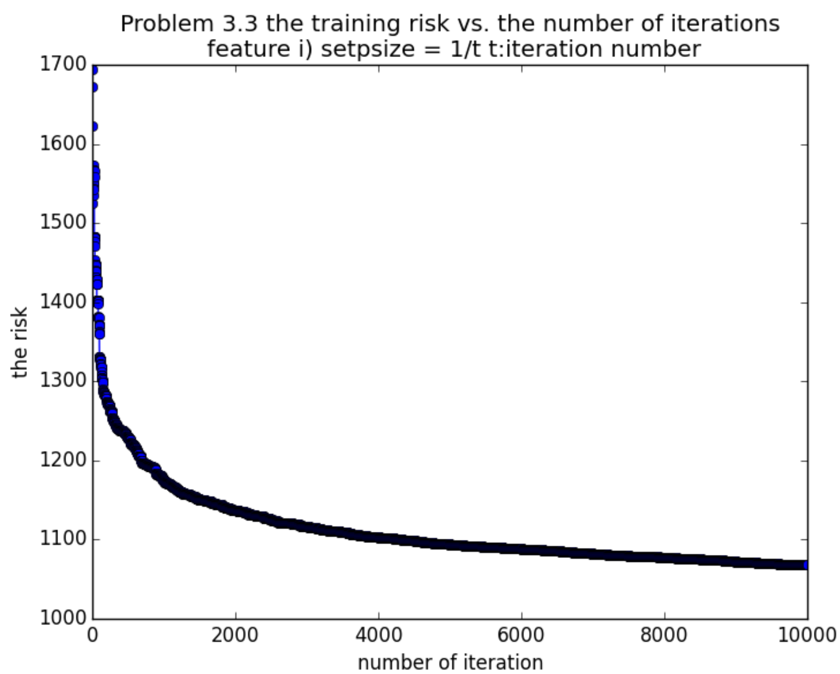


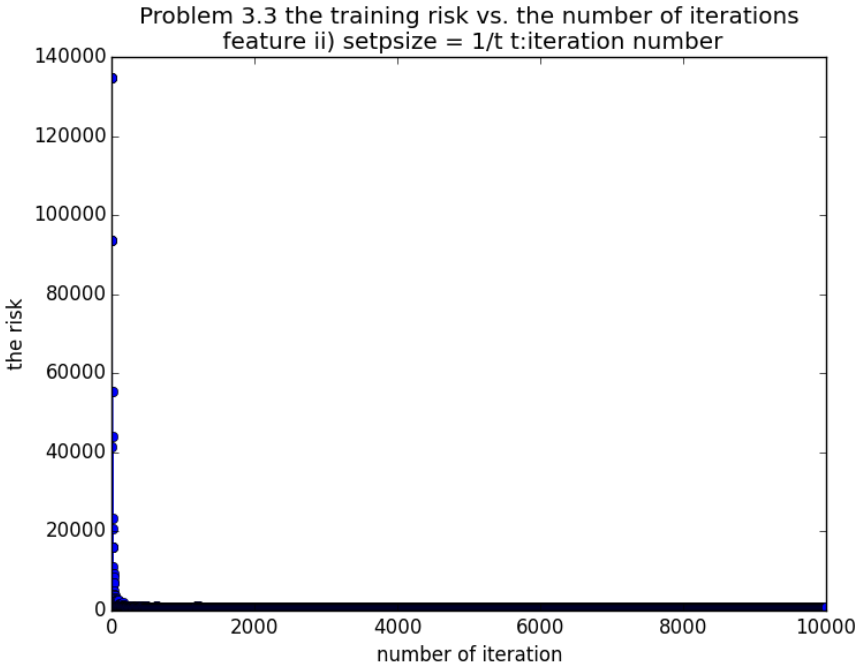
Problem 3.2 the training risk vs. the number of iterations
feature ii) setpsize = 0.0001
the risk
number of iteration
2600
2400
2200
2000
1800
1600
1400
1200
0
2000
4000
6000
8000
10000

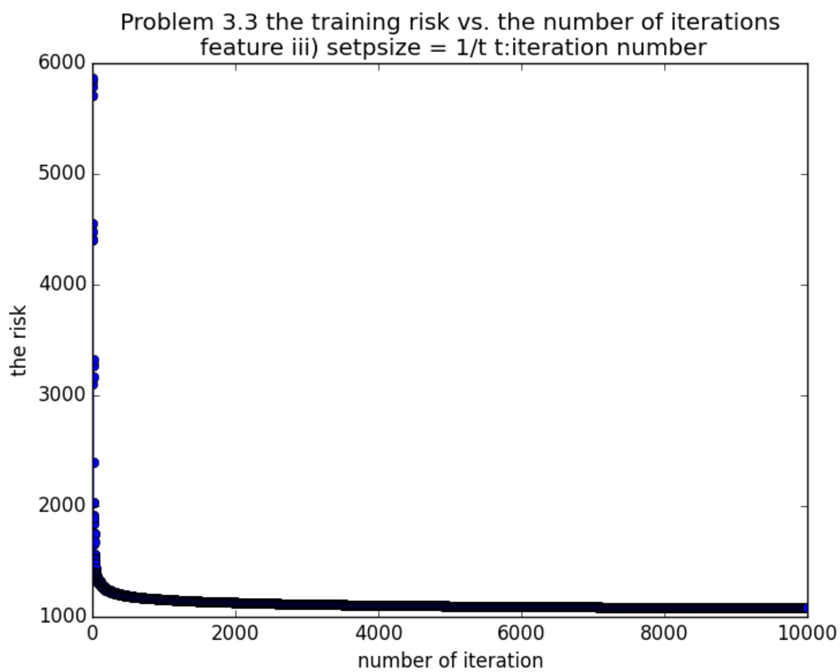


3 .

This strategy is much better than having a constant η by looking at the graphs.




Problem 3.3 the training risk vs. the number of iterations
feature ii) setpsize = 1/t t:iteration number
the risk
number of iteration
0
20000
40000
60000
80000
100000
120000
140000
0
2000
4000
6000
8000
10000


Problem 3.3 the training risk vs. the number of iterations
feature iii) setpsize = 1/t t:iteration number
the risk
number of iteration
1000
2000
3000
4000
5000
6000
0
2000
4000
6000
8000
10000

4 .

a .

Problem 3.4. a.

$f(x) = \sum_i w_i \Phi(x) = \sum_{i=1}^{n} a_i K(x^{(i)}, x)$ $\qquad z^i = y^i f(x^i)$

Φ-space version : $\Delta w_i = \eta\, S(-z^i)\, y\, \Phi_i(x)$ where $S(-z^i) = \frac{1}{1+e^{z^i}}$

For given point data $x^{(i)}$: $\Delta w = \eta\, S(-z^i)\, y^{(i)}\, \Phi(x^i)$ $\circledast$

$w = \sum_i a_i \Phi(x^k)$, $\Delta w = \Delta a_i \Phi(x^i)$ $\circledast\circledast$

By $\circledast$ and $\circledast\circledast$, we get $\Delta a_i = \eta\, S(-z^i)\, y^{(i)}$

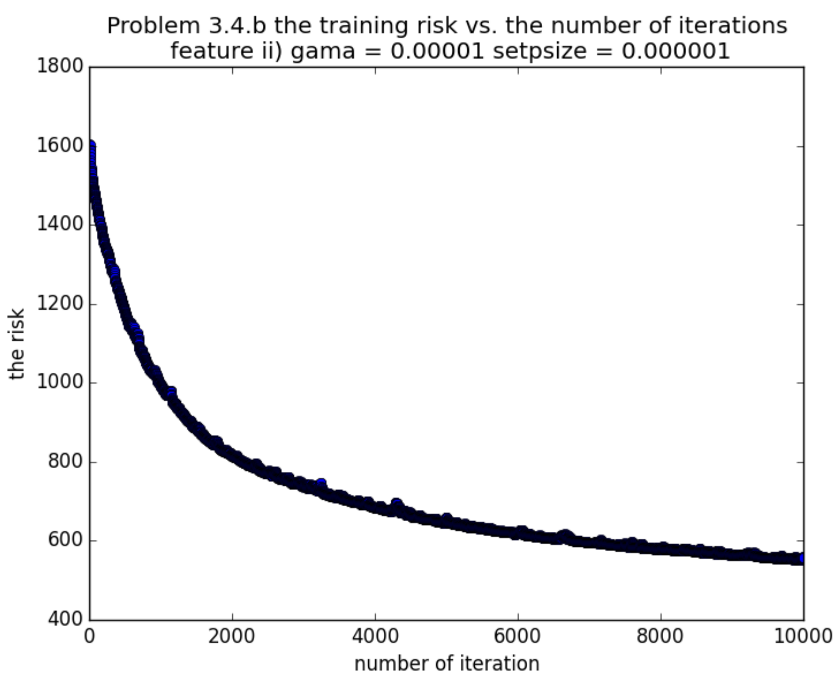
Thus. we showed it

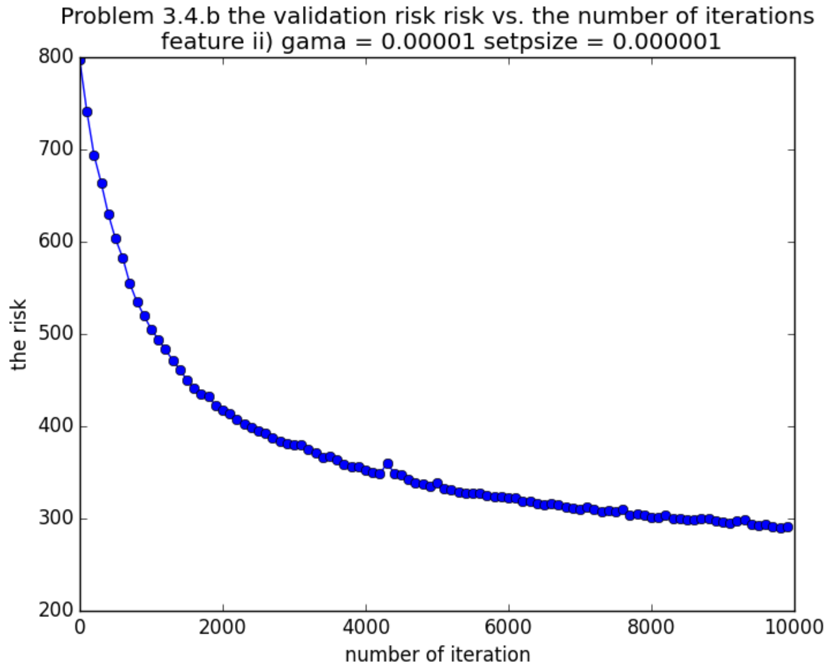
For $\frac{\partial L}{\partial a_i} = \frac{\partial L}{\partial z^i} \cdot \frac{\partial z^i}{\partial a_i} = \frac{\partial \log(1+e^{-z^i})}{\partial z^i} \cdot \frac{\partial z^i}{\partial a_i}$

$= \frac{1}{1+e^{z^i}} \cdot y^i \cdot K(x^{(i)}, x^{(i)})$.

Also, when $K(x^{(i)}, x^{(i)})$, they are same for given data point x^i.

b .

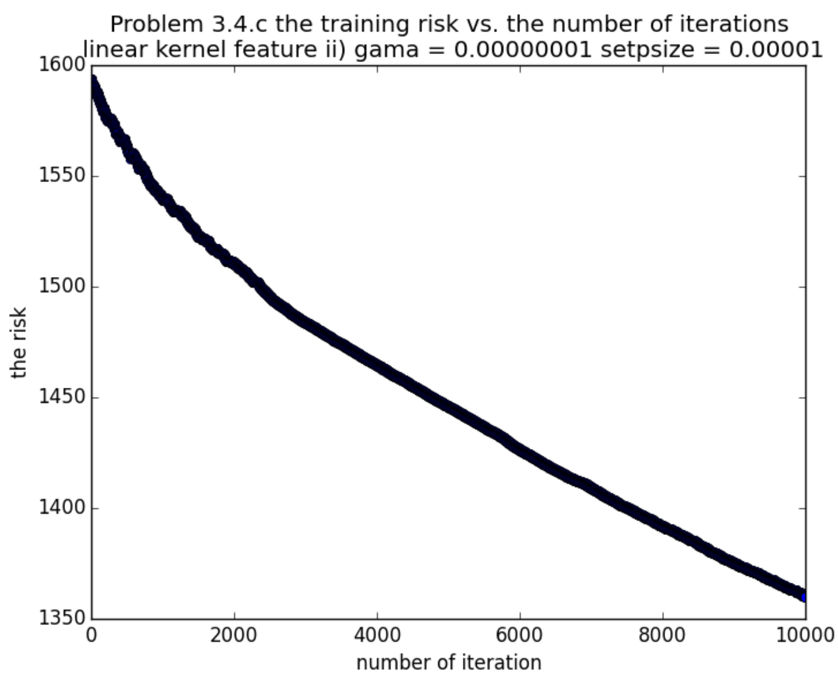


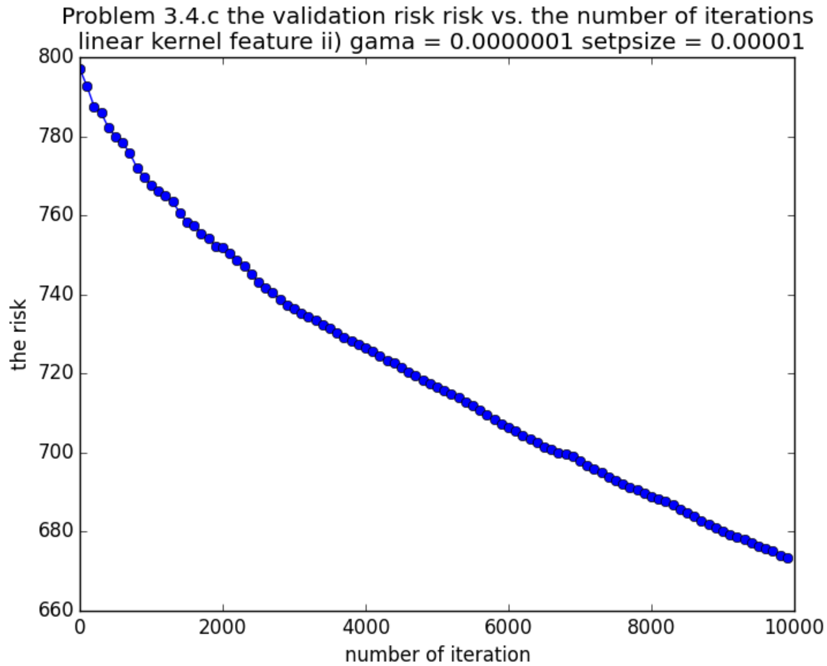


c .

By predict the validation sets of data points and compare to actual validation sets labels as in code, we can see the accuracy for quadratic kernel is even a little bit higher than linear kernel. This means quadratic kernel doesn't overfit the data.

We should decrease γ to improve performance.





Problem 4. solution

The time-stamp of the received message is very big before the midnight and is very small after the midnight. This adding feature is not linear separable. Thus, the linear SVM didn't work well. In order to improve his results, we need to use a quadratic kernel to improve his model. This adding feature is separable at quadratic kernel.

File: problem1.py

```
import scipy.io as sio
import numpy as np
from numpy.linalg import inv
import matplotlib.pyplot as plt

if __name__ == '__main__':
        #read input
        housingData = sio.loadmat('./data/housing_data.mat')
        # print(housingData)

        #part1 Train the model, get W
        Xvalidate = housingData['Xvalidate']
        Yvalidate = housingData['Yvalidate']
        Xtrain = housingData['Xtrain']
        Ytrain = housingData['Ytrain']
        # print(len(Xvalidate)) #1200
        # print(len(Xvalidate[0])) #8
        # print(len(Yvalidate)) #1200
        # print(len(Xtrain)) #19440
        # print(len(Xtrain[0])) #8

        X = np.insert(Xtrain, 8, 1, axis = 1)
        Xplus = X.T.dot(X)
        Xplus = inv(Xplus)
        W = Xplus.dot(X.T).dot(Ytrain)

        #part2 get the Residual sum of Squares
        Xvalidate1 = np.insert(Xvalidate, 8, 1, axis = 1)
        expect = Xvalidate1.dot(W)
        diff = 0

        sub = expect - Yvalidate
        RSS = 0
        for i in range(len(Yvalidate)):
                RSS += np.square(sub[i])
        print('The RSS is ', RSS)

        print('The predicted value is ', np.min(expect), 'to', np.max(expect))

        print('The range is ', np.max(expect) - np.min(expect))

        print('The exact value is ', np.min(Yvalidate), 'to', np.max(Yvalidate))

        print('The range is ', np.max(Yvalidate) - np.min(Yvalidate))

        #part3 plot W
        W = W[:-1]
        x_label = [0, 1, 2, 3, 4, 5, 6, 7]
        plt.title('Problem 1.3 the regression coefficients W')
        plt.xlabel('The Indexs')
        plt.ylabel('coefficients of W')
        plt.plot(x_label, W, 'bo')
```

```
plt.show()

#part4 plosy residuals (f(x) - y)
plt.title('Problem 1.4 Histogram of the residuals')
plt.ylabel('residuals')
plt.hist(sub, bins = len(sub)/10)
plt.show()
```

File:problem2.py

```
import numpy as np
from numpy.linalg import inv

if __name__ == '__main__':
        X = np.array([[0, 3, 1], [1, 3, 1], [0, 1, 1], [1, 1, 1]])
        y = np.array([1, 1, -1, -1])
        w0 = np.array([-2, 1, 0])
        n = 1

        u0 = 1 / (1 + np.exp(-X.dot(w0.T)))
        print('u0 is', u0)

        Q = np.diag(y).dot(X)
        QW = Q.dot(w0)
        derivateWRTw0 = - Q.T.dot(1 / (1 + np.exp(QW)))
        w1 = w0 - n * derivateWRTw0
        print('w1 is ', w1)

        u1 = 1 / (1 + np.exp(-X.dot(w1.T)))
        print('u1 is', u1)

        QW = Q.dot(w1)
        derivateWRTw1 = - Q.T.dot(1 / (1 + np.exp(QW)))
        w2 = w1 - n * derivateWRTw1
        print('w2 is ', w2)
```

File:problem3.1.py

```
import scipy.io as sio
import numpy as np
from numpy.linalg import inv
import matplotlib.pyplot as plt
from scipy import stats
from sklearn import preprocessing


def calculateRisk(X, Y, w):
        power = -np.diag(Y).dot(X).dot(w)
        power = power.clip(-99, 99)
        return np.sum(np.log(1 + np.exp(power)))

if __name__ == '__main__':
        #read input
        spamData = sio.loadmat('./data/spam.mat')

        Xtest = spamData['Xtest']
        Xtrain = spamData['Xtrain']
        Ytrain = spamData['Ytrain']
        Ytrain = Ytrain.T[0]

        #standardize each column, so they each have mean 0 and unit variance
        Xstandardize = preprocessing.scale(Xtrain)
        # print(Xstandardize)

        #add bias
        Xtrain = np.insert(Xtrain, 57, 1, axis = 1)

        #transform the feature
        Xtransform = np.log(Xtrain + 0.1)
        # print(Xtransform)

        #Binarize the feature
        binarizer = preprocessing.Binarizer().fit(Xtrain)
        Xbinarize = binarizer.transform(Xtrain)
        # print(Xbinarize)


        #q1
        # #using Xstandardize
        w = np.zeros((57, 1))
        ylabel1 = []
        Q = np.diag(Ytrain).dot(Xstandardize)
        QT = Q.T
        for i in range(1000):
                QW = Q.dot(w)
                QW = QW.clip(-99, 99)
                derivateWRTw = - QT.dot(1 / (1 + np.exp(QW)))
                w = w - 0.001 * derivateWRTw
                risk = calculateRisk(Xstandardize, Ytrain, w)
                ylabel1 += [risk]
```

```
        print('The ', i, 'th risk is ', risk)
x_label1 = [i for i in range(len(ylabel1))]

plt.title('Problem 3.1 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label1, ylabel1, 'bo-')
plt.show()

# #using Xtransform
w = np.zeros((58, 1))
ylabel2 = []
Q = np.diag(Ytrain).dot(Xtransform)
QT = Q.T
for i in range(1000):
        QW = Q.dot(w)
        QW = QW.clip(-99, 99)
        derivateWRTw = - QT.dot(1 / (1 + np.exp(QW)))
        w = w - 0.00001 * derivateWRTw
        risk = calculateRisk(Xtransform, Ytrain, w)
        ylabel2 += [risk]
        print('The ', i, 'th risk is ', risk)
x_label2 = [i for i in range(len(ylabel2))]

plt.title('Problem 3.1 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label2, ylabel2, 'bo-')
plt.show()


# #using Xbinarize
w = np.zeros((58, 1))
ylabel3 = []
Q = np.diag(Ytrain).dot(Xbinarize)
QT = Q.T
for i in range(1000):
        QW = Q.dot(w)
        QW = QW.clip(-99, 99)
        derivateWRTw = - QT.dot(1 / (1 + np.exp(QW)))
        w = w - 0.00001 * derivateWRTw
        risk = calculateRisk(Xbinarize, Ytrain, w)
        ylabel3 += [risk]
        print('The ', i, 'th risk is ', risk)
x_label3 = [i for i in range(len(ylabel3))]

plt.title('Problem 3.1 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label3, ylabel3, 'bo-')
plt.show()
```

File: problem3.2.py

```
import scipy.io as sio
import numpy as np
from numpy.linalg import inv
import matplotlib.pyplot as plt
from scipy import stats
from sklearn import preprocessing

def calculateRisk(Q, w):
        power = -Q.dot(w)
        power = power.clip(-99, 99)
        return np.sum(np.log(1 + np.exp(power)))

if __name__ == '__main__':
        #read input
        spamData = sio.loadmat('./data/spam.mat')

        Xtest = spamData['Xtest']
        Xtrain = spamData['Xtrain']
        Ytrain = spamData['Ytrain']
        Ytrain = Ytrain.T[0]

        #standardize each column, so they each have mean 0 and unit variance
        Xstandardize = preprocessing.scale(Xtrain)
        # print(Xstandardize)

        #add bias
        Xtrain = np.insert(Xtrain, 57, 1, axis = 1)

        #transform the feature
        Xtransform = np.log(Xtrain + 0.1)
        # print(Xtransform)

        #Binarize the feature
        binarizer = preprocessing.Binarizer().fit(Xtrain)
        Xbinarize = binarizer.transform(Xtrain)
        # print(Xbinarize)


        #q2
        # using Xstandardize
        w = np.zeros((57, 1))
        ylabel1 = []
        Q = np.diag(Ytrain).dot(Xstandardize)
        for i in range(10000):
                index = np.random.randint(0, 3450)
                xi = np.reshape(Xstandardize[index], (57,1))
                yi = Ytrain[index]
                zi = yi * xi.T.dot(w)
                w = w + 0.001 * yi * xi / (1 + np.exp(zi))
                risk = calculateRisk(Q, w)
                ylabel1 += [risk]
                print('The ', i, 'th risk is ', risk)
```

```
x_label1 = [i for i in range(len(ylabel1))]
plt.title('Problem 3.2 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label1, ylabel1, 'bo-')
plt.show()

# #using Xtransform
w = np.zeros((58, 1))
ylabel2 = []
Q = np.diag(Ytrain).dot(Xtransform)
for i in range(10000):
        index = np.random.randint(0, 3450)
        xi = np.reshape(Xtransform[index], (58,1))
        yi = Ytrain[index]
        zi = yi * xi.T.dot(w)
        w = w + 0.0001 * yi * xi / (1 + np.exp(zi))
        risk = calculateRisk(Q, w)
        ylabel2 += [risk]
        print('The ', i, 'th risk is ', risk)
x_label2 = [i for i in range(len(ylabel2))]
plt.title('Problem 3.2 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label2, ylabel2, 'bo-')
plt.show()


# # #using Xbinarize
w = np.zeros((58, 1))
ylabel3 = []
Q = np.diag(Ytrain).dot(Xbinarize)
for i in range(10000):
        index = np.random.randint(0, 3450)
        xi = np.reshape(Xbinarize[index], (58,1))
        yi = Ytrain[index]
        zi = yi * xi.T.dot(w)
        w = w + 0.01 * yi * xi / (1 + np.exp(zi))
        risk = calculateRisk(Q, w)
        ylabel3 += [risk]
        print('The ', i, 'th risk is ', risk)
x_label3 = [i for i in range(len(ylabel3))]
plt.title('Problem 3.2 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label3, ylabel3, 'bo-')
plt.show()
```

File: problem3.3.py

```
import scipy.io as sio
import numpy as np
from numpy.linalg import inv
import matplotlib.pyplot as plt
from scipy import stats
from sklearn import preprocessing

def calculateRisk(Q, w):
        power = -Q.dot(w)
        power = power.clip(-99, 99)
        return np.sum(np.log(1 + np.exp(power)))

if __name__ == '__main__':
        #read input
        spamData = sio.loadmat('./data/spam.mat')

        Xtest = spamData['Xtest']
        Xtrain = spamData['Xtrain']
        Ytrain = spamData['Ytrain']
        Ytrain = Ytrain.T[0]

        #standardize each column, so they each have mean 0 and unit variance
        Xstandardize = preprocessing.scale(Xtrain)
        # print(Xstandardize)

        #add bias
        Xtrain = np.insert(Xtrain, 57, 1, axis = 1)

        #transform the feature
        Xtransform = np.log(Xtrain + 0.1)
        # print(Xtransform)

        #Binarize the feature
        binarizer = preprocessing.Binarizer().fit(Xtrain)
        Xbinarize = binarizer.transform(Xtrain)
        # print(Xbinarize)

        #q2
        # using Xstandardize
        w = np.zeros((57, 1))
        ylabel1 = []
        Q = np.diag(Ytrain).dot(Xstandardize)
        for i in range(10000):
                index = np.random.randint(0, 3450)
                xi = np.reshape(Xstandardize[index], (57,1))
                yi = Ytrain[index]
                zi = yi * xi.T.dot(w)
                w = w + yi * xi / (1 + np.exp(zi)) / (i + 1)
                risk = calculateRisk(Q, w)
                ylabel1 += [risk]
                print('The ', i, 'th risk is ', risk)
        x_label1 = [i for i in range(len(ylabel1))]
```

```
plt.title('Problem 3.3 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label1, ylabel1, 'bo-')
plt.show()

#using Xtransform
w = np.zeros((58, 1))
ylabel2 = []
Q = np.diag(Ytrain).dot(Xtransform)
for i in range(10000):
        index = np.random.randint(0, 3450)
        xi = np.reshape(Xtransform[index], (58,1))
        yi = Ytrain[index]
        zi = yi * xi.T.dot(w)
        w = w + yi * xi / (1 + np.exp(zi)) / (i + 1)
        risk = calculateRisk(Q, w)
        ylabel2 += [risk]
        print('The ', i, 'th risk is ', risk)
x_label2 = [i for i in range(len(ylabel2))]
plt.title('Problem 3.3 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label2, ylabel2, 'bo-')
plt.show()


# #using Xbinarize
w = np.zeros((58, 1))
ylabel3 = []
Q = np.diag(Ytrain).dot(Xbinarize)
for i in range(10000):
        index = np.random.randint(0, 3450)
        xi = np.reshape(Xbinarize[index], (58,1))
        yi = Ytrain[index]
        zi = yi * xi.T.dot(w)
        w = w + yi * xi / (1 + np.exp(zi)) / (i + 1)
        risk = calculateRisk(Q, w)
        ylabel3 += [risk]
        print('The ', i, 'th risk is ', risk)
x_label3 = [i for i in range(len(ylabel3))]
plt.title('Problem 3.3 the training risk vs. the number of iterations \n fe
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label3, ylabel3, 'bo-')
plt.show()
```

```
File: problem.3.4.b.py

import scipy.io as sio
import numpy as np
from numpy.linalg import inv
import matplotlib.pyplot as plt
from scipy import stats
from sklearn import preprocessing
import random

def calculateRisk(Y, alpha, sum1):
        fx = sum1.dot(alpha)
        power = - np.diag(Y).dot(fx)
        power = power.clip(-99, 99)
        return np.sum(np.log(1 + np.exp(power)))

if __name__ == '__main__':
        #read input
        spamData = sio.loadmat('./data/spam.mat')

        Xtest = spamData['Xtest']
        Xtrain = spamData['Xtrain']
        Ytrain = spamData['Ytrain']
        Ytrain = Ytrain.T[0]

        #standardize each column, so they each have mean 0 and unit variance
        #add bias
        Xtrain = np.insert(Xtrain, 57, 1, axis = 1)

        #transform the feature
        Xtransform = np.log(Xtrain + 0.1)
        # print(Xtransform)

        #partition samples
        samples_indexs = [i for i in range(3450)]
        random.shuffle(samples_indexs)
        validation_sets_index = samples_indexs[:1150]
        validation_sets = []
        validation_sets_labels = []
        samples_sets = []
        samples_sets_labels = []
        for index in validation_sets_index:
                validation_sets += [Xtransform[index]]
                validation_sets_labels += [Ytrain[index]]
        samples_indexs = samples_indexs[1150:3450]
        for index in samples_indexs:
                samples_sets += [Xtransform[index]]
                samples_sets_labels += [Ytrain[index]]

        validation_sets = np.array(validation_sets)
        validation_sets_labels = np.array(validation_sets_labels)
        samples_sets = np.array(samples_sets)
        samples_sets_labels = np.array(samples_sets_labels)
```

```
#part b
# using Xtransform
alpha = np.zeros((2300, 1))
gama = 0.00001
ylabel1 = []
ylabel2 = []
sum1 = np.square(samples_sets.dot(samples_sets.T) + 1) # for triang set
sum2 = np.square(validation_sets.dot(samples_sets.T) + 1) # for validation
for i in range(10000):
        if i % 100 == 0:
                validationRisk = calculateRisk(validation_sets_labels, alpha
                ylabel2 += [validationRisk]
                print('The ', i, 'th risk is ', validationRisk)
        index = np.random.randint(0, 2300)
        xi = np.reshape(samples_sets[index], (58,1))
        yi = samples_sets_labels[index]
        zi = yi * alpha.T.dot(np.square(samples_sets.dot(xi) + 1))
        zi = zi.clip(-99, 99)
        alpha[index] = alpha[index] + 0.000001 * yi / (1 + np.exp(zi))
        alpha = (1 - gama) * alpha
        risk = calculateRisk(samples_sets_labels, alpha, sum1)
        ylabel1 += [risk]
        # print('The ', i, 'th risk is ', risk)
x_label1 = [i for i in range(len(ylabel1))]
x_label2 = [i * 100 for i in range(len(ylabel2))]

pred = []
for i in range(1150):
        xi = np.reshape(validation_sets[i], (58,1))
        fx = alpha.T.dot(np.square(samples_sets.dot(xi) + 1))
        probbe1 = 1 / (1 + np.exp(-fx))
        if probbe1 > 0.5:
                pred += [1]
        else:
                pred += [-1]

same = [i for i in range(1150) if pred[i] == validation_sets_labels[i]]

print('the accuracy is', len(same)/1150)

plt.title('Problem 3.4.b the training risk vs. the number of iterations \n
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label1, ylabel1, 'bo-')
plt.show()

plt.title('Problem 3.4.b the validation risk risk vs. the number of iterati
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label2, ylabel2, 'bo-')
plt.show()
```

File: problem3.4.c.py

```
import scipy.io as sio
import numpy as np
from numpy.linalg import inv
import matplotlib.pyplot as plt
from scipy import stats
from sklearn import preprocessing
import random

def calculateRisk(Y, alpha, sum1):
        fx = sum1.dot(alpha)
        power = - np.diag(Y).dot(fx)
        power = power.clip(-99, 99)
        return np.sum(np.log(1 + np.exp(power)))

if __name__ == '__main__':
        #read input
        spamData = sio.loadmat('./data/spam.mat')

        Xtest = spamData['Xtest']
        Xtrain = spamData['Xtrain']
        Ytrain = spamData['Ytrain']
        Ytrain = Ytrain.T[0]

        #standardize each column, so they each have mean 0 and unit variance
        #add bias
        Xtrain = np.insert(Xtrain, 57, 1, axis = 1)

        #transform the feature
        Xtransform = np.log(Xtrain + 0.1)
        # print(Xtransform)

        #partition samples
        samples_indexs = [i for i in range(3450)]
        random.shuffle(samples_indexs)
        validation_sets_index = samples_indexs[:1150]
        validation_sets = []
        validation_sets_labels = []
        samples_sets = []
        samples_sets_labels = []
        for index in validation_sets_index:
                validation_sets += [Xtransform[index]]
                validation_sets_labels += [Ytrain[index]]
        samples_indexs = samples_indexs[1150:3450]
        for index in samples_indexs:
                samples_sets += [Xtransform[index]]
                samples_sets_labels += [Ytrain[index]]

        validation_sets = np.array(validation_sets)
        validation_sets_labels = np.array(validation_sets_labels)
        samples_sets = np.array(samples_sets)
        samples_sets_labels = np.array(samples_sets_labels)
```

```
#part c
alpha = np.zeros((2300, 1))
gama = 0.00000001
ylabel1 = []
ylabel2 = []
sum1 = samples_sets.dot(samples_sets.T) + 1 # for trianng set
sum2 = validation_sets.dot(samples_sets.T) + 1 # for validation set
for i in range(10000):
        if i % 100 == 0:
                validationRisk = calculateRisk(validation_sets_labels, alpha
                ylabel2 += [validationRisk]
                print('The ', i, 'th risk is ', validationRisk)
        index = np.random.randint(0, 2300)
        xi = np.reshape(samples_sets[index], (58,1))
        yi = samples_sets_labels[index]
        zi = yi * alpha.T.dot(samples_sets.dot(xi) + 1)
        zi = zi.clip(-99, 99)
        alpha[index] = alpha[index] + 0.00001 * yi / (1 + np.exp(zi))
        alpha = (1 - gama) * alpha
        risk = calculateRisk(samples_sets_labels, alpha, sum1)
        ylabel1 += [risk]
        # print('The ', i, 'th risk is ', risk)
x_label1 = [i for i in range(len(ylabel1))]
x_label2 = [i * 100 for i in range(len(ylabel2))]


pred = []
for i in range(1150):
        xi = np.reshape(validation_sets[i], (58,1))
        fx = alpha.T.dot(np.square(samples_sets.dot(xi) + 1))
        probbe1 = 1 / (1 + np.exp(-fx))
        if probbe1 > 0.5:
                pred += [1]
        else:
                pred += [-1]

same = [i for i in range(1150) if pred[i] == validation_sets_labels[i]]

print('the accuracy is', len(same)/1150)

plt.title('Problem 3.4.c the training risk vs. the number of iterations \n
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label1, ylabel1, 'bo-')
plt.show()

plt.title('Problem 3.4.c the validation risk risk vs. the number of iterati
plt.xlabel('number of iteration')
plt.ylabel('the risk')
plt.plot(x_label2, ylabel2, 'bo-')
```