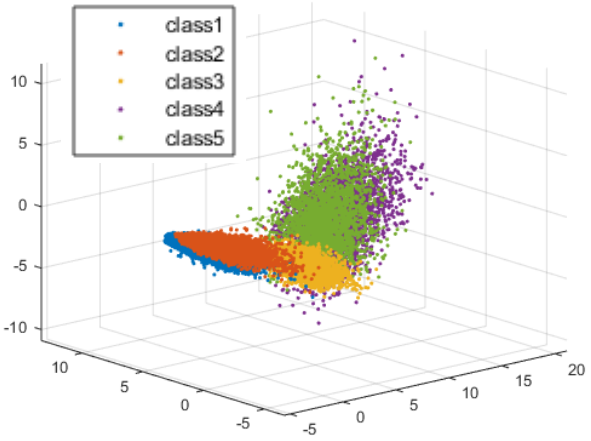
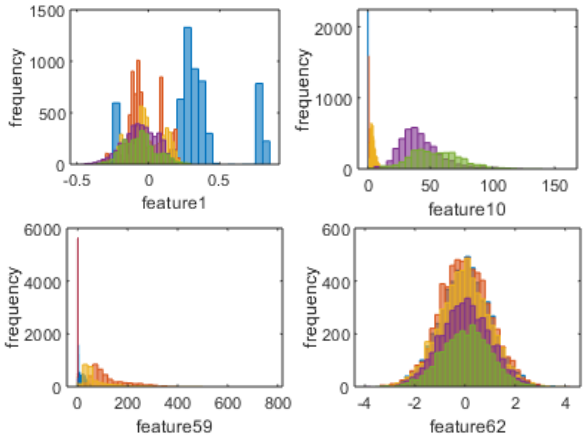
Coursework2 Report-Luxi ZHANG

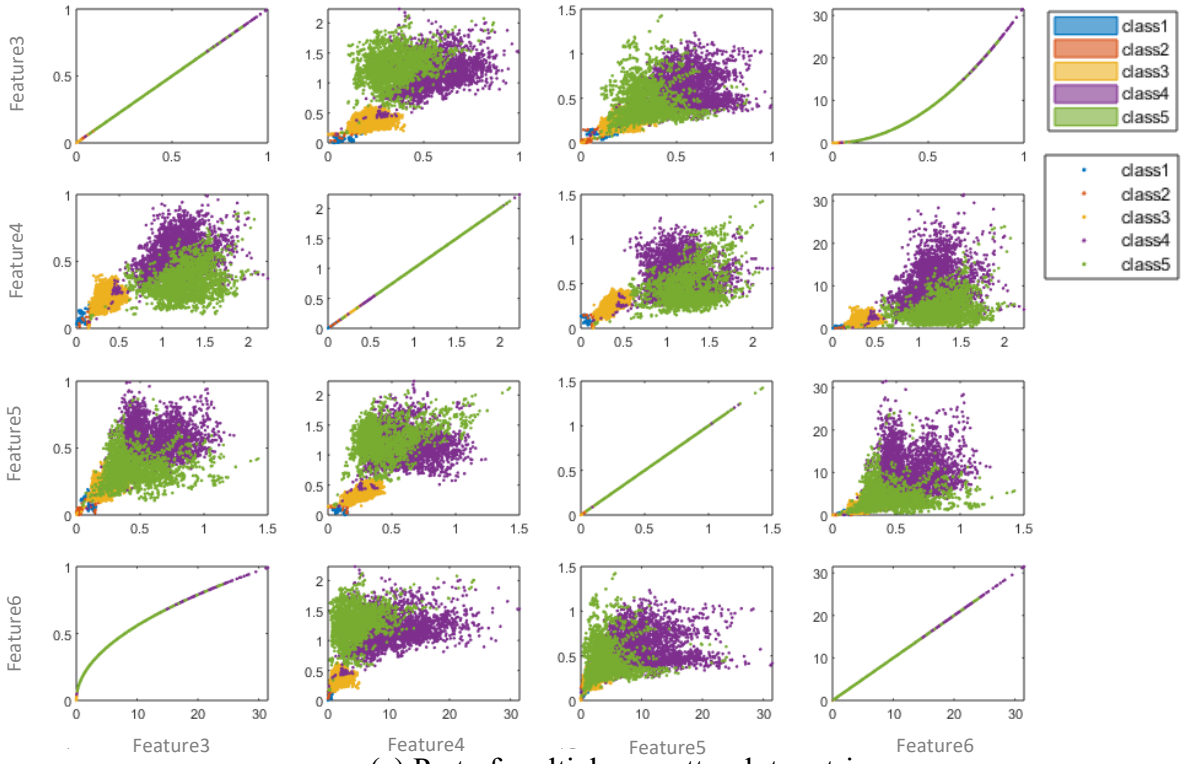
Q1. I visualize the dataset to observe the dataset with several methods. (code showing in appendix)



(a) 3D distribution after PCA



(b) Part of distribution against each feature



(c) Part of multiclass scatterplot matrix

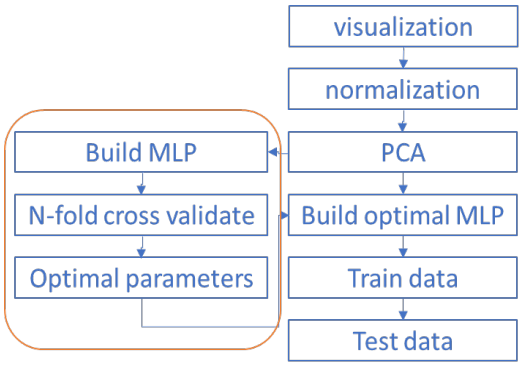
Firgure1 Visualization of the data

Figure 1(a) is a 3-dimensional scatter plot by PCA, it remains about 58% variance, figure 1(b) is a part of distribution against each feature, and figure 1(c) is a part of multiclass scatterplot matrix. (the whole figures are too large to put here, so I only put a part here to explain what is happening)

From figure 1(a), we can find these five classes **cannot** be classified well by a linear method, so algorithm suitable for non-linear classification will be chosen. In addition, the boundaries between some classes are not so clear, so it is a challenge in classification.

From figure 1(b), we can find scale of each feature varies (the absolute value from no more than 1 to hundreds), so **normalization** will be needed in pre-processing. In addition, the data set has approximate normal distribution in some features such as feature62, while it may not so close to distribution in some other features, such as feature1, 10 and 59. As a result, if we use Gaussian distribution to fit every feature, error may occur.

From figure 1(c), we can find some features are associated, such feature3 against feature6, so it will be efficient to implement classification if we use **principal component analysis** to reduce the dimension/ number of features. What's more, these dependent features will also lead to error in fitting with Gaussian distribution.



Firgure2 Classification pipeline

Based on analysis above, the classification pipeline shows on the left (figure 2).
In pre-processing steps, I normalize the data and do PCA to transform all features in the same scale and reduce the dimension. It makes sense to the efficiency and accuracy.
KNN and MLP maybe better choices for this classification based on the analysis. Gaussian Naïve Bayes will work fast, but because the date doesn't fulfil the assumptions very well, its output may not as accurate as the previous ones. Deep learning can solve the task accurately, but the time cost is inacceptable. In addition, I also implement them to compared as following. (average accuracy and time cost from N-fold cross validate, n=5.)

Table1 Comparison of three classifiers

	Gaussian Naïve Bayes	KNN (optimal k=3)	BP (30 hidden units, λ=1, iterations=50)
Accuracy	97.08%	98.30%	98.77%
time cost	0.04 sec	3.52 sec	11.6 sec

I select the MLP (3 layers, 1 hidden layer) with Backpropagation method because its more accurate than KNN and the addition time cost (in second scale) is acceptable. In addition, the time cost for KNN increases fast with the increase of the size of test set while time cost for BP methods has no significant change. To implement the BP method, we should find the optimal structure for the task, we should decide the number of units in hidden layer, lambda for overfitting penalty and suitable numbers of iteration. Then for the new dataset from the same task we can use the optimal parameters to build MLP to classify them.

Q2. In Function TrainClassifierX, I did the following to implement training. (code showing in appendix)

Pre-Process
  Normalization, return parameter σ , μ
  Implement PCA (remaining 99% variance), return parameter U
Train the with BP method
  Set the parameters for network structure
  Initialization weight matrix θ
  Repeat (number of iterations)
    implement forward propagation to get $h_\theta(x^i)$ for any x^i,(sigmoid function)
    Compute cost function with penalty on overfitting

$$J(\theta) = -\frac{1}{m}\left[\sum_{i=1}^{m}\sum_{k=1}^{K} y_k^{(i)} \log\left(h_\theta(x^{(i)})\right)_k + \left(1 - y_k^{(i)}\right)\log\left(1 - h_\theta(x^{(i)})\right)_k\right] + \frac{\lambda}{2\cdot m}\sum_{l=1}^{L-1}\sum_{i=1}^{sl}\sum_{j=1}^{sl+1}\left(\theta_j^{(l)}\right)^2$$

    Implement Backpropagation to compute partial derivatives $\frac{\partial}{\partial \theta_{ji}^{l}} J(\theta)$
    Implement advanced optimization method with backpropagation to try to minimize $J(\theta)$
  End
  Return parameter θ

In ClassifyX, I did the following to implement classification/predict. (code showing in appendix)

Pre-Process
  Normalization (with parameter σ , μ)
  Implement PCA (with parameter U)
Predict test dataset
  Compute the output layer (with parameter θ)
  Predict as the maximum class

Q3. There are three main parameters need to be chosen in my implement, number of iterations, hidden layer units and λ to penalty overfitting. To get better parameters, I use for loops to modify

and set these parameters as inputs of TrainClassifierX function, and then used n-fold (n=5) cross validate method to choose parameters that generate better performance based on the validate set. To evaluate the performance, both accuracy and efficiency should be taken into consideration, so I calculated accuracy, confusion matrice and time cost. The accuracy is computed based on the validate set and the ratio of size of training dataset to size of validate dataset is 4:1. Time cost is calculated by 'tic' and 'toc' in MATLAB. The time cost is the average time cost of TrainClassifierX Function and ClassifyX Function in n-fold (n=5) cross validate test. (Figures in the following tables are approximate because the datasets are assigned randomly each time running the code. code showing in appendix)

Number of iterations

Table2 Comparison in different numbers of iterations

	10	20	30	40	50	60	70	80	90	100
accuracy	93.88%	97.50%	98.11%	98.38%	98.72%	98.84%	98.98%	99.09%	99.08%	99.09%
time cost/sec	2.5133	4.6468	6.5879	9.1332	11.0948	13.8371	16.3175	18.9022	21.9399	23.7548

We can find that with implement the algorithm with more interations can get more accurate output but the time cost increase as well, so it should stop at a suitable iteration. I sected 70 as the number of iterations.

Number of hidden units and overfitting penalty λ

Table3 Comparison in different combination of number of hidden units and λ

	20 hidden units			30 hidden units			40 hidden units		
	λ=0	λ=1	λ=3	λ=0	λ=1	λ=3	λ=0	λ=1	λ=3
accuracy	98.89%	98.86%	98.78%	98.92%	98.99%	98.81%	99.02%	99.03%	98.91%
time cost/sec	15.11	15.12	15.41	16.72	17.27	17.63	18.30	18.53 s	18.37 s

Some of the trials of combination show in Table 3 (70 iterations). We can find that large λ makes slow convergence but do well in avoiding overfitting and increasing hidden units contributes to accurate output, but it leads to the slight increase of time cost as well. To make a balance, I choose λ=1 and units hidden units=30.

Classification accuracy and confusion matrix

With the given dataset (size=24000), I took 80% as training data(size=19200), and 20% as test data(size=4800). For 30 hidden units, λ=1 and 70 iterations, the confusion matrix is following.

Table4 Confusion matrix

	predict=1	predict=2	predict=3	predict=4	predict=5	total
label=1	1136	0	0	0	0	1136
label=2	1	1234	2	0	0	1237
label=3	0	6	1100	3	0	1109
label=4	0	0	5	764	16	785
label=5	0	2	0	12	519	533
total	1137	1242	1107	779	535	4800

$$accuracy = \frac{1136 + 1234 + 1100 + 764 + 519}{4800} = 99.02\%$$

Advantages:

This algorithm performs well in the non-linear multiple classification, especially in accuracy, and the time cost is acceptable.

It takes several parameters to do predict tasks. Once the training completed, we can use the trained parameters to do classification in limited time, not like non-parameter method KNN. In KNN, the time cost increases with the increase of the size of test set, because it resorts distances.

This algorithm takes $\frac{\lambda}{2 \cdot m} \sum_{l=1}^{L-1} \sum_{i=1}^{sl} \sum_{j=1}^{sl+1} \left(\theta_j^{(l)}\right)^2$ into the computation of cost, to reducing overfitting.

Disadvantages:

It needs time to get convergence. With small number of iterations, it gives worse predict. As a result, it doesn't run as fast as Gaussian Naïve Bayes Classifier (accuracy=97%, time cost=0.04sec). In order to get a better predict, it sacrifices some time. If we don't have such needs on accuracy, Gaussian Naïve Bayes Classifier can be an alternative method.

Appendix

Q1 visualization.m

```
clear;
load data
%n=size(data,1);
%elems = randperm(n)';
inputs=data(:,2:65);
labels=data(:,1);

%% each feature
[m, m1] = size(inputs);
idx1=labels==1;
idx2=labels==2;
idx3=labels==3;
idx4=labels==4;
idx5=labels==5;

for i=1:64
        %5 classes againest each feature
        subplot(8,8,i),h=histogram(inputs(idx1,i));h.EdgeColor=h.FaceColor;hold
on;
        subplot(8,8,i),h=histogram(inputs(idx2,i));h.EdgeColor=h.FaceColor;hold
on;
        subplot(8,8,i),h=histogram(inputs(idx3,i));h.EdgeColor=h.FaceColor;hold
on;
        subplot(8,8,i),h=histogram(inputs(idx4,i));h.EdgeColor=h.FaceColor;hold
on;
        subplot(8,8,i),h=histogram(inputs(idx5,i));h.EdgeColor=h.FaceColor;

        %xlabel(['feature',num2str(i)]);
        %ylabel('frequency');
end

%% scatter matrix
figure;
[m, m1] = size(inputs);
idx1=find(labels==1);
idx2=find(labels==2);
idx3=find(labels==3);
idx4=find(labels==4);
idx5=find(labels==5);
f=4;%number of features
for i=1:f
    for j=1:f
        %5 classes in scatter matrix
        subplot(f,f,(i-1)*f+j),plot(inputs(idx1,i),inputs(idx1,j),'.');hold on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx2,i),inputs(idx2,j),'.');hold on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx3,i),inputs(idx3,j),'.');hold on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx4,i),inputs(idx4,j),'.');hold on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx5,i),inputs(idx5,j),'.');
        %{
        % to plot part of the scatter matrix
        ii=i+57;
        jj=j+57;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx1,ii),inputs(idx1,jj),'.');hold
on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx2,ii),inputs(idx2,jj),'.');hold
on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx3,ii),inputs(idx3,jj),'.');hold
on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx4,ii),inputs(idx4,jj),'.');hold
on;
        subplot(f,f,(i-1)*f+j),plot(inputs(idx5,ii),inputs(idx5,jj),'.');
        %}
```

```
    end
end

%% 3d
figure
 %implement normalization
    mu = mean(inputs,1);%normalization parameters
    inputs = bsxfun(@minus, inputs, mu);
    sigma = std(inputs,1);%normalization parameters
    inputs = bsxfun(@rdivide, inputs, sigma);

    %implement PCA
    [m, m1] = size(inputs);
    Sigma=1/m*(inputs')*inputs;
    [U,S,~]=svd(Sigma);%compute U S (V)
    %reduce to 3D
    inputs=inputs*U(:,1:3);
    %compute variance
    variance=sum(sum(S(1:3,1:30)))/sum(sum(S));
for i=1:5
    idx=find(labels==i);
    plot3(inputs(idx,1),inputs(idx,2),inputs(idx,3),'.');
    hold on;
end
legend('class1','class2','class3','class4','class5')
grid on
```

Q2 TrainClassifierX.m

```
function parameters = TrainClassifierX(inputs, output)%,lambda,units,iter

    %implement normalization
    parameters.mu = mean(inputs,1);%normalization parameters
    inputs = bsxfun(@minus, inputs, parameters.mu);
    parameters.sigma = std(inputs,1);%normalization parameters
    inputs = bsxfun(@rdivide, inputs, parameters.sigma);

    %implement PCA
    [m, m1] = size(inputs);
    Sigma=1/m*(inputs')*inputs;
    [U,S,~]=svd(Sigma);%compute U S (V)
    %find the value k to remain 99% variance
    for K=1:m1
        if (sum(sum(S(1:K,1:K)))/sum(sum(S))>=0.99)
            break;
        end
    end
    inputs=inputs*U(:,1:K);%Pca on inputs
    parameters.U=U(:,1:K);%Pca paprameters

    %initialize papameters for bp network
    parameters.input_layer_size=K; %number of features after pca
    parameters.hidden_layer_size=30;%units; %units in hidden layer
    parameters.num_labels=5; % 5 labels

    %randam initialze weighs
    initial_Theta1 =
randInitializeWeights(parameters.input_layer_size,parameters.hidden_layer_size);
    initial_Theta2 =
randInitializeWeights(parameters.hidden_layer_size,parameters.num_labels);

    % Unroll parameters
    initial_nn_params = [initial_Theta1(:) ; initial_Theta2(:)];
    %  set lambda and iter
```

```
    lambda = 1;
    iter=70;
    % Create "short hand" for the cost function to be minimized
    costFunction = @(p) nnCostFunction(p, ...
                                       parameters.input_layer_size, ...
                                       parameters.hidden_layer_size, ...
                                       parameters.num_labels,...
                                       inputs, output, lambda);

    % Now, costFunction takes in only one argument (the neural network
parameters)
    [nn_params, ~] = fmincg(costFunction, initial_nn_params, iter);

    % Obtain Theta1 and Theta2 back from nn_params
    parameters.Theta1 = reshape(nn_params(1:parameters.hidden_layer_size * ...
        (parameters.input_layer_size + 1)), parameters.hidden_layer_size, ...
        (parameters.input_layer_size + 1));

    parameters.Theta2 = reshape(nn_params((1 + (parameters.hidden_layer_size
* ...
        (parameters.input_layer_size + 1))):end),...
        parameters.num_labels, (parameters.hidden_layer_size + 1));

end
 function g = sigmoid(z)
%Compute sigmoid functoon
g = 1.0 ./ (1.0 + exp(-z));
end

function g = sigmoidGradient(z)
%returns the gradient of the sigmoid function evaluated at z
g=sigmoid(z).*(1-sigmoid(z));
end

function W = randInitializeWeights(L_in, L_out)
%Randomly initialize the weights of a layer with L_in
%incoming connections and L_out outgoing connections
%The first column of W corresponds to the parameters for the bias unit
epsilon_init=0.12;
W=rand(L_out, 1+L_in)*2*epsilon_init-epsilon_init;
end

function [J,grad] = nnCostFunction(nn_params,input_layer_size, ...
                                   hidden_layer_size, ...
                                   num_labels,X, y, lambda)
%Implements the neural network cost function for a two layer
%neural network which performs classification

% Reshape nn_params back into the parameters Theta1 and Theta2,
%  the weight matrices for our 2 layer neural network
Theta1 = reshape(nn_params(1:hidden_layer_size * (input_layer_size + 1)), ...
                 hidden_layer_size, (input_layer_size + 1));

Theta2 = reshape(nn_params((1 + (hidden_layer_size * (input_layer_size +
1))):end), ...
                 num_labels, (hidden_layer_size + 1));

% Setup some variables
m = size(X, 1);
J = 0;
%Theta1_grad = zeros(size(Theta1));
%Theta2_grad = zeros(size(Theta2));
```

```
% Feedforward the neural network and return the cost in the variable J.
a1=[ones(m,1) X];
z2=a1*Theta1';
a2=[ones(m,1) sigmoid(z2)];
z3=a2*Theta2';
a3=sigmoid(z3);

%cost without regularization
for k=1:size(Theta2,1)
    %index=find(y==k);
    J=J+1/m*sum(-(y==k)'*log(a3(:,k))-(1-(y==k))'*(log(1-a3(:,k))));
end

%cost with regularization
J=J+lambda/2/m*(sum(sum(Theta1(:,2:end).^2))+sum(sum(Theta2(:,2:end).^2)));

%bp
%d3=zeros(size(a3));
%d2=zeros(size(a2));
% Implement the backpropagation algorithm to compute the gradients
% Theta1_grad and Theta2_grad.
Delta1 = zeros(size(Theta1));
Delta2 = zeros(size(Theta2));
for i=1:m
    yi=zeros(1,size(Theta2,1));
    yi(y(i))=1;
    delta3=a3(i,:)-yi;
    t=Theta2'*delta3';
    delta2 = t(2:end,:) .* sigmoidGradient(z2(i, :)');
%    delta2 = t(2:end,:) .* sigmoidGradient(z2(i, :)');
    Delta1 = Delta1 + delta2* a1(i, :);
%    Delta1 = Delta1 + delta2(2:end) * X(i, :);
    Delta2 = Delta2 + delta3' * a2(i,:);
end
%Implement regularization with the gradients.
Theta1_grad = Delta1 / m;
Theta1_grad(:, 2:end) = Theta1_grad(:, 2:end) + lambda/m*Theta1(:, 2:end);
Theta2_grad = Delta2 / m;
Theta2_grad(:, 2:end) = Theta2_grad(:, 2:end) + lambda/m*Theta2(:, 2:end);

% Unroll gradients
grad = [Theta1_grad(:) ; Theta2_grad(:)];

end
function [X, fX, i] = fmincg(f, X, length)
% Minimize a continuous differentialble multivariate function.

RHO = 0.01;    % a bunch of constants for line searches
SIG = 0.5;     % RHO and SIG are the constants in the Wolfe-Powell conditions
INT = 0.1;     % don't reevaluate within 0.1 of the limit of the current bracket
EXT = 3.0;     % extrapolate maximum 3 times the current bracket
MAX = 20;      % max 20 function evaluations per line search
RATIO = 100;   % maximum allowed slope ratio

argstr = ['feval(f, X)'];  % compose string used to call function
i = 0;           % zero the run length counter
ls_failed = 0;   % no previous line search has failed
fX = [];
[f1,df1] = eval(argstr);  % get function value and gradient
i = i + (length<0);
s = -df1;% search direction is steepest
d1 = -s'*s; % this is the slope
z1 = 1/(1-d1);% initial step
```

```
while i < abs(length)      % while not finished
  i = i + (length>0);

  X0 = X; f0 = f1; df0 = df1;    % make a copy of current values
  X = X + z1*s;                  % begin line search
  [f2,df2] = eval(argstr);
  i = i + (length<0);
  d2 = df2'*s;
  f3 = f1; d3 = d1; z3 = -z1;   % initialize point 3 equal to point 1
  %if length>0, M = MAX; else M = min(MAX, -length-i); end
  M = MAX;
  success = 0; limit = -1;% initialize quanteties
  while 1
    while ((f2 > f1+z1*RHO*d1) || (d2 > -SIG*d1)) && (M > 0)
      limit = z1;   % tighten the bracket
      if f2 > f1
        z2 = z3 - (0.5*d3*z3*z3)/(d3*z3+f2-f3);  % quadratic fit
      else
        A = 6*(f2-f3)/z3+3*(d2+d3);  % cubic fit
        B = 3*(f3-f2)-z3*(d3+2*d2);
        z2 = (sqrt(B*B-A*d2*z3*z3)-B)/A;
      end
      if isnan(z2) || isinf(z2)
        z2 = z3/2;  % if we had a numerical problem then bisect
      end
      z2 = max(min(z2, INT*z3),(1-INT)*z3);% don't accept too close to limits
      z1 = z1 + z2; % update the step
      X = X + z2*s;
      [f2,df2] = eval(argstr);
      M = M - 1; i = i + (length<0);
      d2 = df2'*s;
      z3 = z3-z2; % z3 is now relative to the location of z2
    end
    if f2 > f1+z1*RHO*d1 || d2 > -SIG*d1
      break;    %  failure
    elseif d2 > SIG*d1
      success = 1; break; % success
    elseif M == 0
      break;   % failure
    end
    A = 6*(f2-f3)/z3+3*(d2+d3);  % make cubic extrapolation
    B = 3*(f3-f2)-z3*(d3+2*d2);
    z2 = -d2*z3*z3/(B+sqrt(B*B-A*d2*z3*z3)); % num. error possible - ok!
    if ~isreal(z2) || isnan(z2) || isinf(z2) || z2 < 0
      if limit < -0.5  % if we have no upper limit
        z2 = z1 * (EXT-1); % the extrapolate the maximum amount
      else
        z2 = (limit-z1)/2; % otherwise bisect
      end
    elseif (limit > -0.5) && (z2+z1 > limit)
      z2 = (limit-z1)/2;   % bisect
    elseif (limit < -0.5) && (z2+z1 > z1*EXT) % extrapolation beyond limit
      z2 = z1*(EXT-1.0);   % set to extrapolation limit
    elseif z2 < -z3*INT
      z2 = -z3*INT;
    elseif (limit > -0.5) && (z2 < (limit-z1)*(1.0-INT))
      z2 = (limit-z1)*(1.0-INT);
    end
    f3 = f2; d3 = d2; z3 = -z2; % set point 3 equal to point 2
    z1 = z1 + z2; X = X + z2*s; % update current estimates
    [f2,df2] = eval(argstr);
    M = M - 1; i = i + (length<0);
    d2 = df2'*s;
  end  % end of line search
```

```
  if success  % if line search succeeded
    f1 = f2; fX = [fX' f1]';
%    fprintf('%4i,%4.6e;', i, f1);
%    scatter(i,f1);
    s = (df2'*df2-df1'*df2)/(df1'*df1)*s - df2;   % Polack-Ribiere direction
    tmp = df1; df1 = df2; df2 = tmp;   % swap derivatives
    d2 = df1'*s;
    if d2 > 0            % new slope must be negative
      s = -df1;        % otherwise use steepest direction
      d2 = -s'*s;
    end
    z1 = z1 * min(RATIO, d1/(d2-realmin));   % slope ratio but max RATIO
    d1 = d2;
    ls_failed = 0;  % this line search did not fail
  else
    fprintf('fail');
    X = X0; f1 = f0; df1 = df0;  % restore point from before failed line search
    if ls_failed || i > abs(length) % line search failed twice in a row
      break; % or we ran out of time, so we give up
    end
    tmp = df1; df1 = df2; df2 = tmp; % swap derivatives
    s = -df1; % try steepest
    d1 = -s'*s;
    z1 = 1/(1-d1);
    ls_failed = 1; % this line search failed
  end
end
end
```

ClassifierX.m

```
function class = ClassifyX(input, parameters)
    %%implement normalization for test data
    input = bsxfun(@minus, input, parameters.mu);
    input = bsxfun(@rdivide, input, parameters.sigma);

    input=input*parameters.U;

    m = size(input, 1);
    %num_labels = size(parameters.Theta2, 1);

    % predict with Theta
    h1 = sigmoid([ones(m, 1) input] * parameters.Theta1');
    h2 = sigmoid([ones(m, 1) h1] * parameters.Theta2');
    %[dummy, p] = max(h2, [], 2);
    [~, class] = max(h2, [], 2);

end
function g = sigmoid(z)
%Compute sigmoid functoon
g = 1.0 ./ (1.0 + exp(-z));
end
```

Q3 CrossvalidateCheck

```
% crossvalidate to choose parameters and compute accuracy and confusion matrix
clear;

assert(fopen('TrainClassifierX.m') > 0,'Could not find TrainClassifierX.m
function file')
assert(fopen('ClassifyX.m') > 0,'Could not find ClassifyX.m function file')
load data
% Each datapoint is described by 3 distinct features and labelled with a
% single integer value.
```

```
n=size(data,1);
elems = randperm(n)';
%p=zeros(1,5);
%t=zeros(1,5);
for lambda=[0 0.5 0.7 1 3 5] %set different lambda
    for iter=10:10:100 %set different iterations
        for units=20:5:40 %set different units
    for i=1:5
    % set n fold cross validate set
    test_idx=elems(1:floor(n/5));
    train_idx=elems(floor(n/5)+1:n);
    elems=[elems(floor(n/5)+1:n);elems(1:floor(n/5))];
    train_data=data(train_idx,2:65);
    train_labels=data(train_idx,1);
    test_data=data(test_idx,2:65);
    test_labels=data(test_idx,1);
    tic;
    %start compute time cost
    %train data
    parameters = TrainClassifierX(train_data, train_labels,lambda,units,iter);
    %test data
    predicted_labels = ClassifyX(test_data, parameters);
    %check output
    assert(max(predicted_labels) < 6 && min(predicted_labels) > 0, 'Classifier
output label in invalid range.')
    %compute accuracy
    p(i)=length(find(predicted_labels==test_labels))/length(test_labels);
    %disp('ClassifyX has been implemented correctly.')
    %disp('Sanity check passed!')
    t(i)=toc;
    %end compute time cost
    %disp(toc);
    %disp('TrainClassifierX has been implemented correctly.')
    %compute confusion matrix
    confu=zeros(5,5);
    %initialization
    for classi=1:5
        for classj=1:5
            %compute

confu(classi,classj)=length(find(((test_labels==classi).*predicted_labels)==clas
sj));
        end
    end
    end
    %show performance
    %disp(lambda);
    %disp(layers);
    fprintf('%2.0f %2.0f %f %f %f\n',iter,units,lambda,mean(p),mean(t));
    %disp(p);
    %disp(mean(p));
    %disp(mean(t));
        end
    end
end
return
```