1. Logistic regression Hessian (10 points)

Determine a formula for the gradient and the Hessian of the regularized logistic regression objective function. Argue that the objective function

$$J(\boldsymbol{\theta}) = -\ell(\boldsymbol{\theta}) + \lambda \|\boldsymbol{\theta}\|^2$$

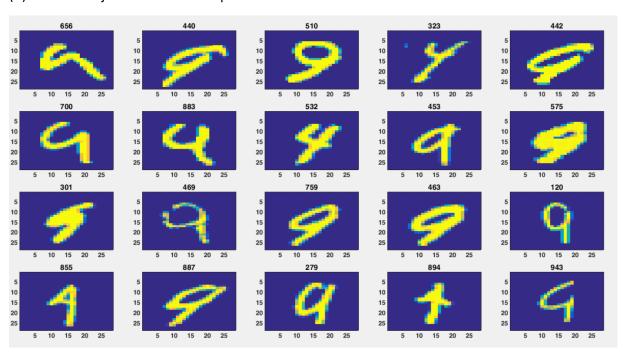
is convex, and that for regularization parameter $\lambda>0,$ the objective function is strictly convex.

<u></u>	1. $J(\theta) = \sum_{i=1}^{n} \log \left(1 + \frac{y_i d\tilde{x}_i}{2}\right) + A\ \theta\ ^2$
1	$= \sum_{i=1}^{i=1} log(1 + e^{y_i \overline{\partial} \widetilde{X}_i}) + \lambda \overline{\partial} \theta$ $\frac{\partial J}{\partial \theta} = \sum_{i=1}^{\infty} y_i \widetilde{X}_i e^{y_i \overline{\partial} \widetilde{X}_i} \frac{1}{1 + e^{y_i \overline{\partial} \widetilde{X}_i}} + 2\lambda \theta$
	$\frac{\partial J}{\partial \theta} = \sum_{i=1}^{\infty} y_i \tilde{x}_i e^{y_i \theta \tilde{x}_i} \frac{1}{1 + e^{y_i \theta \tilde{x}_i}} + 2\lambda \theta$
	$\frac{\partial}{\partial \theta^{T}} \left(\frac{\partial \mathcal{T}}{\partial \theta} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} + 2\lambda \mathbf{I}$
N. S.	$\frac{\partial}{\partial \theta^{T}} \left(\frac{\partial \mathcal{J}}{\partial \theta} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \left(\frac{\partial \mathcal{J}}{\partial \theta^{T}} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \left(\frac{\partial \mathcal{J}}{\partial \theta^{T}} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \left(\frac{\partial \mathcal{J}}{\partial \theta^{T}} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \left(\frac{\partial \mathcal{J}}{\partial \theta^{T}} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \left(\frac{\partial \mathcal{J}}{\partial \theta^{T}} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \chi_{i}^{2} \left(\frac{\partial \mathcal{J}}{\partial \theta^{T}} \right) = \sum_{i=1}^{N} y_{i}^{2} \chi_{i}^{2} \chi$
U	This expression is To in general. Therefore, J(A) is convex If Azo, second term is >0 for x \u2240. Therefor, expression is >0. So, J(B) is strictly convex

2. Handwritten digit classification with logistic regression (5 points each)

Download the file mnist_49_3000.mat from Canvas under Files \rightarrow Data and Helper Functions. This is a subset of the MNIST handwritten digit database, which is a well-known benchmark database for classification algorithms. This subset contains examples of the digits 4 and 9.

Test shows 48 errors (i.e. 4.8% misclassification rate). Termination criterion was 10% error of optimizer $(\hat{\theta})$. Value of objective function at optimum is 307.84.



Code for calculating thetahat

```
hes(theta(:,k));
  theta_old=theta(:,k);
  theta(:,k+1)=theta(:,k)-hes(theta(:,k))\grad(theta(:,k));
  k=k+1;
end
thetahat=theta(:,k);
J(thetahat)
save('thetahat')
```

Code for calculating gradient

```
function grad=grad(theta)
global x_train y_train lambda

xTilde_train=[ones(1,size(x_train,2)); x_train];
grad=2*lambda*theta;
for i=1:numel(y_train)

grad=grad+y_train(i)*xTilde_train(:,i)*exp(y_train(i)*theta'*xTilde_train(:,i))/(1+exp(y_train(i)*theta'*xTilde_train(:,i)));
end
end
```

Code for calculating Hessian

```
function hes=hes(theta)
global x_train y_train lambda

xTilde_train=[ones(1,size(x_train,2)); x_train];
hes=2*lambda*eye(size(theta,1));
for i=1:numel(y_train)

hes=hes+y_train(i)^2*xTilde_train(:,i)*xTilde_train(:,i)'*exp(y_train(i)*theta'*xTilde_train(:,i)))^2;
end
end
```

Code for calculating LR objective function

```
function J=J(theta)
global x_train y_train lambda

xTilde_train=[ones(1,size(x_train,2)); x_train];
J=lambda*(norm(theta))^2;
for i=1:numel(y_train)
    J=J+log(1+exp(y_train(i)*theta'*xTilde_train(:,i)));
end
end
```

Code for calculating etahat

```
function pr=etahat(x_test)
global thetahat

pr=1/(1+exp(-thetahat'*[1;x_test]));
end
```

Code for classifier

```
function [y_pred,conf]=LRclsf(x_test)

if etahat(x_test)>=.5
    y_pred=-1;
else
    y_pred=1;
end
conf=abs(etahat(x_test)-.5);
end
```

Code for obtaining results

```
close all; clear all; clc
load mnist 49 3000
load thetahat
[d,n]=size(x);
x test=x(:,2001:3000);
y test=y(2001:3000);
for i=1:size(x test,2)
    [y_pred(1,i),conf(i)]=LRclsf(x_test(:,i));
error=abs(y_pred-y_test);
ind=find(error)
misclsConf=conf(ind);
errorSum=0;
for i=1:numel(error)
   errorSum=errorSum+error(i)/2;
end
errorSum
misclas rate=errorSum/numel(y test)
[misclsConfSrt,IndVec] = sort(misclsConf);
ind1=fliplr(ind(IndVec));
k=1;
plotInd=ind1(1:20);
for i=plotInd
```

```
subplot(4,5,k)
imagesc(reshape(x_test(:,i),[sqrt(d),sqrt(d)])');

%    title(num2str(conf(i)))
    title(num2str(i))
    k=k+1;
end
```