Gradient Descent and Perceptron for OCR in Matlab

Cyril Gorlla

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1 Gradient Descent and Perceptron for OCR in Matlab

1.1 Cyril Gorlla

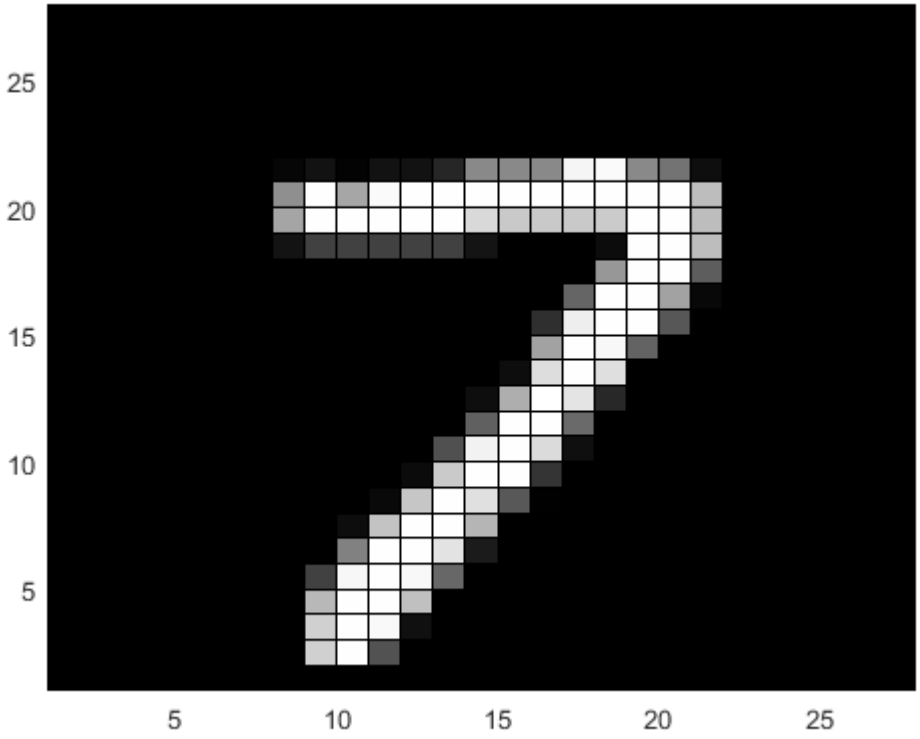
1.2 University of California San Diego

We implement various machine learning approaches to classifying digits from the well-known MNIST dataset.

[4]:
```
load mnisttrain.mat
load mnisttest.mat
```

We will classify 7 and 9. The first 1000 images of each dataset are 7s, while the last 1000 are 9s.

[9]:
```
dig = reshape (mnisttrain(999,:),28,28);
(dig(:,28:-1:1))';
digit = (dig(:,28:-1:1))';
pcolor(digit);
colormap(gray);
```



1.3 Linear Regression

First, we will implement naive linear regression.

$w = (X'X)^{-1}X'Y$

Prediction: $y = x * w$

[10]:
```
labels = cat(1,-ones(1000,1),ones(1000,1));
w = transpose(pinv(mnisttrain*transpose(mnisttrain))*(mnisttrain)) * labels;
pred = mnisttest*w;
pred(pred<0) = -1;
pred(pred>0) = 1;
sum(pred==labels)/2000
```

```
ans =

    0.9350
```

We achieve 93.5% accuracy.

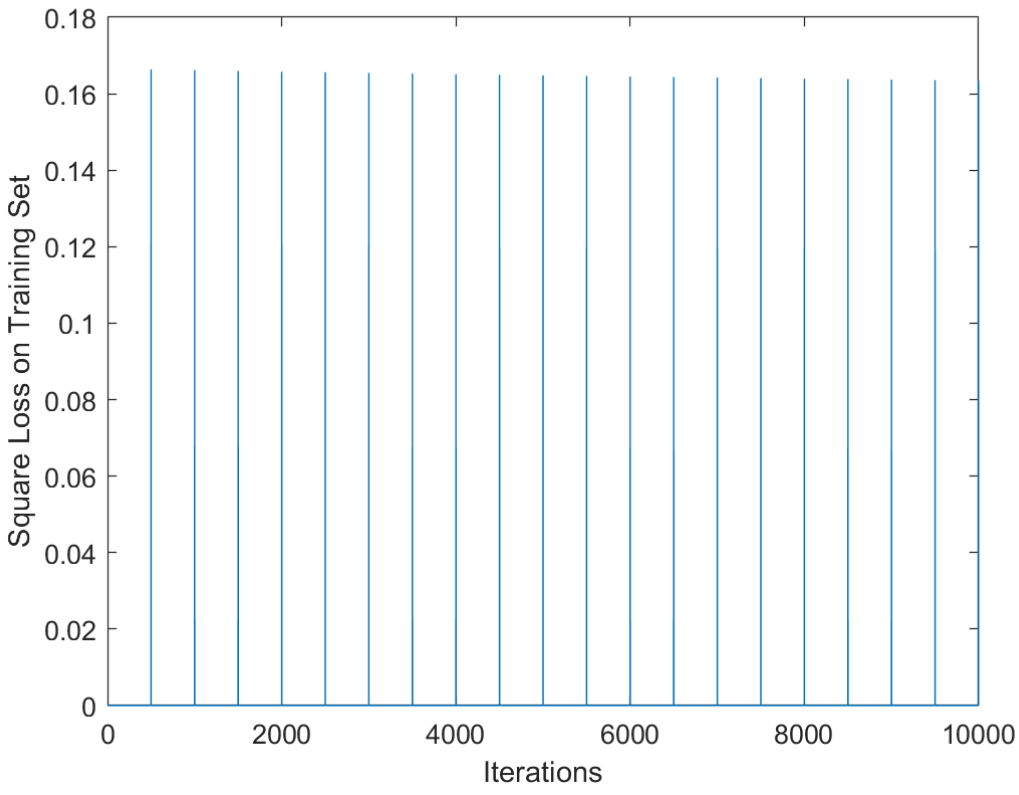
1.4 Gradient Descent for Linear Regression

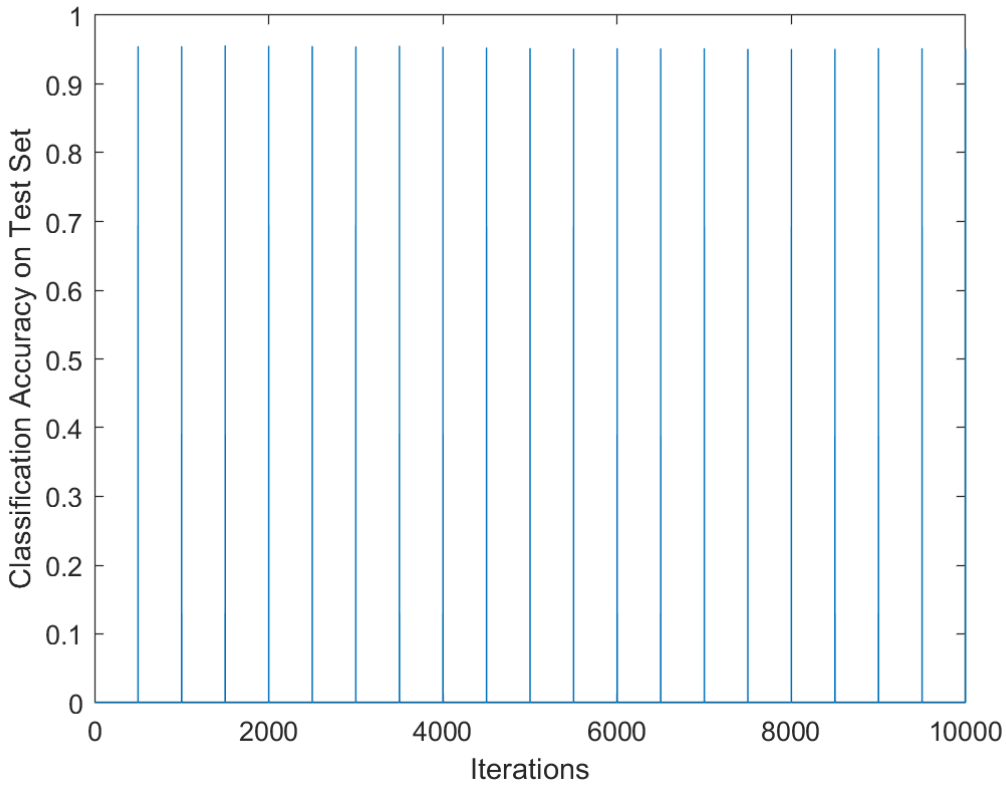
$\eta = \frac{1}{\lambda(x)}$

if $sign(w_t * x_t) \neq sign(y_t)$:

$w_{t+1} = w_t - \eta * (x' * x * w_t - x' * y_t)$

[11]:
```
C = mnisttrain' * mnisttrain;
rate = 1/max(eig(mnisttrain' * mnisttrain));
w = zeros(size(mnisttrain,2),1);
iterations = 10000;
testacc = zeros(iterations,1);
for i=1:iterations
i;
w = w - rate * (mnisttrain' * mnisttrain * w - mnisttrain' * labels);
yprediction2 = mnisttest*w;
if mod(i,500) == 0
yprediction2(yprediction2<0) = -1;
yprediction2(yprediction2>0) = 1;
testacc(i) = sum(yprediction2==labels)/2000;
end
end;
```





1.5 Perceptron

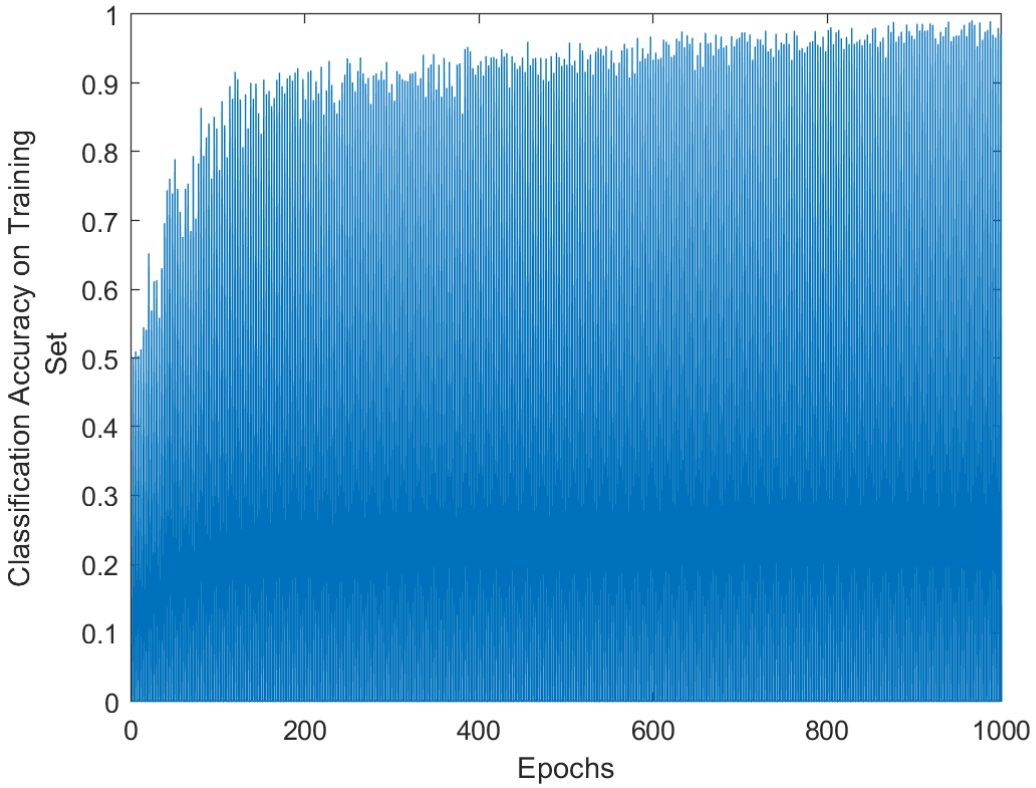
Initial guess $w_1 = 0$.

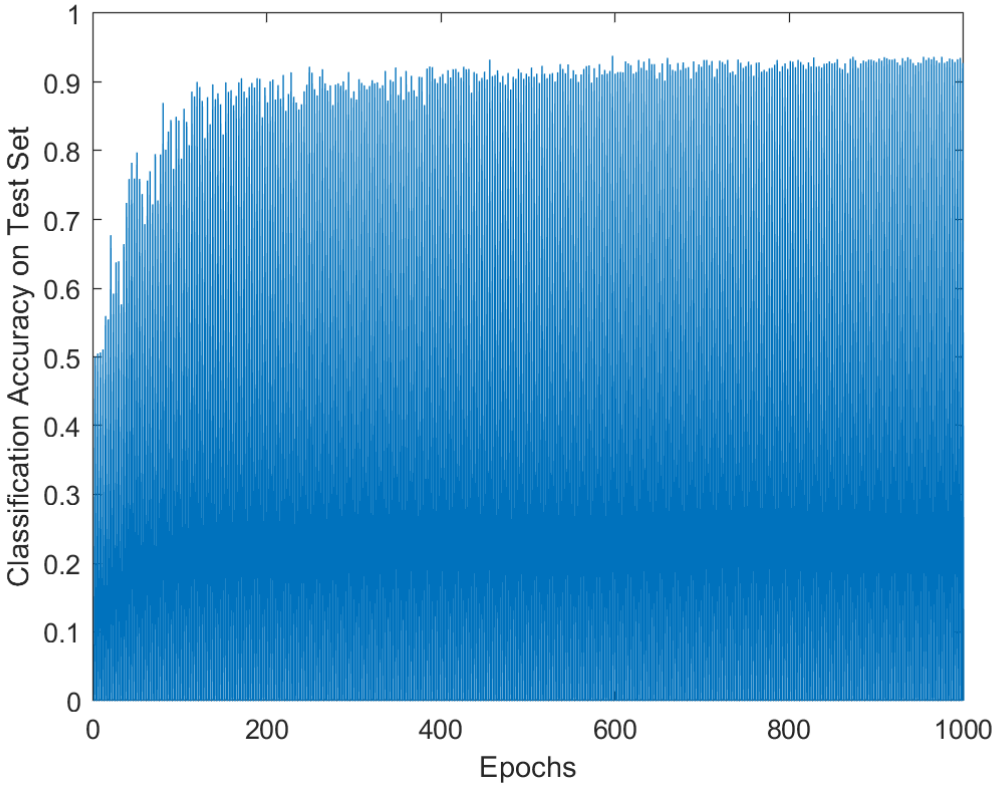
On receiving example x_i: Predict $sign(w_i \cdot x)$ as the label for example x_i.

If incorrect, update $w_{i+1} = w_i + l(x_i)x_i$ else $w_{i+1} = w_i$.

[ ]:
```
w = zeros(784,1);
perceptrain = zeros(1000,1);
perceptest = zeros(1000,1);
for i = 1:1000;i
for j = 1 : 2000;
if sign(w' * mnisttrain(j,:)') ~= sign(labels(j));
w =  w + 1 * (labels(j) * mnisttrain(j,:)');
end;if mod(i,3) ==0;
train = mnisttrain * w;
train(train<0) = -1;
train(train>0) = 1;
test = mnisttest * w;
test(test < 0) = -1;
test(test>0) = 1;
perceptrain(i) = sum(train == labels)/2000;
perceptest(i) = sum(test == labels)/2000;end;
```

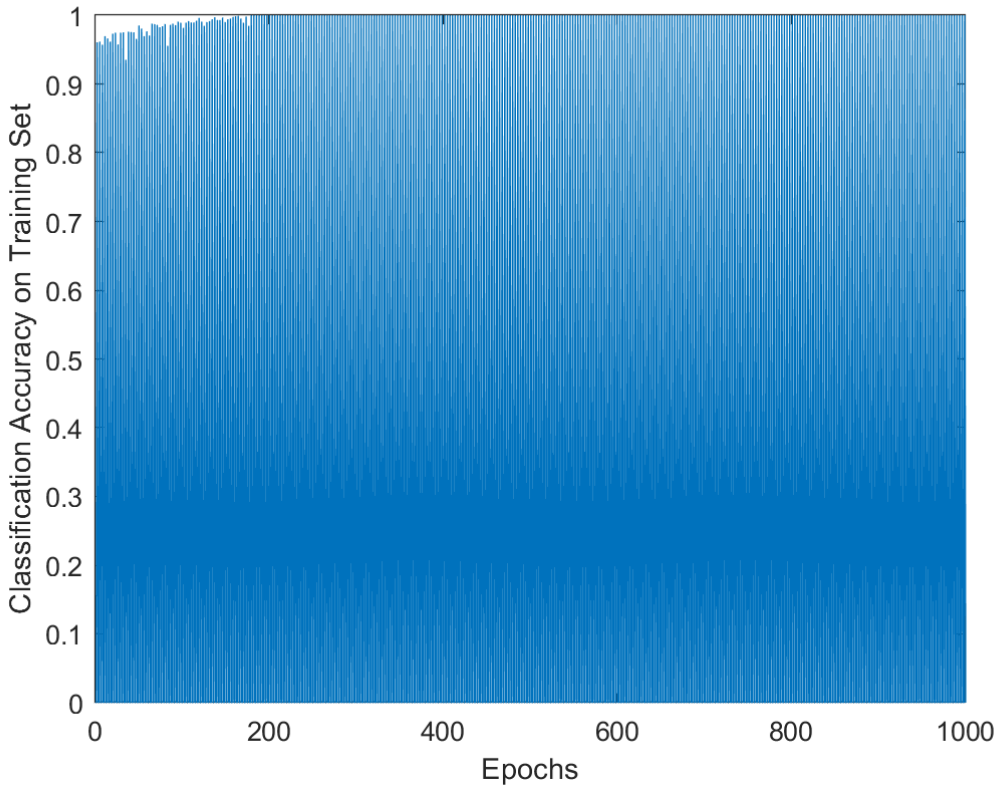
```
end;
end;
```

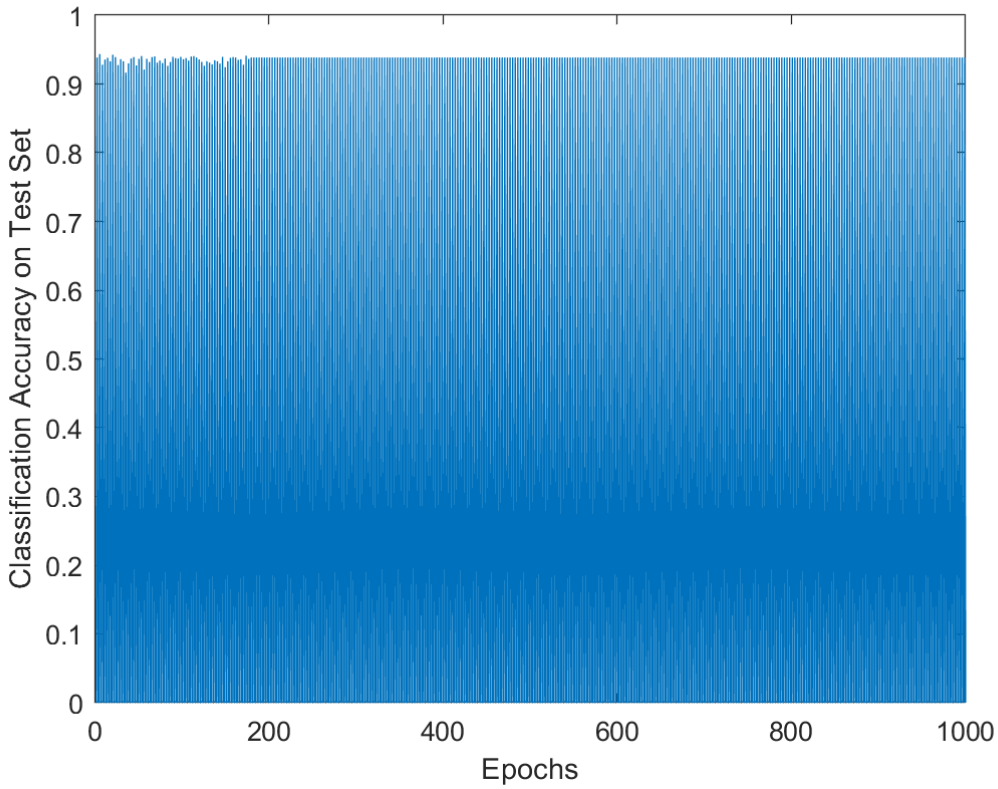

Classification Accuracy on Training Set
Epochs
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
200
400
600
800
1000



1.5.1 Random Training Examples

The perceptron convergence theorem states that there is a perceptron rule w^* that perfectly classifies linearly separable data. This can be seen in the above graphs "leveling off." By randomizing the order of training examples, it is possible to greatly accelerate the rate of convergence.


Classification Accuracy on Training Set
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
200
400
600
800
1000
Epochs


Classification Accuracy on Test Set
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0
200
400
600
800
1000
Epochs