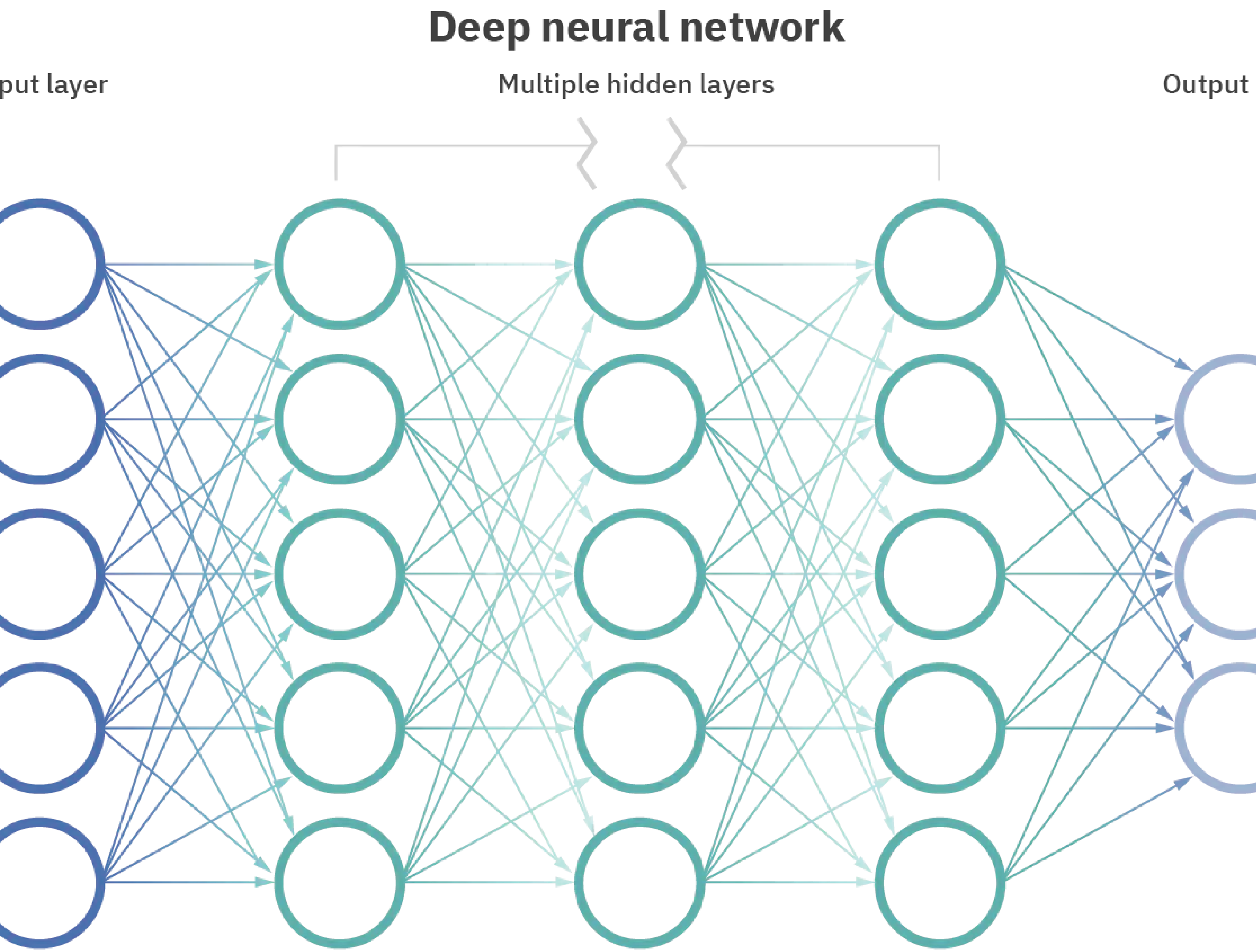
PROJECT

Deep Learning with Artificial Neural Network



QUES.

We implement a neural network that takes the input image and recognizes the digit that it represents. The training data is the MNIST9 database, which contains 70,000 images of handwritten numbers. In general, 60,000 images are used for training, and the remaining 10,000 images are used for the validation test. Each digit image is a 28-by-28 pixel black-and-white image, as shown here.

Ans:

Considering the training time, this example employs only 10,000 images with the training data and verification data in an 8:2 ratio. Therefore, we have 8,000 MNIST images for training and 2,000 images for validation of the performance of the neural network.

The function MnistConv, which trains the network using the back-propagation algorithm, takes the neural network's weights and training data and returns the trained weights.

```
function [W1, W5, Wo] = MnistConv(W1, W5, Wo, X, D)
alpha = 0.01;
beta = 0.95;
momentum1 = zeros(size(W1));
momentum5 = zeros(size(W5));
momentumo = zeros(size(Wo));
N = length(D);
bsize = 100;
blist = 1:bsize:(N-bsize+1);
% One epoch loop
%
for batch = 1:length(blist)
dW1 = zeros(size(W1));
dW5 = zeros(size(W5));
dWo = zeros(size(Wo));
% Mini-batch loop
%
begin = blist(batch);
for k = begin:begin+bsize-1
% Forward pass = inference
%
x = X(:, :, k); % Input, 28x28
y1 = Conv(x, W1); % Convolution, 20x20x20
y2 = ReLU(y1); %
y3 = Pool(y2); % Pool, 10x10x20
y4 = reshape(y3, [], 1); % 2000
v5 = W5*y4; % ReLU, 360
y5 = ReLU(v5); %
v = Wo*y5; % Softmax, 10
y = Softmax(v); %
% One-hot encoding
%
d = zeros(10, 1);
d(sub2ind(size(d), D(k), 1)) = 1;
```

```
% Backpropagation
%
e = d - y; % Output layer
delta = e;
e5 = Wo' * delta; % Hidden(ReLU) layer
delta5 = (y5 > 0) .* e5;
e4 = W5' * delta5; % Pooling layer
e3 = reshape(e4, size(y3));
e2 = zeros(size(y2));
W3 = ones(size(y2)) / (2*2);
for c = 1:20
e2(:, :, c) = kron(e3(:, :, c), ones([2 2])) .* W3(:, :, c);
end
delta2 = (y2 > 0) .* e2; % ReLU layer
delta1_x = zeros(size(W1)); % Convolutional layer
for c = 1:20
delta1_x(:, :, c) = conv2(x(:, :), rot90(delta2(:, :, c), 2),'valid');
end
dW1 = dW1 + delta1_x;
dW5 = dW5 + delta5*y4';
dWo = dWo + delta *y5';
end
% Update weights
%
dW1 = dW1 / bsize;
dW5 = dW5 / bsize;
dWo = dWo / bsize;
momentum1 = alpha*dW1 + beta*momentum1;
W1 = W1 + momentum1;
momentum5 = alpha*dW5 + beta*momentum5;
W5 = W5 + momentum5;
momentumo = alpha*dWo + beta*momentumo;
Wo = Wo + momentumo;
end
end
```

The following listing shows the function Conv, which the function MnistConv calls. This function takes the input image and the convolution filter matrix and returns the feature maps.

```
function [W1, W5, Wo] = MnistConv(W1, W5, Wo, X, D)
alpha = 0.01;
beta = 0.95;
momentum1 = zeros(size(W1));
momentum5 = zeros(size(W5));
momentumo = zeros(size(Wo));
N = length(D);
bsize = 100;
blist = 1:bsize:(N-bsize+1);
% One epoch loop
%
for batch = 1:length(blist)
dW1 = zeros(size(W1));
dW5 = zeros(size(W5));
dWo = zeros(size(Wo));
% Mini-batch loop
%
begin = blist(batch);
for k = begin:begin+bsize-1
% Forward pass = inference
%
x = X(:, :, k); % Input, 28x28
y1 = Conv(x, W1); % Convolution, 20x20x20
y2 = ReLU(y1); %
y3 = Pool(y2); % Pool, 10x10x20
y4 = reshape(y3, [], 1); % 2000
v5 = W5*y4; % ReLU, 360
```

```
y5 = ReLU(v5); %
v = Wo*y5; % Softmax, 10
y = Softmax(v); %
% One-hot encoding
%
d = zeros(10, 1);
d(sub2ind(size(d), D(k), 1)) = 1;
% Backpropagation
%
e = d - y; % Output layer
delta = e;
e5 = Wo' * delta; % Hidden(ReLU) layer
delta5 = (y5 > 0) .* e5;
e4 = W5' * delta5; % Pooling layer
e3 = reshape(e4, size(y3));
e2 = zeros(size(y2));
W3 = ones(size(y2)) / (2*2);
for c = 1:20
e2(:, :, c) = kron(e3(:, :, c), ones([2 2])) .* W3(:, :, c);
end
delta2 = (y2 > 0) .* e2; % ReLU layer
delta1_x = zeros(size(W1)); % Convolutional layer
for c = 1:20
delta1_x(:, :, c) = conv2(x(:, :), rot90(delta2(:, :, c), 2),'valid');
end
dW1 = dW1 + delta1_x;
dW5 = dW5 + delta5*y4';
dWo = dWo + delta *y5';
end
% Update weights
%
dW1 = dW1 / bsize;
dW5 = dW5 / bsize;
dWo = dWo / bsize;
momentum1 = alpha*dW1 + beta*momentum1;
W1 = W1 + momentum1;
momentum5 = alpha*dW5 + beta*momentum5;
W5 = W5 + momentum5;
momentumo = alpha*dWo + beta*momentumo;
Wo = Wo + momentumo;
end
end
```

The function MnistConv also calls the function Pool, which is implemented in the following listing . This function takes the feature map and returns the image after the 2´2 mean pooling process.

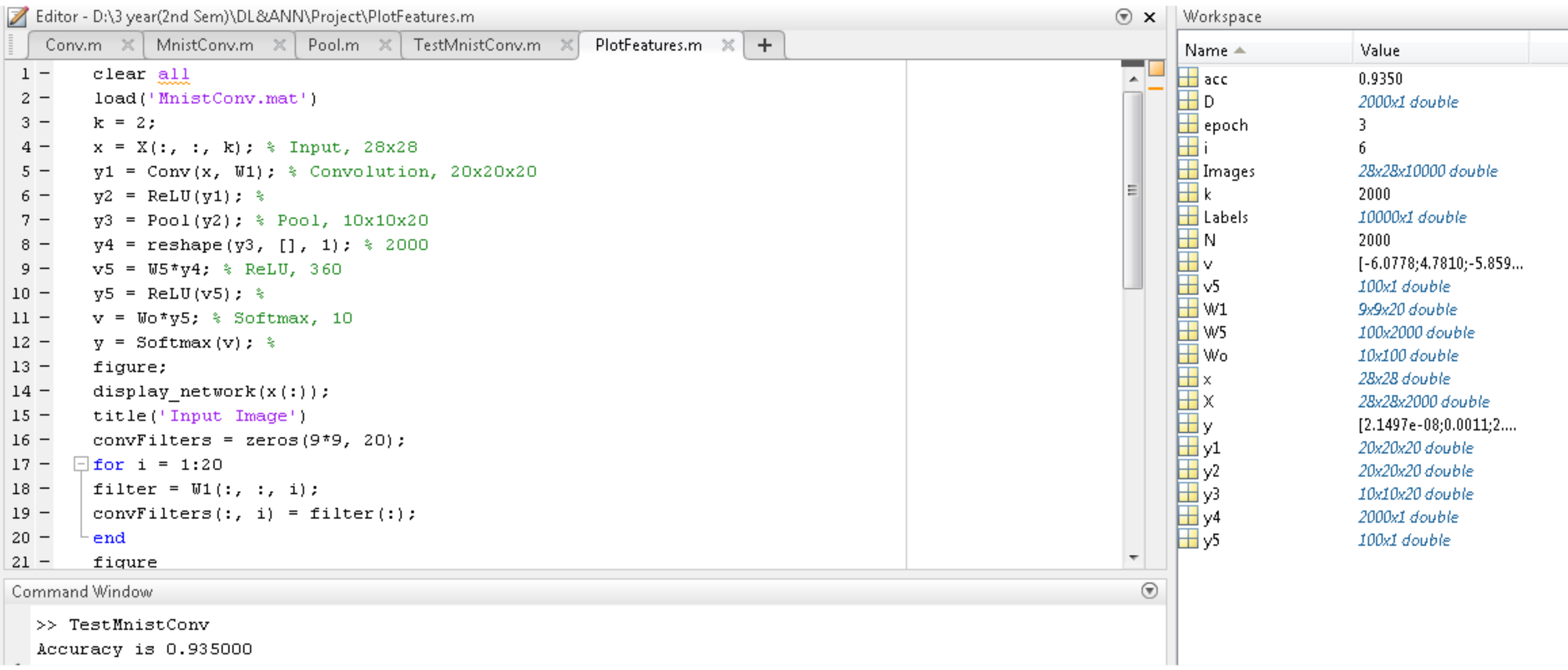
```
function y = Pool(x)
%
% 2x2 mean pooling
%
[xrow, xcol, numFilters] = size(x);
y = zeros(xrow/2, xcol/2, numFilters);
for k = 1:numFilters
filter = ones(2) / (2*2); % for mean
image = conv2(x(:, :, k), filter, 'valid');
y(:, :, k) = image(1:2:end, 1:2:end);
end
end
```

TestMnistConv.m file tests the function MnistConv.10 This program calls the function MnistConv and trains the network three times. It provides the 2,000 test data points to the trained network and displays its accuracy. The test run of this example yielded an accuracy of 93% in 2 minutes and 30 seconds.

```
clear all
Images = loadMNISTImages('t10k-images.idx3-ubyte');
```

```
Images = reshape(Images, 28, 28, []);
Labels = loadMNISTLabels('t10k-labels.idx1-ubyte');
Labels(Labels == 0) = 10; % 0 --> 10
rng(1);
% Learning
%
W1 = 1e-2*randn([9 9 20]);
W5 = (2*rand(100, 2000) - 1) * sqrt(6) / sqrt(360 + 2000);
Wo = (2*rand( 10, 100) - 1) * sqrt(6) / sqrt( 10 + 100);
X = Images(:, :, 1:8000);
D = Labels(1:8000);
for epoch = 1:3
[W1, W5, Wo] = MnistConv(W1, W5, Wo, X, D);
end
save('MnistConv.mat');
% Test
%
X = Images(:, :, 8001:10000);
D = Labels(8001:10000);
acc = 0;
N = length(D);
for k = 1:N
x = X(:, :, k); % Input, 28x28
y1 = Conv(x, W1); % Convolution, 20x20x20
y2 = ReLU(y1); %
y3 = Pool(y2); % Pool, 10x10x20
y4 = reshape(y3, [], 1); % 2000
v5 = W5*y4; % ReLU, 360
y5 = ReLU(v5); %
v = Wo*y5; % Softmax, 10
y = Softmax(v); %
[~, i] = max(y);
if i == D(k)
acc = acc + 1;
end
end
acc = acc / N;
fprintf('Accuracy is %f\n', acc);
```

Followig is the output:



The final result after passing the convolution and pooling layers is as many smaller images as the number of the convolution filters; ConvNet converts the input image into the many small feature maps.

Program for plotfeatures is:

```
clear all
load('MnistConv.mat')
k = 2;
x = X(:, :, k); % Input, 28x28
y1 = Conv(x, W1); % Convolution, 20x20x20
y2 = ReLU(y1); %
y3 = Pool(y2); % Pool, 10x10x20
y4 = reshape(y3, [], 1); % 2000
v5 = W5*y4; % ReLU, 360
y5 = ReLU(v5); %
v = Wo*y5; % Softmax, 10
y = Softmax(v); %
figure;
display_network(x(:));
title('Input Image')
convFilters = zeros(9*9, 20);
for i = 1:20
filter = W1(:, :, i);
convFilters(:, i) = filter(:);
end
figure
display_network(convFilters);
title('Convolution Filters')
fList = zeros(20*20, 20);
for i = 1:20
feature = y1(:, :, i);
fList(:, i) = feature(:);
end
figure
display_network(fList);
title('Features [Convolution]')
fList = zeros(20*20, 20);
for i = 1:20
feature = y2(:, :, i);
fList(:, i) = feature(:);
end
figure
display_network(fList);
title('Features [Convolution + ReLU]')
fList = zeros(10*10, 20);
for i = 1:20
feature = y3(:, :, i);
fList(:, i) = feature(:);
end
figure
display_network(fList);
title('Features [Convolution + ReLU + MeanPool]')
```

Now the outputs are:

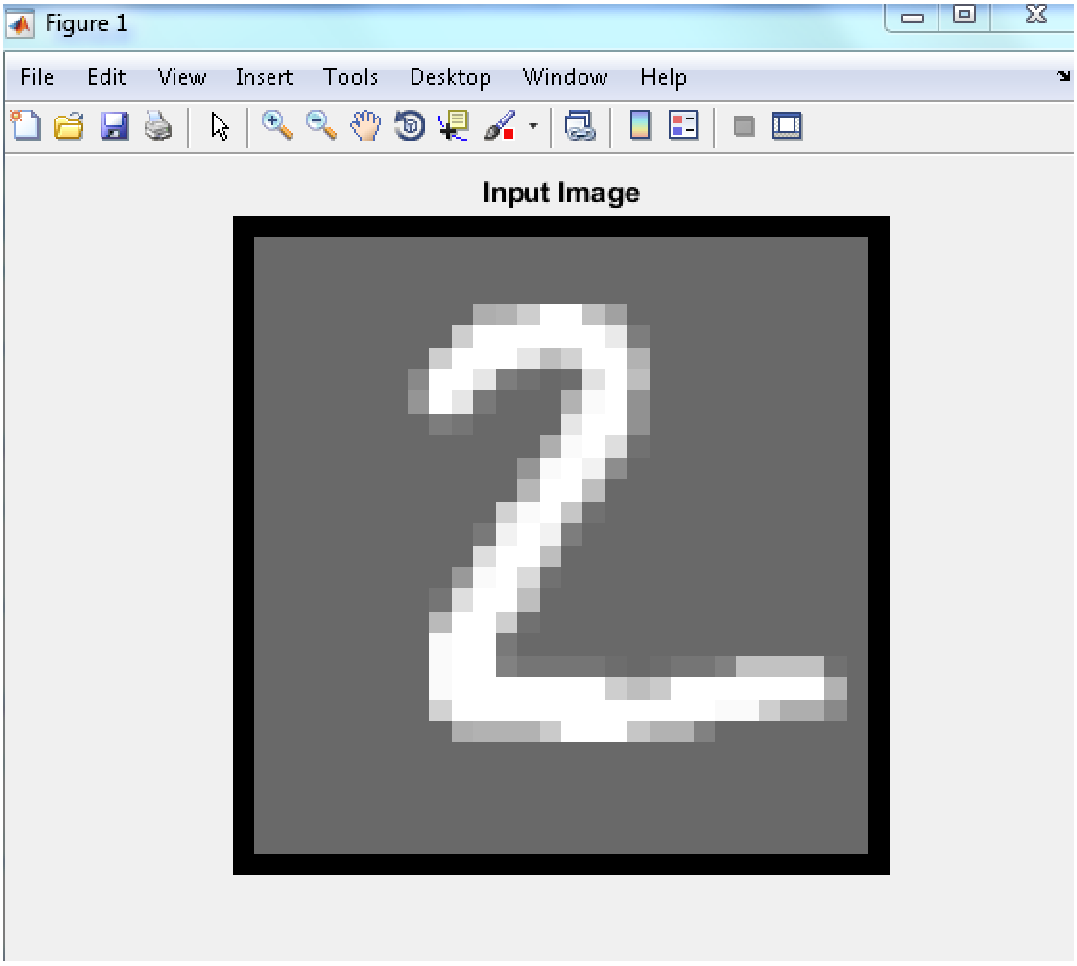


Figure 1
File Edit View Insert Tools Desktop Window Help
Input Image

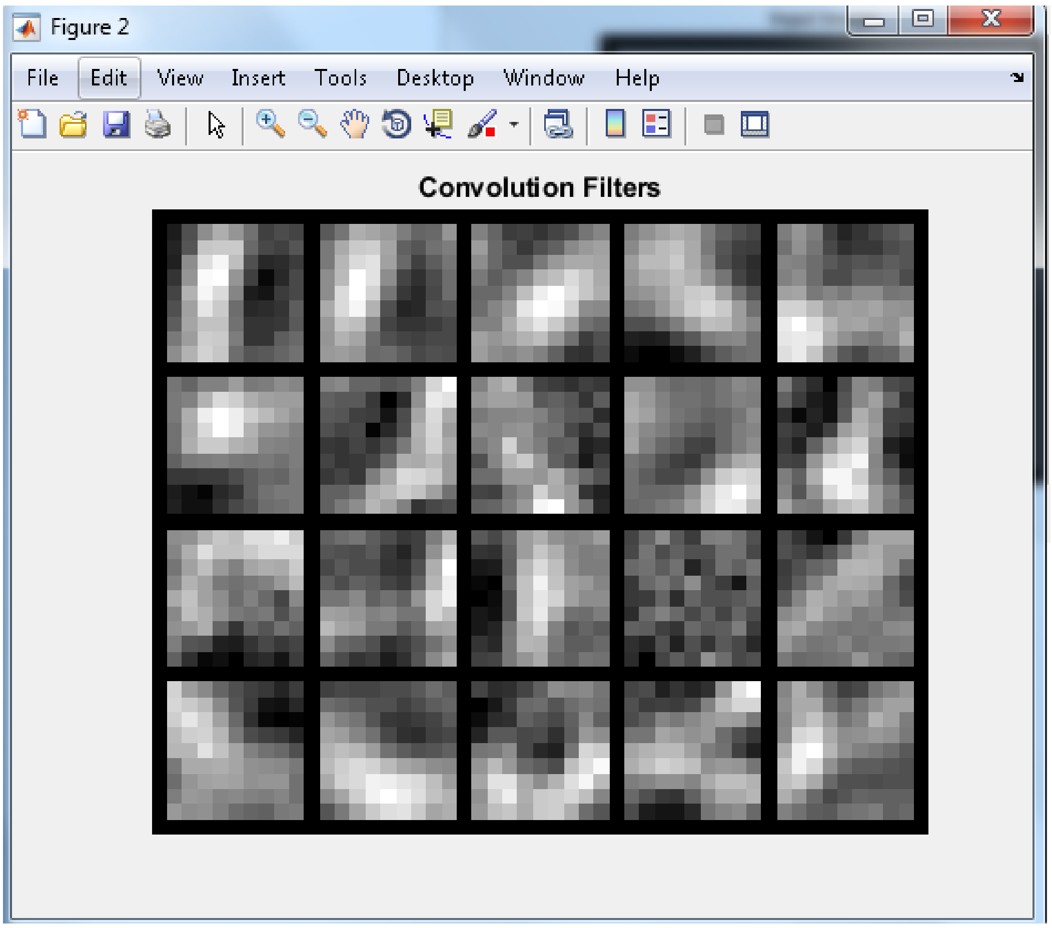


Figure 2
File Edit View Insert Tools Desktop Window Help
Convolution Filters

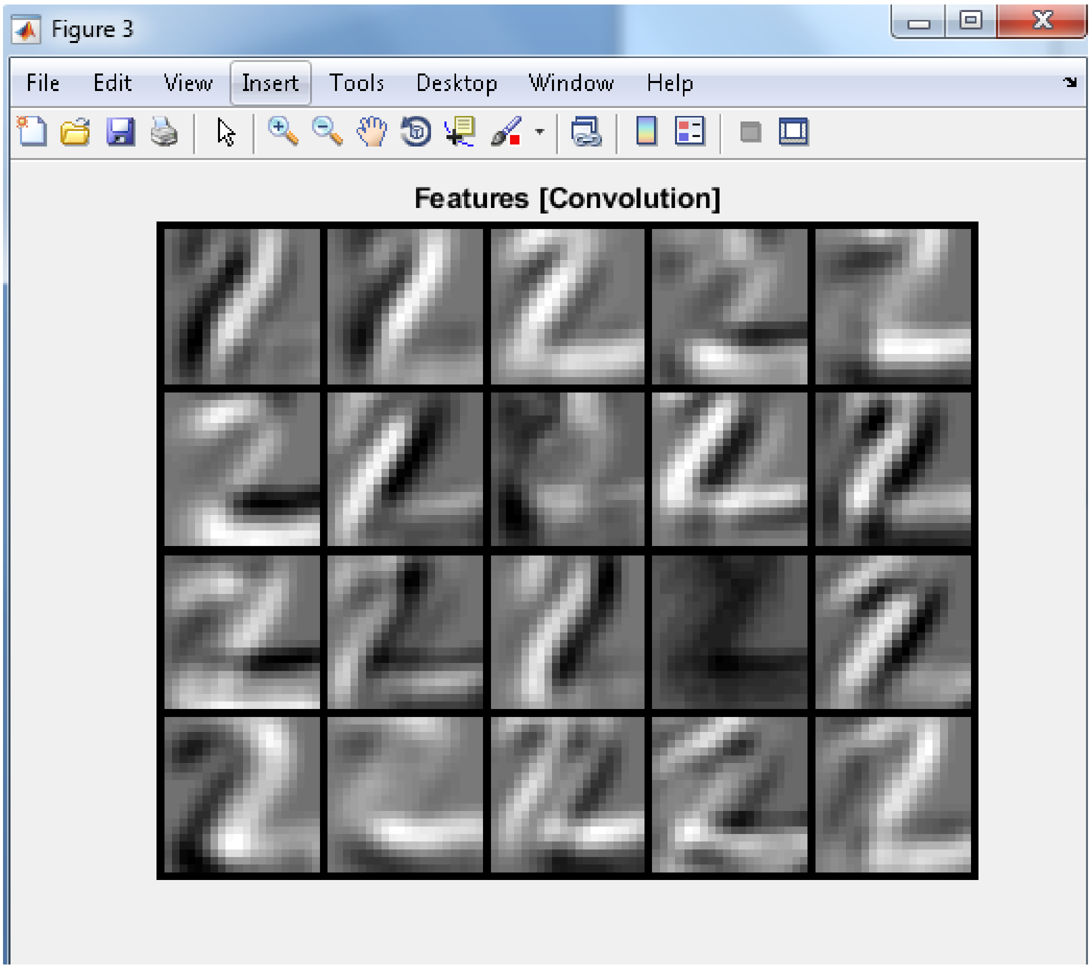


Figure 3
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Features [Convolution]

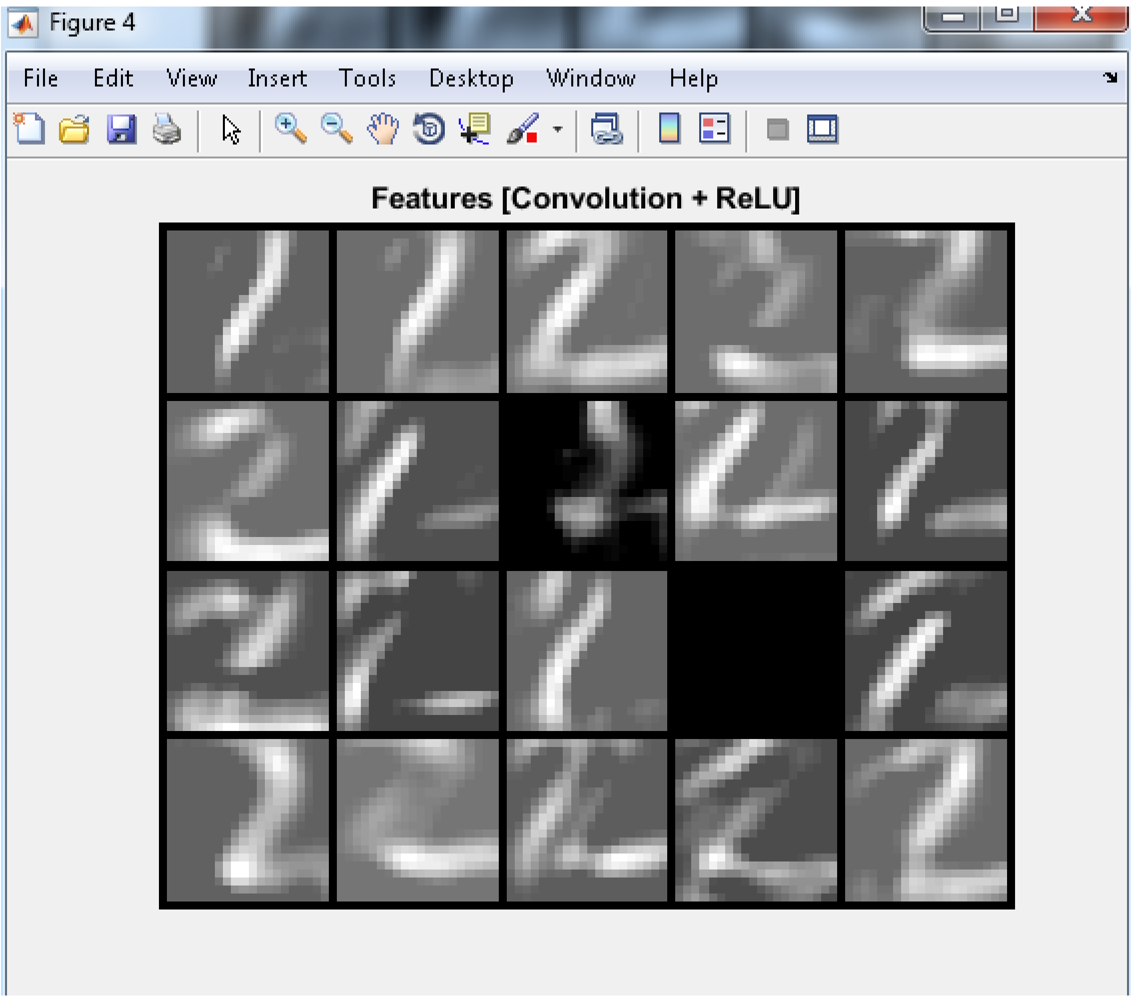
Figure 4
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Features [Convolution + ReLU]

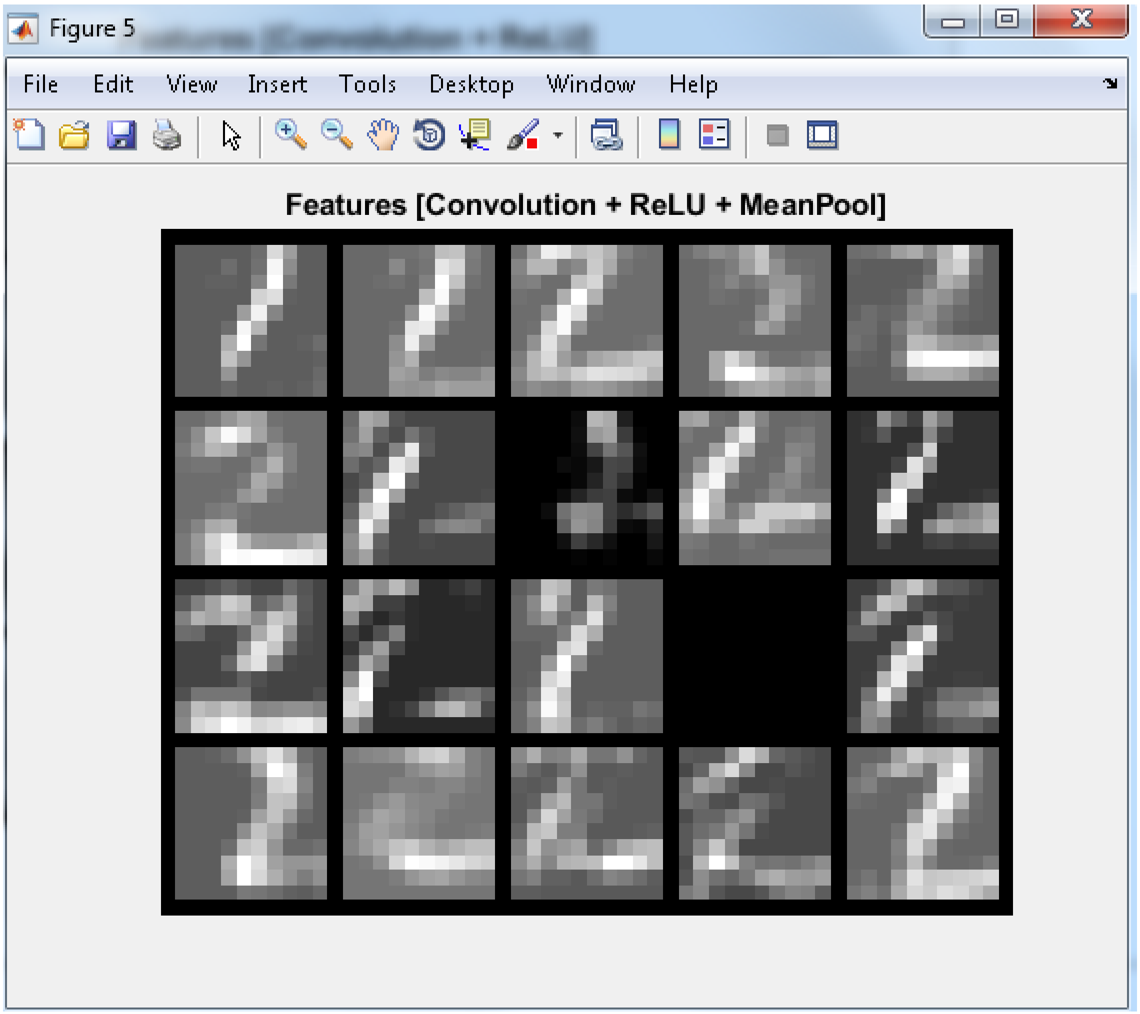
Figure 5
File Edit View Insert Tools Desktop Window Help
Features [Convolution + ReLU + MeanPool]