

EE3700 Introduction to Machine Learning

Classifying Images with Deep Convolutional Neural Networks

Hsi-Pin Ma 馬席彬

http://lms.nthu.edu.tw/course/40724 Department of Electrical Engineering National Tsing Hua University



Outline

- Building Blocks of Convolutional Neural Networks
- Implementing Deep Convolutional Neural Networks in TensorFlow



Features in ML Algorithms

• Salient (relevant) features is key to performance of ML algorithms

- Traditional ML rely on features from *domain experts* or *computational feature extraction techniques*
- Neural networks (NNs) can *learn* the features *automatically* from raw data that most useful for a particular task
 - Consider NN as a feature extraction engine, the early layers extract *low-level features*

• Feature Hierarchy

– Multilayer NN construct a so-called *feature hierarchy* by combining the low-level features in a layer-wise fashion to form high-level features



Convolutional Neural Networks

- CNN computes *feature maps* from an input image
- CNNs perform very well for image-related tasks
 - Sparse-connectivity: A single element in the feature map is connected to only a small patch of pixels
 - Parameter-sharing: The same weights are used for different patches of the input image

Components

- Convolutional layers (conv)
- Pooling layers (P)
- Full connected layers (FC)



Building Blocks of Convolutional Neural Networks



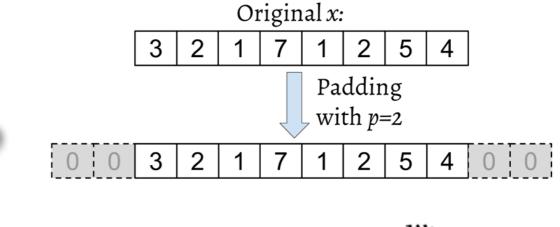
Performing Discrete Convolutions

• A discrete convolution in one dimension

-*x*, *w*: one-dimensional vector, *x*: input/signal, *w*: filter/kernel

Padding (zero-padding): p

 $y = x * w \to y[i] = \sum_{k=-\infty}^{\infty} x[i-k]w[k]$



3

5

1⁄4

Example
 x:
 *
 w:

 -x, w: n, m elements
 3 2 1 7 1 2 5 4

$$\frac{1}{2}$$
 $\frac{3}{4}$ 1 $\frac{1}{4}$

 -s: stride, shift
 Step 1: Rotate the filter
 w^r : $\frac{1}{4}$ 1 $\frac{3}{4}$ $\frac{1}{2}$
 $s=2$

 Step 2: For each output element *i*, compute the dot-product $x[i:i+4].w^r$ (move filter by 2 cells)
 $y[1]$: $3 2 1 7 1 2 5 4$
 $y[2]$: $\frac{3 2 1 7 1 2 5 4}{\frac{1}{4} 1 \frac{3}{4} \frac{1}{2}}$

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y:

8

 $\frac{1}{4} + 2 + 5 \times \frac{3}{4} + 4 \times \frac{1}{2}$

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Effect of Zero-Padding in a Convolution

• Three commonly modes

- Full padding: *p=m-*1. Increase the dimension of the output. Most used in signal processing applications to minimize the boundary effect
- Same padding: Same size of input and output vectors.
 Mostly used in CNNs to make a network architecture design more convenient.
- -Valid padding
- In practice, preserve the spatial size using same padding for the convolutional layers and decrease the spatial size via pooling layers

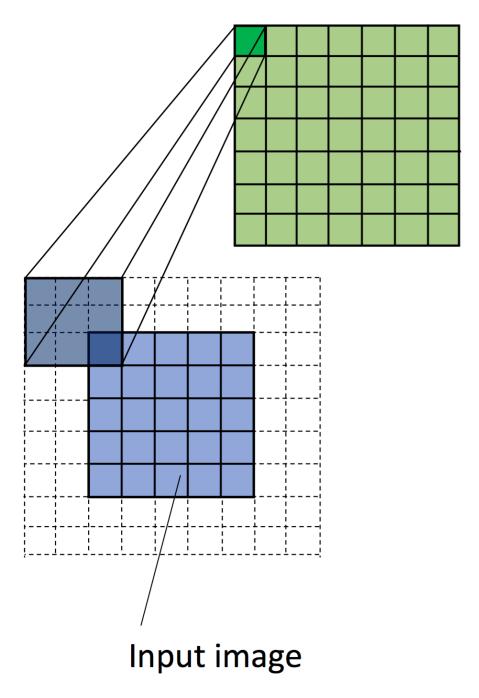


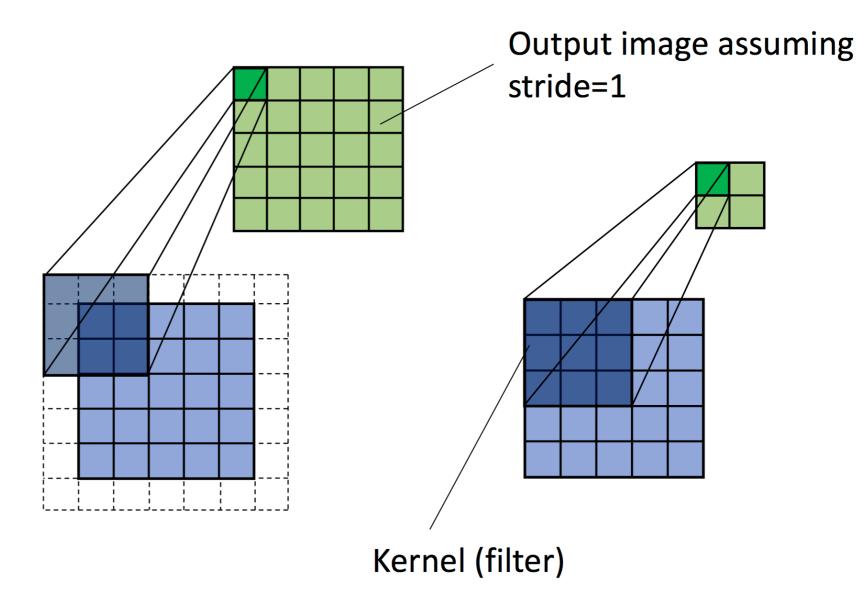
Effect of Zero-Padding in a Convolution

Full padding

Same padding

Valid padding

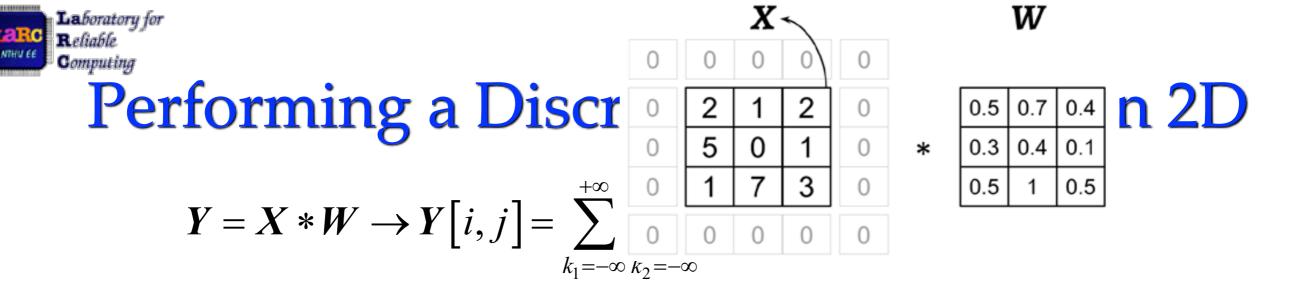


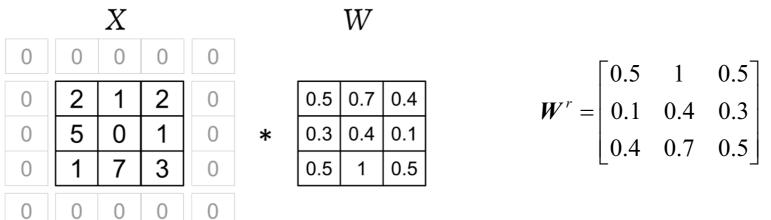




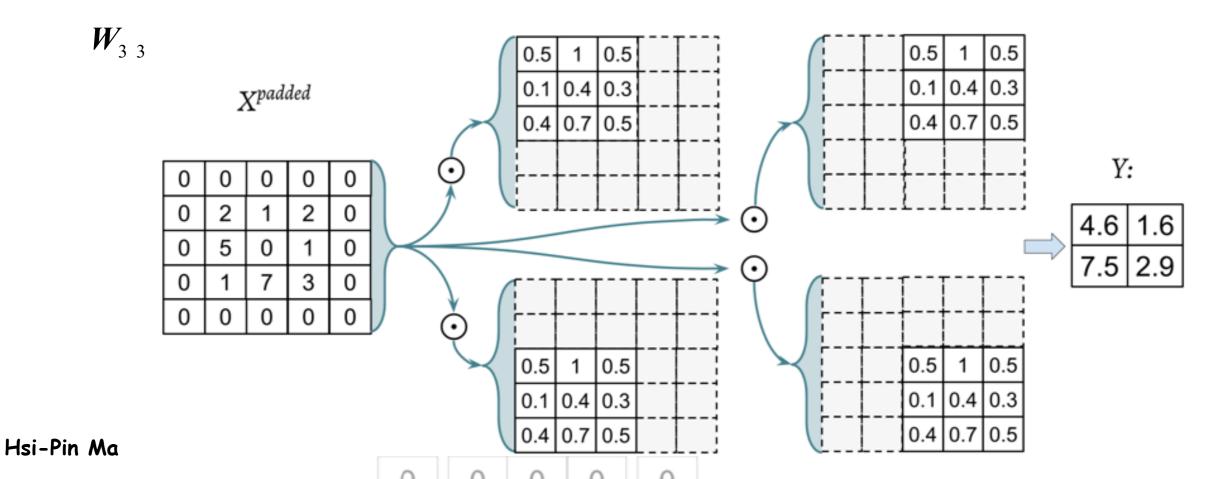
Determining the Size of the Convolutional Output

```
import numpy as np
                                                    o = \left| \frac{n+2p-m}{s} \right| + 1
def convld(x, w, p=0, s=1):
   w rot = np.array(w[::-1])
   x padded = np.array(x)
   if p > 0:
       zero_pad = np.zeros(shape=p)
       x padded = np.concatenate([zero pad, x padded, zero pad])
   res = []
    for i in range(0, int(len(x)/s),s):
       res.append(np.sum(x padded[i:i+w rot.shape[0]] * w rot))
   return np.array(res)
## Testing:
\mathbf{x} = [1, 3, 2, 4, 5, 6, 1, 3]
w = [1, 0, 3, 1, 2]
print('Convld Implementation: ',
                                                          floor(1.77) = |1.77| = 1
     conv1d(x, w, p=2, s=1))
print('Numpy Results: ',
     np.convolve(x, w, mode='same'))
  Convld Implementation: [ 5. 14. 16. 26. 24. 34. 19. 22.]
  Numpy Results:
                 [ 5 14 16 26 24 34 19 22]
```





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2D Convolution

```
import numpy as np
import scipy.signal
```

```
def conv2d(X, W, p=(0,0), s=(1,1)):
    W_rot = np.array(W)[::-1,::-1]
    X \text{ orig} = np.array(X)
    n1 = X \text{ orig.shape}[0] + 2*p[0]
    n2 = X_{orig.shape[1]} + 2*p[1]
    X_padded = np.zeros(shape=(n1,n2))
    X padded[p[0]:p[0] + X orig.shape[0],
             p[1]:p[1] + X \text{ orig.shape}[1]] = X \text{ orig}
    res = []
    for i in range(0, int((X padded.shape[0] -
                            W rot.shape[0])/s[0])+1, s[0]):
        res.append([])
        for j in range(0, int((X_padded.shape[1] -
                                 W rot.shape[1])/s[1])+1, s[1]):
            X sub = X padded[i:i+W rot.shape[0], j:j+W rot.shape[1]]
            res[-1].append(np.sum(X_sub * W_rot))
    return(np.array(res))
X = [[1, 3, 2, 4], [5, 6, 1, 3], [1, 2, 0, 2], [3, 4, 3, 2]]
W = [[1, 0, 3], [1, 2, 1], [0, 1, 1]]
print('Conv2d Implementation: \n',
      conv2d(X, W, p=(1,1), s=(1,1))
```

```
print('Scipy Results: \n',
```

Hsi-Pin Mc scipy.signal.convolve2d(X, W, mode='same'))

Conv2d Implementation: [[11. 25. 32. 13.] [19. 25. 24. 13.] [13. 28. 25. 17.] [11. 17. 14. 9.]] Scipy Results: [[11 25 32 13] [19 25 24 13] [13 28 25 17] [11 17 14 9]]

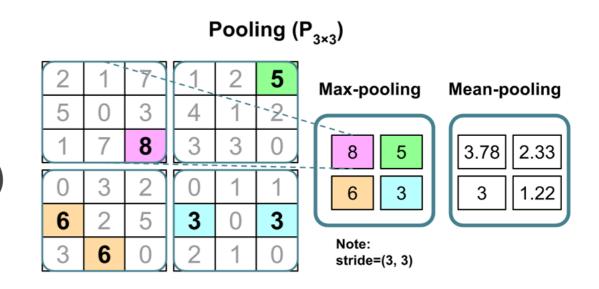


Subsampling

Two forms of subsampling

- max-pooling
- mean-pooling (average-pooling)

Advantages of pooling

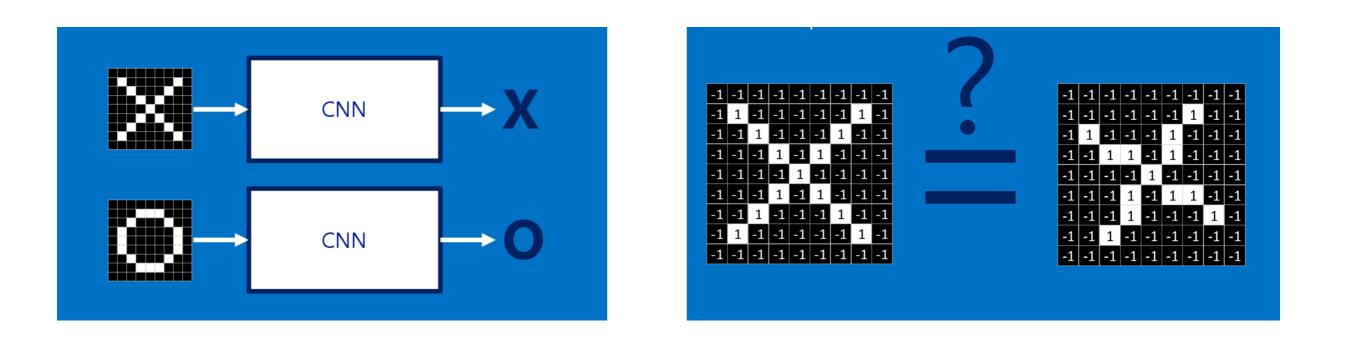


- Introducing some sort of local invariance to generate features that are more robust to noise in the input data
- Decrease the size of features and result in high computation efficiency and also can reduce the degree of overfitting



A Simple Walk Through

• To classify X's and O's from images

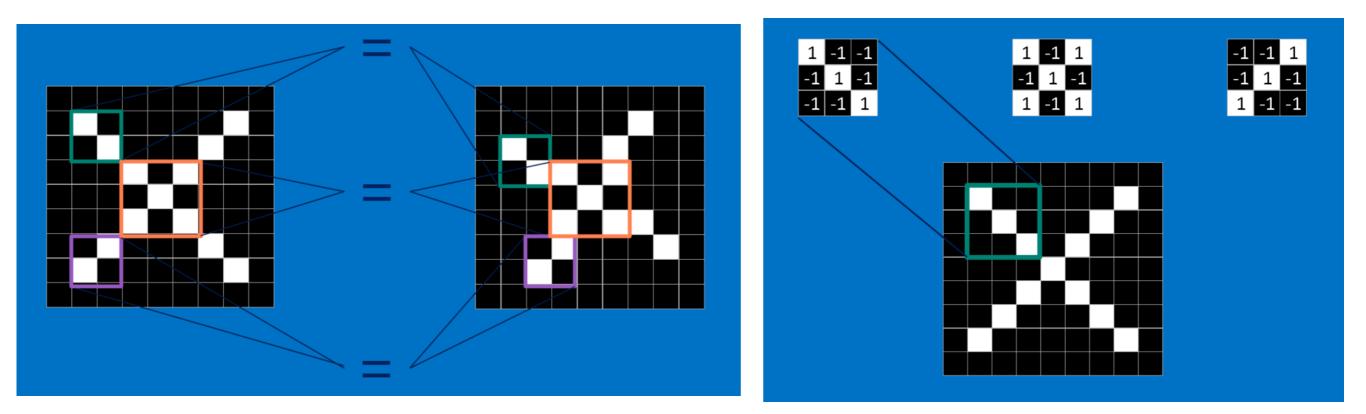


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Features

• CNN compare images piece by piece (features)



Convolution

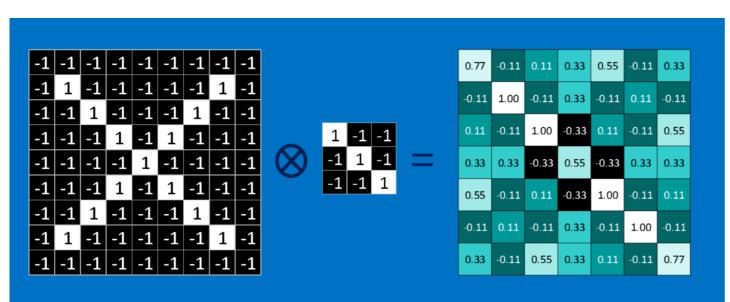
• Define white 1, black -1

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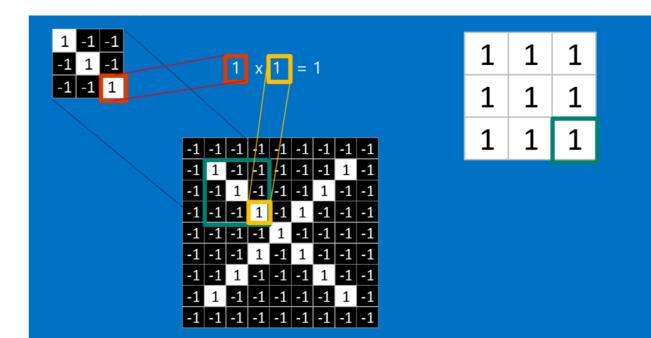
Reliable Computing

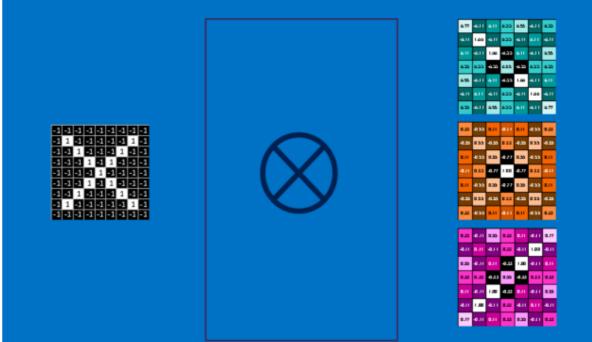
- For the convolution results
 - close to 1: strong matches
 - close to -1: strong matches to the photographic negative of the feature

•near 0: no match



A map of where in the image the feature is found

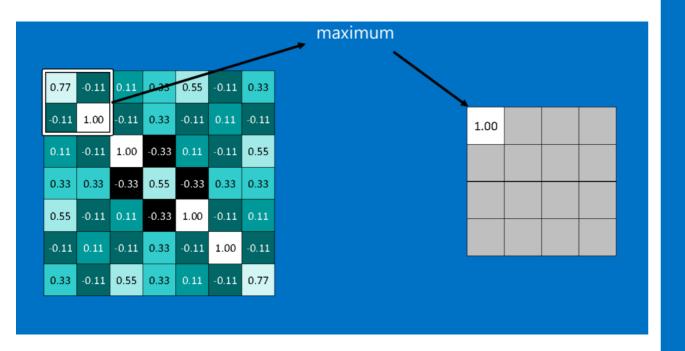


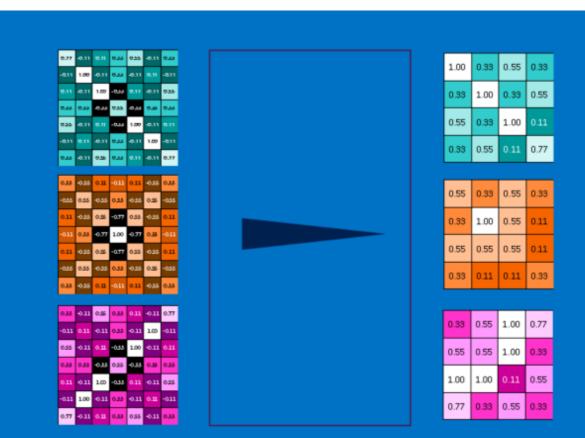




Pooling

• Take large images to shrink them down while preserving the most important information in them

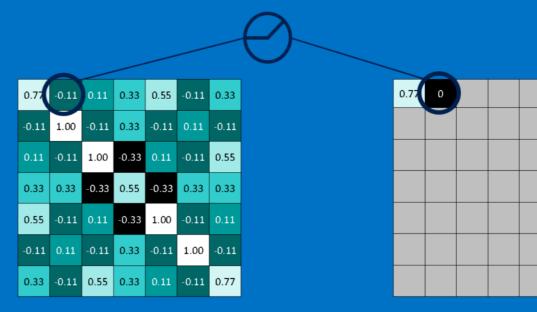


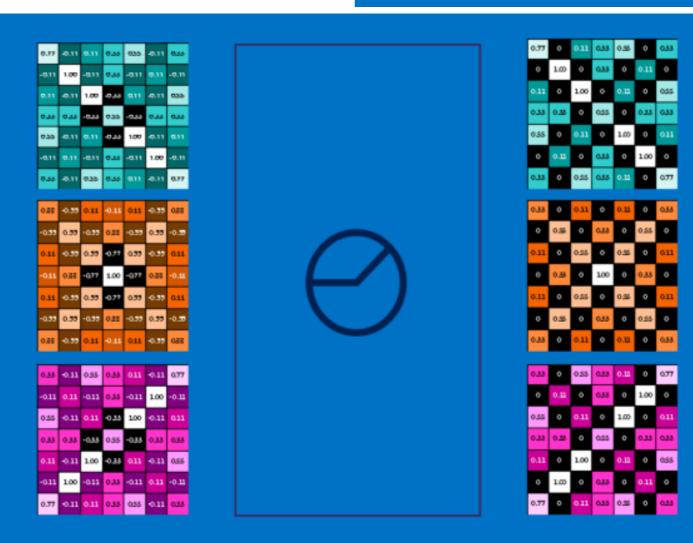




Rectified Linear Units (ReLU)

• Whenever a negative number occurs, swap it out for a 0.

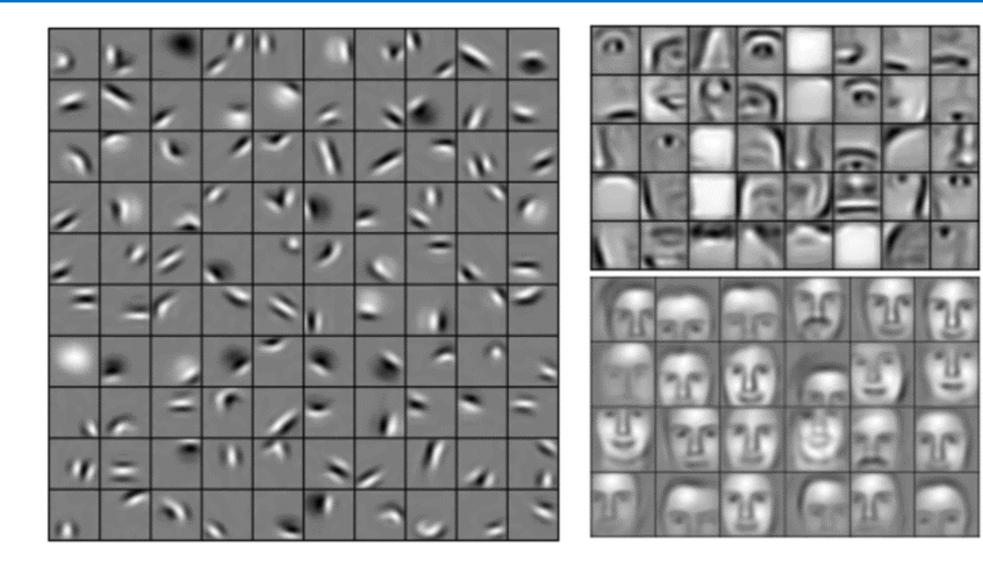






Deep Learning

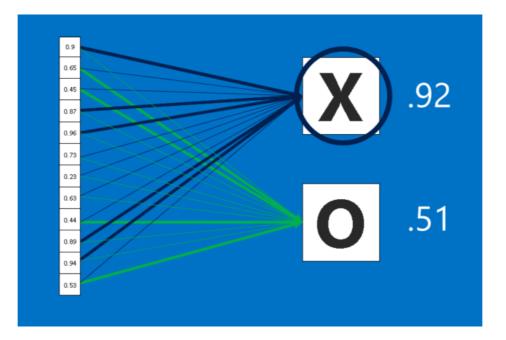




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Fully Connected Layers







Working with Multiple Input orColor Channelsw[:,:,c]

• Using multiple channels as input to a convolutional Next requires to use a rank-3 tensor or a 3D array $X_{N_1 \times N_2 \times C_{in}}$ C_{in} W[:,:,c]

Given a sample
$$\mathbf{X}_{n_1 \times n_2 \times c_{in}'}$$

a kernel matrix $\mathbf{W}_{m_1 \times m_2 \times c_{in}'}$ width here here $ht \times C_{in} \times C_{out}^{c=1}$ $W[:,:,c] *_{C_{in}} [:,3,c]$
a kernel matrix $\mathbf{W}_{m_1 \times m_2 \times c_{in}'}$ by the ere of the

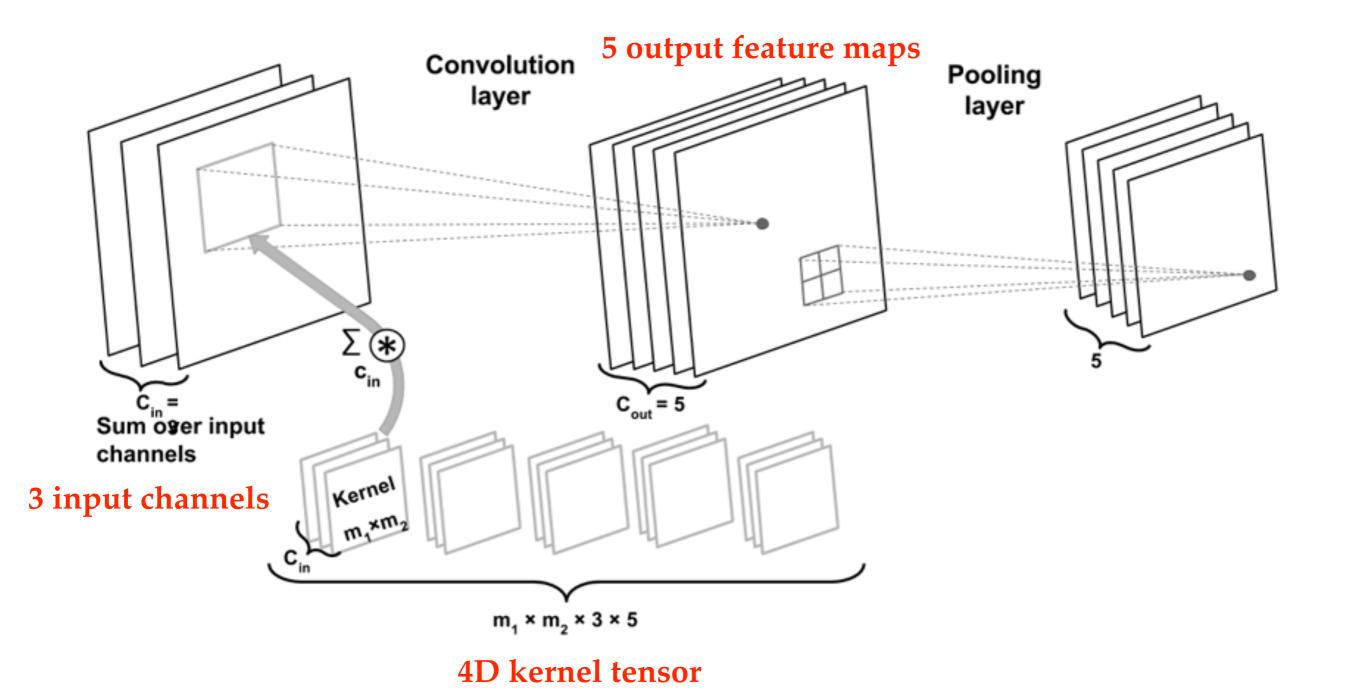
Consider the number of output feature maps

Given a sample
$$X_{n_1 \times n_2 \times C_{in}}$$

key mel matrix $W_{m_1 \times m_2 \times C_{in} \times C_{out}} \Rightarrow$
and bias vector $b_{C_{out}}$
 $V^{Conv}[:,:,k] = \sum_{c=1}^{C_{in}} W[:,:,c,k] * X[:,:,c]$
 $A[:,:,k] = \Psi^{Conv}[:,:,k] + b[k]$
 $H[:,:,k] = \phi(A[:,:,k])$



An Example



^{Laboratory for} ^{Computing} Regularizing a Neural Network with Dropout

Choosing the size of a network has always been a challenging problem

 The *capacity* of a network refers to the level of complexity of the function that it can learn. underfit vs. overfit issue

Ways to address the problem

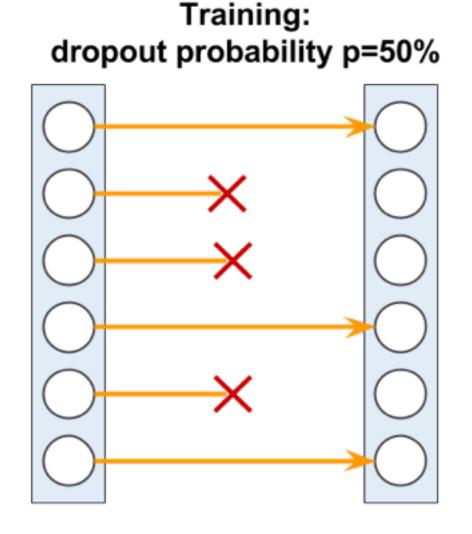
- Build a network with relatively large capacity with L2 regularization
- -Dropout

•Can be considered as the consensus (averaging) of an ensemble of models

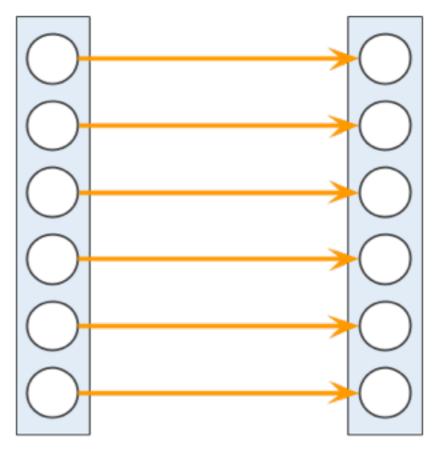


Dropout

- Dropout is usually applied to the hidden units of higher layers with probability *P*_{drop}
- Random dropout at training and evaluate with all units



Evaluation: use all units



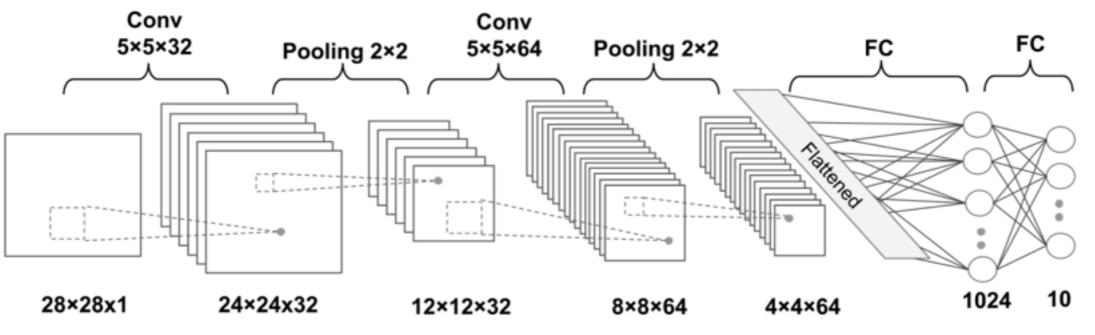


Implementing Deep Convolutional Neural Networks in TensorFlow



Use a CNN to Classify Handwritten Digits

- Input tensor: 28x28x1 (28x28 greyscale images)
- kernel size: 5x5
- 1st convolutional output 32 feature maps and 2nd output 64 feature maps
- Each convolution layer is followed by a subsampling layer in the form of a max-pooling





Load and Preprocess the Data (1/3)

```
## unzips mnist
import sys
import gzip
import shutil
import os
if (sys.version_info > (3, 0)):
   writemode = 'wb'
else:
   writemode = 'w'
zipped_mnist = [f for f in os.listdir('./')
                if f.endswith('ubyte.gz')]
for z in zipped mnist:
   with gzip.GzipFile(z, mode='rb') as decompressed, open(z[:-3], writemode) as outfile:
        outfile.write(decompressed.read())
```



import struct

import numpy as np

Load and Preprocess the Data (2/3)

```
def load mnist(path, kind='train'):
    """Load MNIST data from `path`"""
    labels path = os.path.join(path,
                                '%s-labels-idx1-ubyte'
                                % kind)
    images path = os.path.join(path,
                                '%s-images-idx3-ubyte'
                               % kind)
    with open(labels path, 'rb') as lbpath:
        magic, n = struct.unpack('>II',
                                 lbpath.read(8))
        labels = np.fromfile(lbpath,
                             dtype=np.uint8)
    with open(images_path, 'rb') as imgpath:
        magic, num, rows, cols = struct.unpack(">IIII",
                                                imgpath.read(16))
        images = np.fromfile(imgpath,
                             dtype=np.uint8).reshape(len(labels), 784)
```



Load and Preprocess the Data (3/3)

```
X_data, y_data = load_mnist('./', kind='train')
print('Rows: %d, Columns: %d' % (X_data.shape[0], X_data.shape[1]))
X_test, y_test = load_mnist('./', kind='t10k')
print('Rows: %d, Columns: %d' % (X_test.shape[0], X_test.shape[1]))
X_train, y_train = X_data[:50000,:], y_data[:50000]
X_valid, y_valid = X_data[50000:,:], y_data[50000:]
print('Training: ', X_train.shape, y_train.shape)
print('Validation: ', X_valid.shape, y_valid.shape)
print('Test Set: ', X_test.shape, y_test.shape)
Rows: 60000, Columns: 784
```

Rows: 00000, Columns: 784 Rows: 10000, Columns: 784 Training: (50000, 784) (50000,) Validation: (10000, 784) (10000,) Test Set: (10000, 784) (10000,)



Generate the Mini-batches

```
mean_vals = np.mean(X_train, axis=0)
std_val = np.std(X_train)
X_train_centered = (X_train - mean_vals)/std_val
X_valid_centered = X_valid - mean_vals
X_test_centered = (X_test - mean_vals)/std_val
del X_data, y_data, X_train, X_valid, X_test
```



Implementing a CNN in the TensorFlow Low-Level API



Convolutional Layer (1/2)

```
import tensorflow as tf
import numpy as np
## wrapper functions
def conv layer(input tensor, name,
               kernel size, n output channels,
               padding mode='SAME', strides=(1, 1, 1, 1)):
    with tf.variable scope(name):
        ## get n_input_channels:
        ## input tensor shape:
            [batch x width x height x channels in]
        ##
        input_shape = input_tensor.get_shape().as_list()
        n input channels = input shape[-1]
        weights shape = (list(kernel size) +
                         [n input channels, n output channels])
        weights = tf.get variable(name=' weights',
                                  shape=weights shape)
        print(weights)
        biases = tf.get variable(name=' biases',
                                 initializer=tf.zeros(
                                     shape=[n_output_channels]))
        print(biases)
        conv = tf.nn.conv2d(input=input_tensor,
                            filter=weights,
                            strides=strides,
                            padding=padding mode)
```

print(conv)

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Convolutional Layer (2/2)

```
conv = tf.nn.bias add(conv, biases,
                              name='net pre-activation')
        print(conv)
        conv = tf.nn.relu(conv, name='activation')
        print(conv)
        return conv
## testing
g = tf.Graph()
with g.as default():
    x = tf.placeholder(tf.float32, shape=[None, 28, 28, 1])
    conv_layer(x, name='convtest', kernel_size=(3, 3), n_output_channels=32)
```

```
del g, x
```

```
<tf.Variable 'convtest/_weights:0' shape=(3, 3, 1, 32) dtype=float32_ref>
<tf.Variable 'convtest/_biases:0' shape=(32,) dtype=float32_ref>
Tensor("convtest/Conv2D:0", shape=(?, 28, 28, 32), dtype=float32)
Tensor("convtest/net_pre-activation:0", shape=(?, 28, 28, 32), dtype=float32)
Tensor("convtest/activation:0", shape=(?, 28, 28, 32), dtype=float32)
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```

Fully Connected Layer (1/2)

```
def fc layer(input tensor, name,
             n output units, activation fn=None):
   with tf.variable scope(name):
        input shape = input tensor.get shape().as list()[1:]
        n input units = np.prod(input shape)
       if len(input shape) > 1:
            input_tensor = tf.reshape(input_tensor,
                                      shape=(-1, n input units))
       weights shape = [n input units, n output units]
       weights = tf.get_variable(name='_weights',
                                  shape=weights shape)
        print(weights)
       biases = tf.get variable(name=' biases',
                                 initializer=tf.zeros(
                                     shape=[n output units]))
        print(biases)
       layer = tf.matmul(input tensor, weights)
       print(layer)
        layer = tf.nn.bias add(layer, biases,
                              name='net pre-activation')
        print(layer)
        if activation fn is None:
            return layer
        layer = activation fn(layer, name='activation')
       print(layer)
       return layer
```

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Fully Connected Layer (1/2)

del g, x

```
<tf.Variable 'fctest/_weights:0' shape=(784, 32) dtype=float32_ref><tf.Variable 'fctest/_biases:0' shape=(32,) dtype=float32_ref>
Tensor("fctest/MatMul:0", shape=(?, 32), dtype=float32)
Tensor("fctest/net_pre-activation:0", shape=(?, 32), dtype=float32)
Tensor("fctest/activation:0", shape=(?, 32), dtype=float32)
```



Build CNN (1/6)

```
def build cnn():
    ## Placeholders for X and y:
    tf x = tf.placeholder(tf.float32, shape=[None, 784],
                          name='tf x')
   tf y = tf.placeholder(tf.int32, shape=[None],
                          name='tf y')
    # reshape x to a 4D tensor:
    # [batchsize, width, height, 1]
    tf x image = tf.reshape(tf x, shape=[-1, 28, 28, 1],
                            name='tf x reshaped')
    ## One-hot encoding:
    tf y onehot = tf.one hot(indices=tf y, depth=10,
                             dtype=tf.float32,
                             name='tf y onehot')
    ## 1st layer: Conv 1
    print('\nBuilding 1st layer: ')
   h1 = conv layer(tf x image, name='conv 1',
                    kernel_size=(5, 5),
                    padding mode='VALID',
                    n output channels=32)
    ## MaxPooling
    h1 pool = tf.nn.max pool(h1,
                             ksize=[1, 2, 2, 1],
                             strides=[1, 2, 2, 1],
                             padding='SAME')
```

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Build CNN (2/6)

```
## 2n layer: Conv 2
print('\nBuilding 2nd layer: ')
h2 = conv layer(h1 pool, name='conv 2',
                kernel size=(5,5),
                padding mode='VALID',
                n output channels=64)
## MaxPooling
h2 pool = tf.nn.max pool(h2,
                         ksize=[1, 2, 2, 1],
                         strides=[1, 2, 2, 1],
                         padding='SAME')
## 3rd layer: Fully Connected
print('\nBuilding 3rd layer:')
h3 = fc_layer(h2_pool, name='fc_3',
              n_output_units=1024,
              activation fn=tf.nn.relu)
## Dropout
keep prob = tf.placeholder(tf.float32, name='fc keep prob')
h3 drop = tf.nn.dropout(h3, keep prob=keep prob,
                        name='dropout layer')
## 4th layer: Fully Connected (linear activation)
print('\nBuilding 4th layer:')
h4 = fc layer(h3 drop, name='fc 4',
              n output units=10,
```

activation fn=None)



Build CNN (3/6)

```
## Computing the prediction accuracy
correct_predictions = tf.equal(
    predictions['labels'],
    tf_y, name='correct_preds')
```

```
accuracy = tf.reduce_mean(
    tf.cast(correct_predictions, tf.float32),
    name='accuracy')
```



Build CNN (4/6)

```
def save(saver, sess, epoch, path='./model/'):
    if not os.path.isdir(path):
        os.makedirs(path)
    print('Saving model in %s' % path)
    saver.save(sess, os.path.join(path,'cnn-model.ckpt'),
        global_step=epoch)

def load(saver, sess, path, epoch):
    print('Loading model from %s' % path)
    saver.restore(sess, os.path.join(
            path, 'cnn-model.ckpt-%d' % epoch))
```



Build CNN (5/6)

```
X_data = np.array(training_set[0])
y_data = np.array(training_set[1])
training_loss = []
```

initialize variables

```
if initialize:
    sess.run(tf.global_variables_initializer())
```

```
'tf_y:0': batch_y,
```

```
'fc_keep_prob:0': dropout}
```

```
loss, _ = sess.run(
```

```
['cross_entropy_loss:0', 'train_op'],
```

```
feed_dict=feed)
```

```
avg_loss += loss
```

training_loss.append(avg_loss / (i+1))

print('Epoch %02d Training Avg. Loss: %7.3f' % (

```
epoch, avg_loss), end=' ')
```

if validation_set is not None:

```
feed = {'tf_x:0': validation_set[0],
```

```
'tf_y:0': validation_set[1],
```

```
'fc_keep_prob:0':1.0}
valid_acc = sess.run('accuracy:0', feed_dict=feed)
```

```
Valid_acc = sess.run( accuracy:0 , reed_dicc=reed
```

```
print(' Validation Acc: %7.3f' % valid_acc)
```

else:

```
print()
```



Build CNN (6/6)

```
def predict(sess, X_test, return_proba=False):
    feed = {'tf_x:0': X_test,
        'fc_keep_prob:0': 1.0}
    if return_proba:
        return sess.run('probabilities:0', feed_dict=feed)
    else:
        return sess.run('labels:0', feed_dict=feed)
```



Build TensorFlow Graph Object (1/2)

```
import tensorflow as tf
import numpy as np
```

```
## Define hyperparameters
learning_rate = 1e-4
```

```
random_seed = 123
```

```
np.random.seed(random_seed)
```

```
## create a graph
g = tf.Graph()
with g.as_default():
   tf.set_random_seed(random_seed)
   ## build the graph
   build_cnn()
```

```
## saver:
```

```
saver = tf.train.Saver()
```

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Build TensorFlow Graph Object (2/2)

```
Building 1st layer:
<tf.Variable 'conv_1/_weights:0' shape=(5, 5, 1, 32) dtype=float32_ref>
<tf.Variable 'conv_1/_biases:0' shape=(32,) dtype=float32_ref>
Tensor("conv_1/Conv2D:0", shape=(?, 24, 24, 32), dtype=float32)
Tensor("conv_1/net_pre-activation:0", shape=(?, 24, 24, 32), dtype=float32)
Tensor("conv_1/activation:0", shape=(?, 24, 24, 32), dtype=float32)
```

```
Building 2nd layer:
<tf.Variable 'conv_2/_weights:0' shape=(5, 5, 32, 64) dtype=float32_ref>
<tf.Variable 'conv_2/_biases:0' shape=(64,) dtype=float32_ref>
Tensor("conv_2/Conv2D:0", shape=(?, 8, 8, 64), dtype=float32)
Tensor("conv_2/net_pre-activation:0", shape=(?, 8, 8, 64), dtype=float32)
Tensor("conv_2/activation:0", shape=(?, 8, 8, 64), dtype=float32)
```

```
Building 3rd layer:
  <tf.Variable 'fc_3/_weights:0' shape=(1024, 1024) dtype=float32_ref>
  <tf.Variable 'fc_3/_biases:0' shape=(1024,) dtype=float32_ref>
  Tensor("fc_3/MatMul:0", shape=(?, 1024), dtype=float32)
  Tensor("fc_3/net_pre-activation:0", shape=(?, 1024), dtype=float32)
  Tensor("fc_3/activation:0", shape=(?, 1024), dtype=float32)
```

```
Building 4th layer:
  <tf.Variable 'fc_4/_weights:0' shape=(1024, 10) dtype=float32_ref>
  <tf.Variable 'fc_4/_biases:0' shape=(10,) dtype=float32_ref>
  Tensor("fc_4/MatMul:0", shape=(?, 10), dtype=float32)
  Tensor("fc_4/net_pre-activation:0", shape=(?, 10), dtype=float32)
```

Training the CNN Model

```
## crearte a TF session
## and train the CNN model
with tf.Session(graph=g) as sess:
    train(sess,
        training_set=(X_train_centered, y_train),
        validation_set=(X_valid_centered, y_valid),
        initialize=True,
        random_seed=123)
    save(saver, sess, epoch=20)
```

Epoch	01	Training	Avg.	Loss:	274.884	Validation	Acc:	0.973
Epoch	02	Training	Avg.	Loss:	76.537	Validation	Acc:	0.981
Epoch	03	Training	Avg.	Loss:	51.816	Validation	Acc:	0.984
Epoch	04	Training	Avg.	Loss:	38.888	Validation	Acc:	0.986
Epoch	05	Training	Avg.	Loss:	33.064	Validation	Acc:	0.987
Epoch	06	Training	Avg.	Loss:	27.396	Validation	Acc:	0.990
Epoch	07	Training	Avg.	Loss:	23.094	Validation	Acc:	0.987
Epoch	08	Training	Avg.	Loss:	20.075	Validation	Acc:	0.989
Epoch	09	Training	Avg.	Loss:	16.844	Validation	Acc:	0.991
Epoch	10	Training	Avg.	Loss:	15.895	Validation	Acc:	0.990
Epoch	11	Training	Avg.	Loss:	13.291	Validation	Acc:	0.989
Epoch	12	Training	Avg.	Loss:	10.677	Validation	Acc:	0.991
Epoch	13	Training	Avg.	Loss:	10.241	Validation	Acc:	0.992
Epoch	14	Training	Avg.	Loss:	9.578	Validation	Acc:	0.990
Epoch	15	Training	Avg.	Loss:	7.571	Validation	Acc:	0.992
Epoch	16	Training	Avg.	Loss:	6.860	Validation	Acc:	0.991
Epoch	17	Training	Avg.	Loss:	6.921	Validation	Acc:	0.990
Epoch	18	Training	Avg.	Loss:	5.492	Validation	Acc:	0.991
Epoch	19	Training	Avg.	Loss:	4.859	Validation	Acc:	0.991
Epoch	20	Training	Avg.	Loss:	4.572	Validation	Acc:	0.992

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Prediction Accuracy (1/2)

```
### Calculate prediction accuracy
### on test set
```

```
### restoring the saved model
```

del g

```
## create a new graph
## and build the model
g2 = tf.Graph()
with g2.as default():
   tf.set random seed(random seed)
   ## build the graph
   build_cnn()
    ## saver:
   saver = tf.train.Saver()
## create a new session
## and restore the model
with tf.Session(graph=g2) as sess:
   load(saver, sess,
         epoch=20, path='./model/')
   preds = predict(sess, X test centered,
                    return proba=False)
   print('Test Accuracy: %.3f%%' % (100*
                np.sum(preds == y test)/len(y test)))
```



Prediction Accuracy (2/2)

```
Building 1st layer:
  <tf.Variable 'conv_1/_weights:0' shape=(5, 5, 1, 32) dtype=float32_ref>
  <tf.Variable 'conv_1/_biases:0' shape=(32,) dtype=float32_ref>
  Tensor("conv_1/Conv2D:0", shape=(?, 24, 24, 32), dtype=float32)
  Tensor("conv_1/net_pre-activation:0", shape=(?, 24, 24, 32), dtype=float32)
  Tensor("conv_1/activation:0", shape=(?, 24, 24, 32), dtype=float32)
```

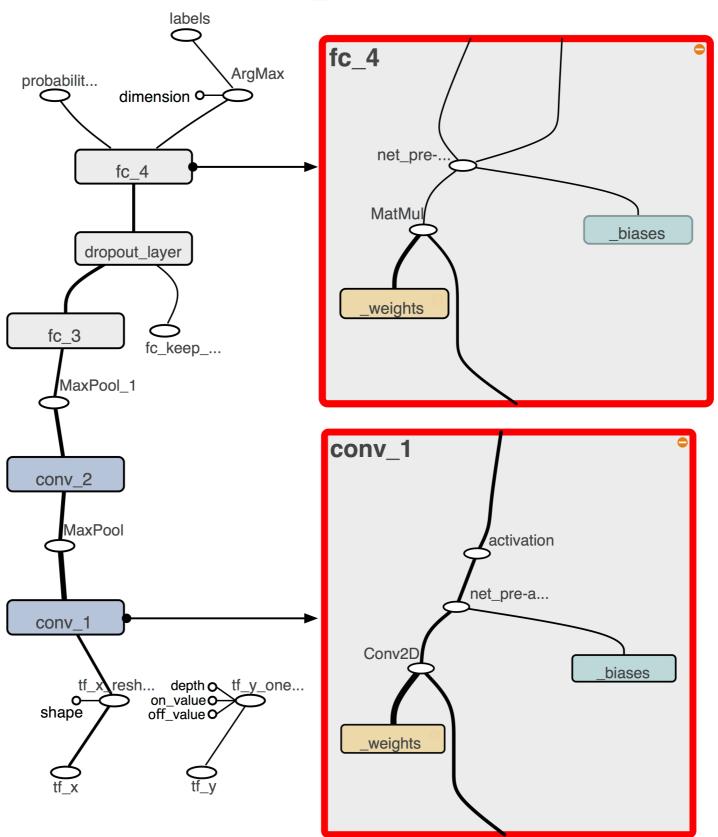
Building 2nd layer:

```
<tf.Variable 'conv_2/_weights:0' shape=(5, 5, 32, 64) dtype=float32_ref>
<tf.Variable 'conv_2/_biases:0' shape=(64,) dtype=float32_ref>
Tensor("conv_2/Conv2D:0", shape=(?, 8, 8, 64), dtype=float32)
Tensor("conv_2/net_pre-activation:0", shape=(?, 8, 8, 64), dtype=float32)
Tensor("conv_2/activation:0", shape=(?, 8, 8, 64), dtype=float32)
```

```
Building 3rd layer:
  <tf.Variable 'fc_3/_weights:0' shape=(1024, 1024) dtype=float32_ref>
  <tf.Variable 'fc_3/_biases:0' shape=(1024,) dtype=float32_ref>
  Tensor("fc_3/MatMul:0", shape=(?, 1024), dtype=float32)
  Tensor("fc_3/net_pre-activation:0", shape=(?, 1024), dtype=float32)
  Tensor("fc_3/activation:0", shape=(?, 1024), dtype=float32)
```

```
Building 4th layer:
  <tf.Variable 'fc_4/_weights:0' shape=(1024, 10) dtype=float32_ref>
  <tf.Variable 'fc_4/_biases:0' shape=(10,) dtype=float32_ref>
  Tensor("fc_4/MatMul:0", shape=(?, 10), dtype=float32)
  Tensor("fc_4/net_pre-activation:0", shape=(?, 10), dtype=float32)
  Loading model from ./model/
  INFO:tensorflow:Restoring parameters from ./model/cnn-model.ckpt-20
  Test Accuracy: 99.310%
```





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Implementing a CNN in the TensorFlow Layers API



Class Definition

```
import tensorflow as tf
import numpy as np
class ConvNN(object):
    def __init__(self, batchsize=64,
                 epochs=20, learning rate=1e-4,
                 dropout rate=0.5,
                 shuffle=True, random seed=None):
        np.random.seed(random_seed)
        self.batchsize = batchsize
        self.epochs = epochs
        self.learning rate = learning rate
        self.dropout_rate = dropout_rate
        self.shuffle = shuffle
        g = tf.Graph()
       with g.as_default():
            ## set random-seed:
            tf.set_random_seed(random_seed)
            ## build the network:
            self.build()
            ## initializer
            self.init_op = \
                tf.global_variables_initializer()
            ## saver
            self.saver = tf.train.Saver()
        ## create a session
```

self.sess = tf.Session(graph=g)

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Build the Model (1/3)

```
def build(self):
    ## Placeholders for X and y:
    tf x = tf.placeholder(tf.float32,
                          shape=[None, 784],
                          name='tf x')
    tf_y = tf.placeholder(tf.int32,
                          shape=[None],
                          name='tf y')
    is train = tf.placeholder(tf.bool,
                          shape=(),
                          name='is_train')
    ## reshape x to a 4D tensor:
    ## [batchsize, width, height, 1]
    tf_x_image = tf.reshape(tf_x, shape=[-1, 28, 28, 1],
                          name='input x 2dimages')
    ## One-hot encoding:
    tf_y_onehot = tf.one_hot(indices=tf_y, depth=10,
                          dtype=tf.float32,
                          name='input y onehot')
    ## 1st layer: Conv 1
    h1 = tf.layers.conv2d(tf x image,
                          kernel_size=(5, 5),
                          filters=32,
                          activation=tf.nn.relu)
    ## MaxPooling
    h1 pool = tf.layers.max_pooling2d(h1,
```



Build the Model (2/3)

```
## 2n layer: Conv 2
h2 = tf.layers.conv2d(h1_pool, kernel_size=(5,5),
                      filters=64,
                      activation=tf.nn.relu)
## MaxPooling
h2 pool = tf.layers.max pooling2d(h2,
                      pool size=(2, 2),
                      strides=(2, 2))
## 3rd layer: Fully Connected
input shape = h2 pool.get shape().as list()
n input units = np.prod(input shape[1:])
h2 pool flat = tf.reshape(h2 pool,
                      shape=[-1, n input units])
h3 = tf.layers.dense(h2 pool flat, 1024,
                      activation=tf.nn.relu)
## Dropout
```



Build the Model (3/3)

Prediction

```
## Loss Function and Optimization
```

cross_entropy_loss = tf.reduce_mean(
 tf.nn.softmax_cross_entropy_with_logits(
 logits=h4, labels=tf_y_onehot),
 name='cross_entropy_loss')

Optimizer:

Finding accuracy

```
correct_predictions = tf.equal(
    predictions['labels'],
    tf_y, name='correct_preds')
```

```
accuracy = tf.reduce_mean(
    tf.cast(correct_predictions, tf.float32),
    name='accuracy')
```



Load and Save the Model

```
os.path.join(path, 'model.ckpt-%d' % epoch))
```



Model Training (1/2)

```
def train(self, training_set,
          validation set=None,
          initialize=True):
    ## initialize variables
    if initialize:
        self.sess.run(self.init op)
    self.train cost = []
    X data = np.array(training set[0])
    y data = np.array(training set[1])
    for epoch in range(1, self.epochs + 1):
        batch_gen = \
            batch generator(X data, y data,
                             shuffle=self.shuffle)
        avg loss = 0.0
        for i, (batch x, batch y) in \
            enumerate(batch gen):
            feed = {'tf x:0': batch x,
                    'tf y:0': batch y,
                    'is train:0': True} ## for dropout
            loss, _ = self.sess.run(
                    ['cross_entropy_loss:0', 'train_op'],
                    feed dict=feed)
            avg loss += loss
```



Model Training (2/2)



Prediction

feed_dict=feed)



Build and Train the Model

cnn = ConvNN(random_seed=123)

cnn.save(epoch=20)

Epoch	01:	Training	Avg.	Loss:	262.962	Validation	Acc:	1.000
Epoch	02:	Training	Avg.	Loss:	73.309	Validation	Acc:	1.000
Epoch	03:	Training	Avg.	Loss:	50.763	Validation	Acc:	1.000
Epoch	04:	Training	Avg.	Loss:	39.567	Validation	Acc:	1.000
Epoch	05:	Training	Avg.	Loss:	32.161	Validation	Acc:	1.000
Epoch	06:	Training	Avg.	Loss:	26.815	Validation	Acc:	0.938
Epoch	07:	Training	Avg.	Loss:	23.939	Validation	Acc:	0.938
Epoch	08:	Training	Avg.	Loss:	19.429	Validation	Acc:	1.000
Epoch	09:	Training	Avg.	Loss:	17.655	Validation	Acc:	1.000
Epoch	10:	Training	Avg.	Loss:	14.999	Validation	Acc:	1.000
Epoch	11:	Training	Avg.	Loss:	13.101	Validation	Acc:	1.000
Epoch	12:	Training	Avg.	Loss:	11.254	Validation	Acc:	1.000
Epoch	13:	Training	Avg.	Loss:	9.751	Validation	Acc:	1.000
Epoch	14:	Training	Avg.	Loss:	9.099	Validation	Acc:	1.000
Epoch	15:	Training	Avg.	Loss:	8.616	Validation	Acc:	1.000
Epoch	16:	Training	Avg.	Loss:	7.116	Validation	Acc:	1.000
Epoch	17:	Training	Avg.	Loss:	6.629	Validation	Acc:	1.000
Epoch	18:	Training	Avg.	Loss:	5.702	Validation	Acc:	1.000
Epoch	19:	Training	Avg.	Loss:	5.537	Validation	Acc:	1.000
Epoch	20:	Training	Avg.	Loss:	4.726	Validation	Acc:	1.000
Saving	g mod	del in ./t	flaye	ers-mod	del/			



Test the Model

```
del cnn
cnn2 = ConvNN(random_seed=123)
cnn2.load(epoch=20, path='./tflayers-model/')
print(cnn2.predict(X_test_centered[:10,:]))
Loading model from ./tflayers-model/
INFO:tensorflow:Restoring parameters from ./tflayers-model/model.ckpt-20
[7 2 1 0 4 1 4 9 5 9]
```

```
preds = cnn2.predict(X_test_centered)
```

```
print('Test Accuracy: %.2f%%' % (100*
```

```
np.sum(y_test == preds)/len(y_test)))
```

Test Accuracy: 99.37%