Introduction of Deep Learning

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Abstract

- Deep learning becomes increasingly important
  - Automatic Machine Translation
  - Object Classification in Photographs
  - Image Caption Generation
  - Automatic Game Playing (AlphaGO)
  - …

Outline

- Introduction of Neural Network
- Introduction of popular Deep Learning Libraries
- Introduction of Deep Neural Network
  - Convolutional Neural Network
  - Auto-encoder
- Implementation of several Deep models
  - Convolutional Neural Network via Tensorflow
  - Auto-encoder via Matlab
- Applications of Deep models in ImageNet (AlexNet)

Introduction of Neural Network

- Basic Architecture
- Linear Classifier
- Transfer Function
- Gradient Descent

Popular Deep Learning Libraries

- Theano
- DeepLearnToolbox
- MatConvNet
- Caffe
- Tensorflow
- Keras

Theano

- What is Theano?
  - Symbolic computation library
  - CPU and GPU infrastructure
  - Optimized compiler
- Theano introduction, installation guides, tutorials, and documents
  - http://deeplearning.net/software/theano/index.html
- GitHub Page
  - https://github.com/Theano/Theano

DeepLearnToolbox

- DeepLearnToolbox
  - A open-source Matlab toolbox for Deep Learning
  - Download in: https://github.com/rasmusbergpalm/DeepLearnToolbox
- Advantage
  - Matlab, easy to use
  - Open-source
- Disadvantage
  - Only CPU version, slow

MatConvNet

- MatConvNet
  - A open-source Matlab toolbox for Convolution Network
  - Download in: https://github.com/vlfeat/matconvnet
- Advantage
  - Matlab, easy to use
  - Pretrained models(VGG, AlexNet)
  - Support GPU
- Disadvantage
  - Complicated than DeepLearnToolbox
  - Support only Convolution Network

Caffe

- What is Caffe?
  - Open source deep learning framework maintained by Berkeley Vision and Learning Center (BVLC)
  - Mainly written in C++ and CUDA C with Python and Matlab interfaces
- Why Using Caffe?
  - Open source
  - Reliability, especially for large scale problem
  - Speed
  - Popularity

Caffe

- Official website (http://caffe.berkeleyvision.org)
- Download from the GitHub page (https://github.com/BVLC/caffe)
- Try the tutorials and reference models (http://caffe.berkeleyvision.org/tutorial/)
- Look through the detailed API documentations (http://caffe.berkeleyvision.org/doxygen/annotated.html)

Tensorflow

- What is Tensorflow?
  - Open source software library for numerical computation using data flow graphs.
  - Mainly written in C++, and defined handy new compositions of operators as writing a Python function.
- Why using Tensorflow?
  - Flexible architecture allows computation to one or more CPUs or GPUs in a desktop, server, or mobile device with a single API.

Tensorflow

- Official website: https://www.tensorflow.org/
- Tutorials: https://www.tensorflow.org/tutorials/
- GitHub page: https://github.com/tensorflow/tensorflow

- Recommended installation and Python coding IDE:
- Anaconda: https://anaconda.org/
- Jupyter Notebook (IDE): http://jupyter.org/

Keras

- What is Keras?
  - Keras is a high-level neural networks library, written in Python and capable of running on top of either Tensorflow and Theano
- Why using Keras?
  - Allows for easy and fast prototyping.
  - Supports both CNN and RNN, as well as combinations of the two.
  - Supports arbitrary connectivity schemes.
  - Runs seamlessly on CPU and GPU.

Keras

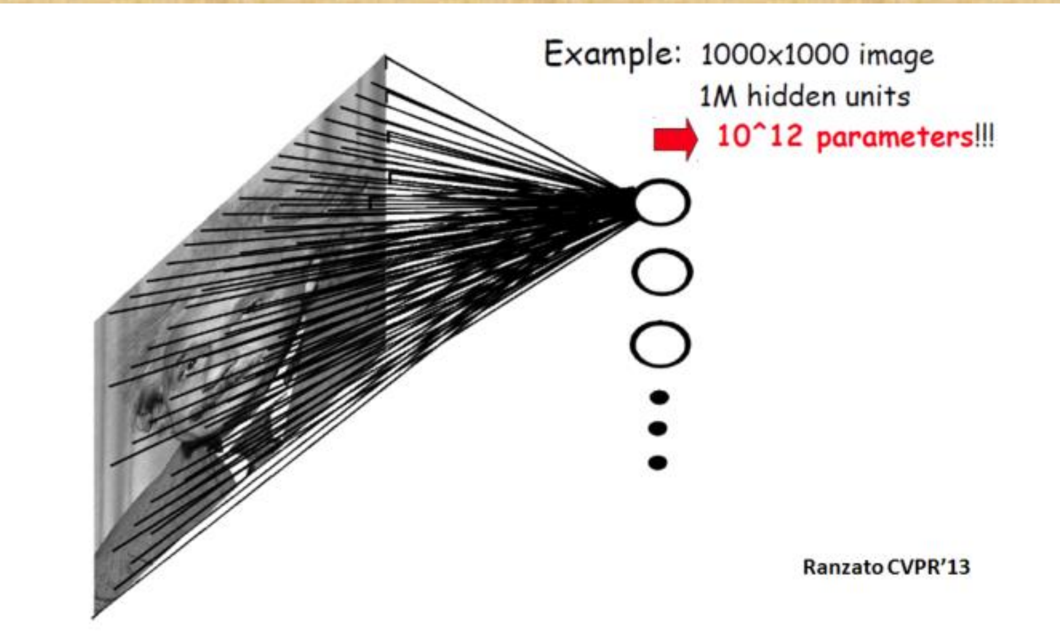
- Official website: https://keras.io/
- GitHub page: https://github.com/fchollet/keras

Introduction of Deep Neural Network

- Convolutional Neural Network (CNN)
- Auto-encoder

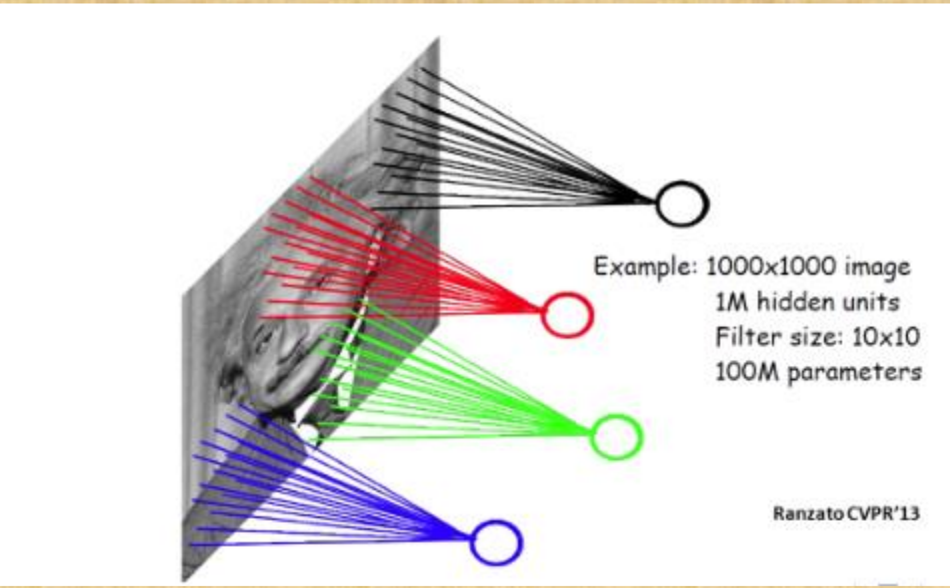
Convolutional Neural Network (CNN)

- Problem of fully connected NN:
  - The number of weights grows largely with the size of the input image
  - Pixels in distance are less correlated



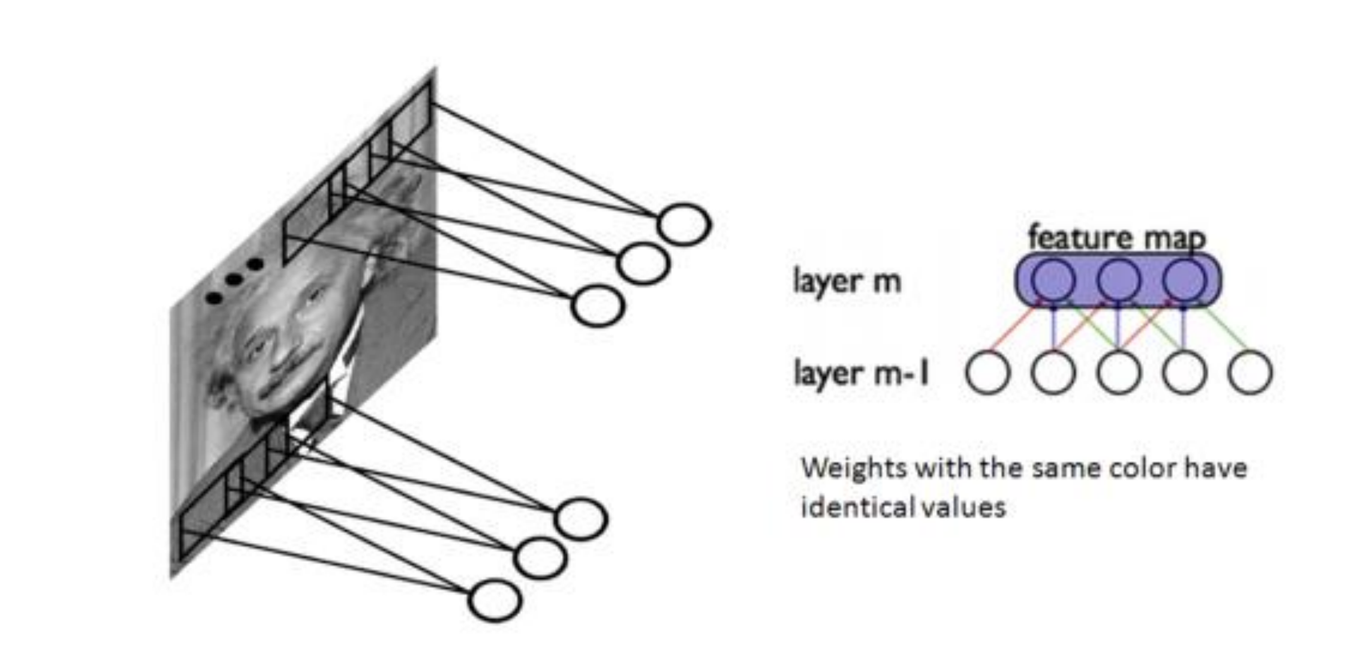
Convolutional Neural Network (CNN)

- Locally connected NN:
  - Sparse connectivity: a hidden unit is only connected to a local patch (weights connected to the patch are called filter or kernel)
  - The learned filter is a spatially local pattern



Convolutional Neural Network (CNN)

- Shared weights:
  - Hidden nodes at different locations share the same weights.
  - It greatly reduces the number of parameters to learn.

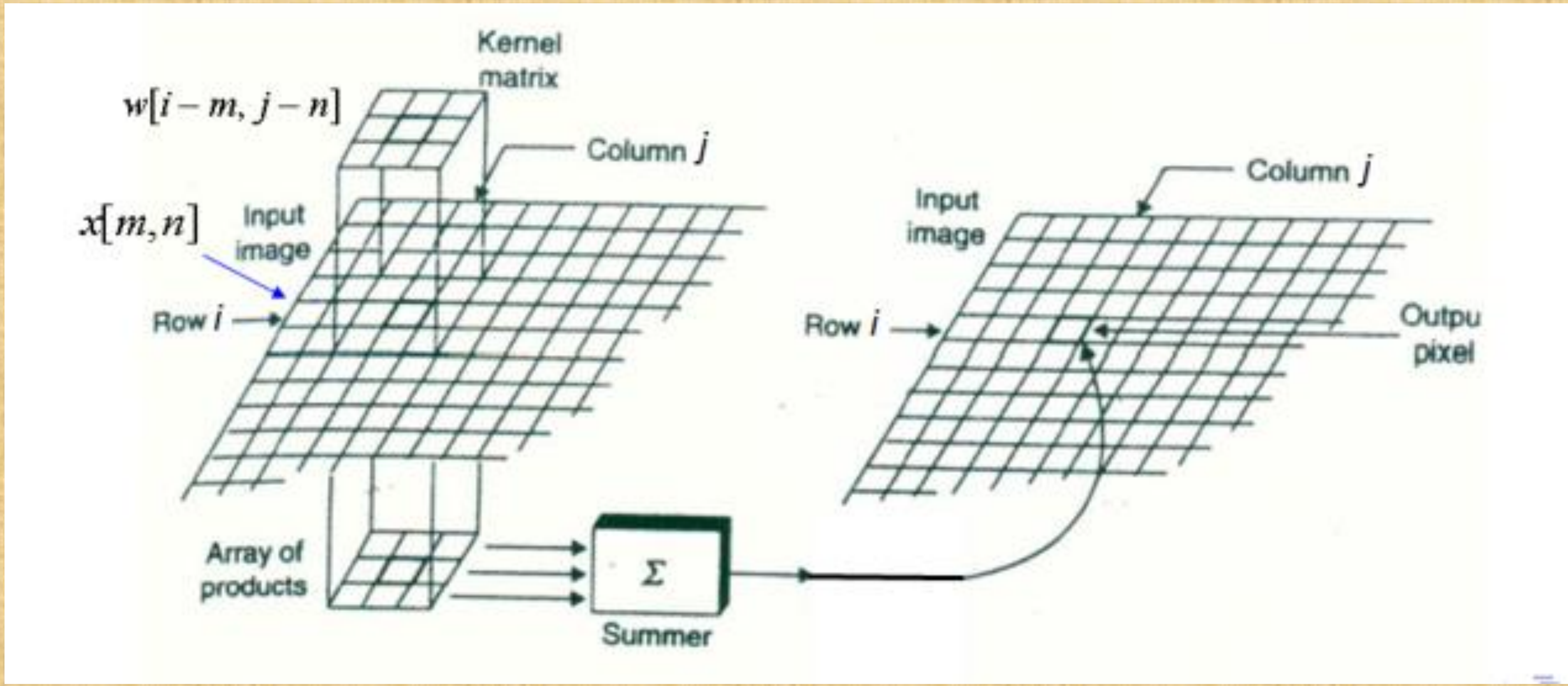


Convolutional Neural Network (CNN)

- Convolution:
  - Computing the responses at hidden nodes is equivalent to convoluting the input image x with a learned filter w
  - After convolution, a filter map net is generated at the hidden layer:

$$net[i,j] = (X * W)[i,j] = \sum_m \sum_n X[m,n]\, W[i-m, j-n]$$

Convolutional Neural Network (CNN)



Convolutional Neural Network (CNN)

- Zero-padding (optional):
  - The valid feature map is smaller than the input after convolution
  - Implementation of neural networks needs to zero-pad the input x to make it wider

Convolutional Neural Network (CNN)

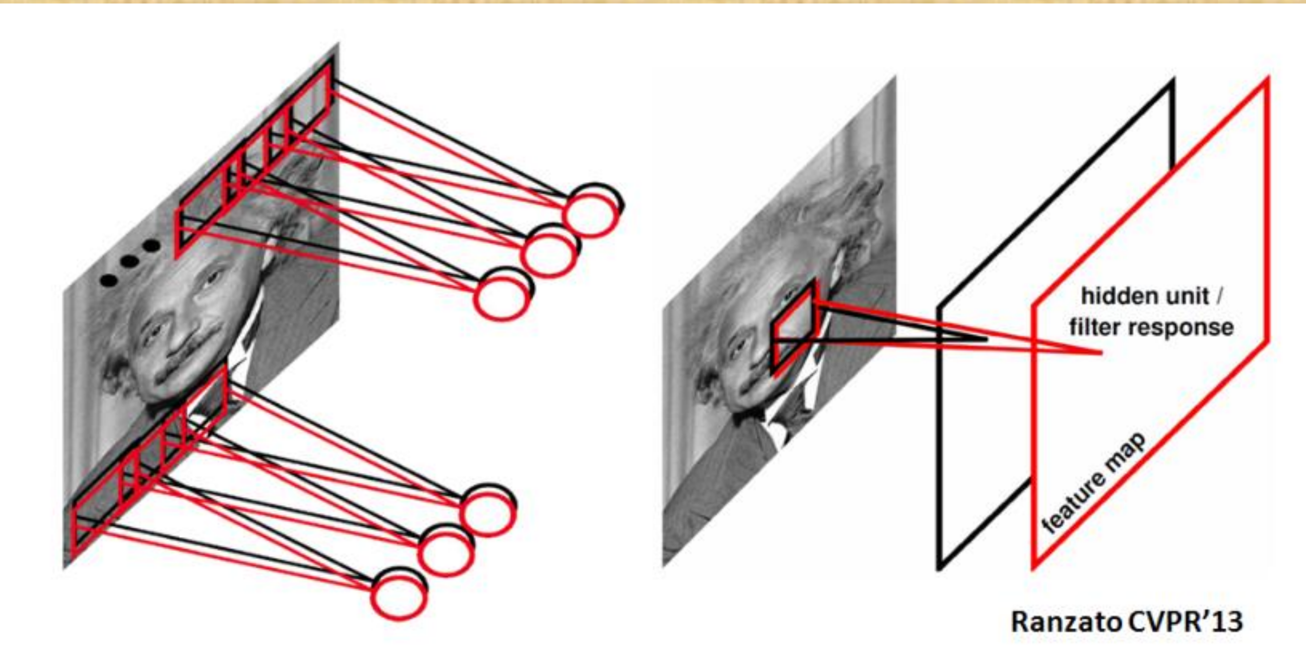
- Downsampled convolutional layer (optional):
  - To reduce computational cost, we may want to skip some positions of the filter and sample only every s pixels in each direction.
  - A downsampled convolution function is defined as:

$$net[i,j] = (X * W)[i \times s, j \times s]$$

Where s is referred as the stride of this downsampled convolution.

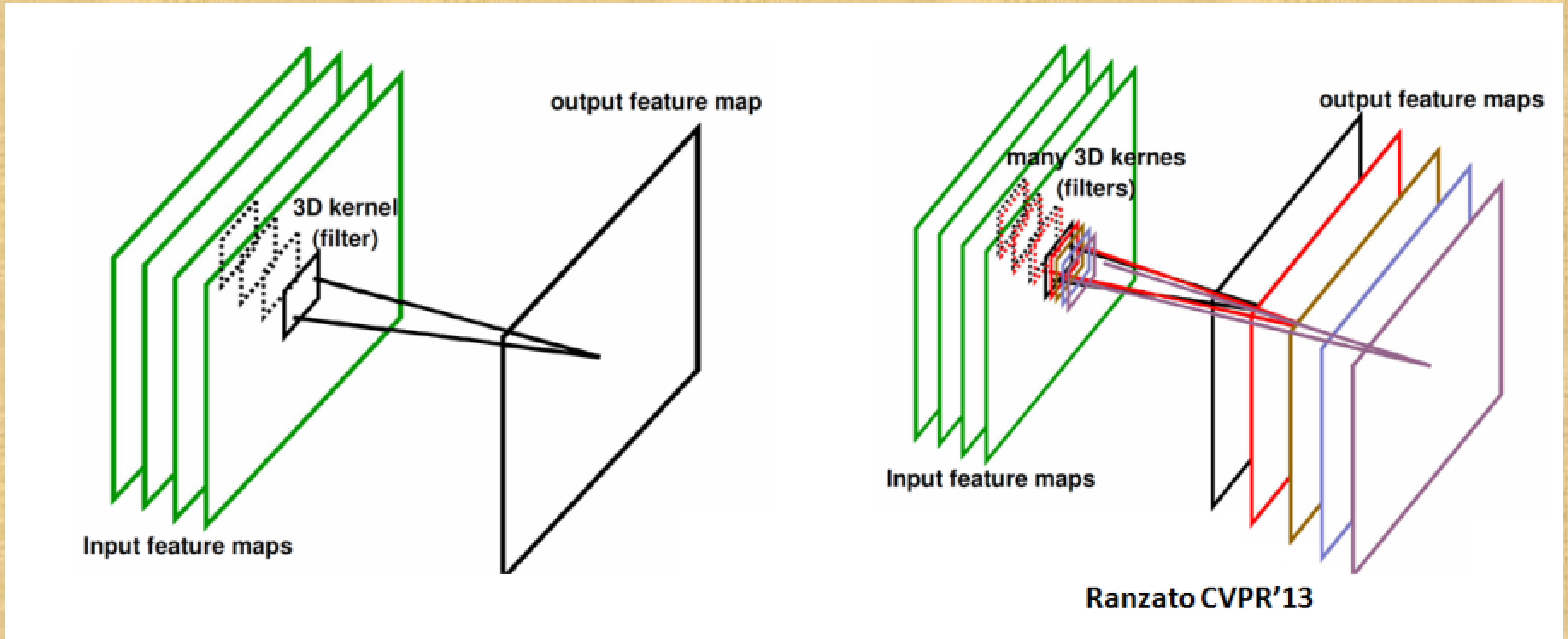
Convolutional Neural Network (CNN)

- Multiple filters:
  - Multiple filters generate multiple feature maps
  - Detect the spatial distributions of multiple visual patterns

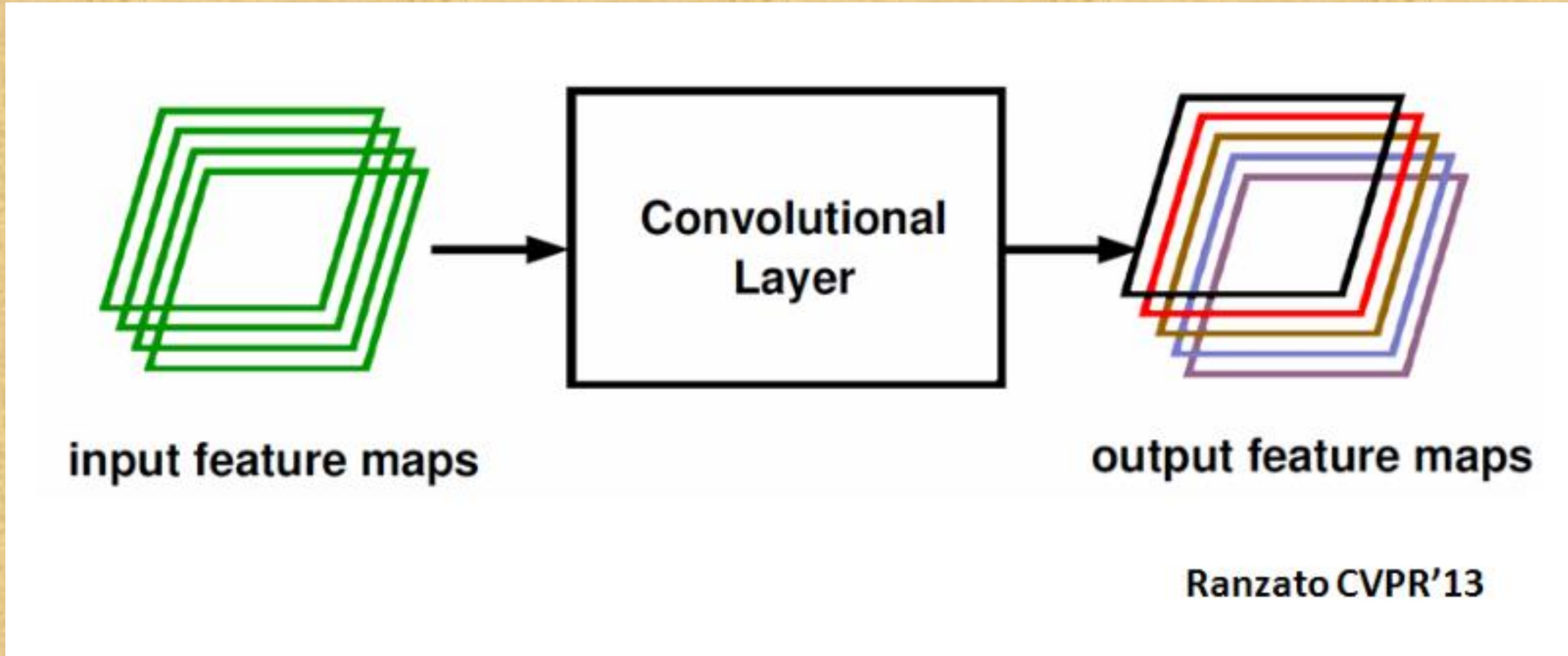


Convolutional Neural Network (CNN)

- Multiple filters: $net = \sum_{k=1}^{K} X^k * W^k$



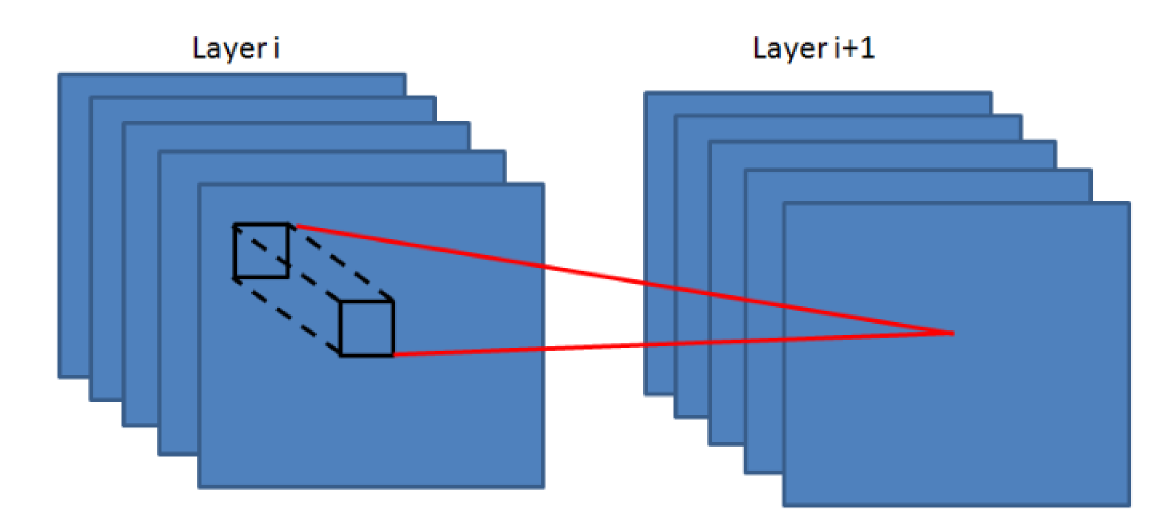
Convolutional Neural Network (CNN)



Convolutional Neural Network (CNN)

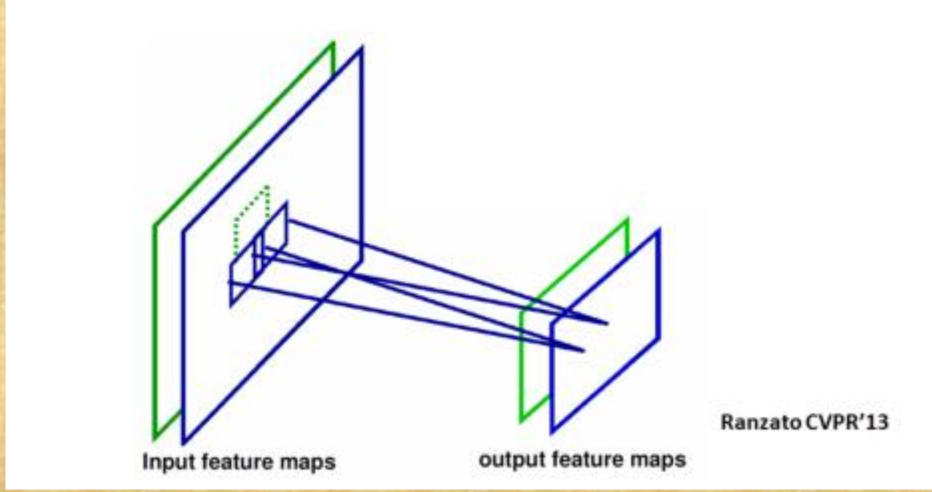
- Local contrast normalization
  - Normalization can be done within a neighborhood along both spatial and feature dimensions:

$$h_{i+1,x,y,k} = \frac{h_{i,x,y,k} - m_{i,N(x,y,k)}}{\sigma_{i,N(x,y,k)}}$$



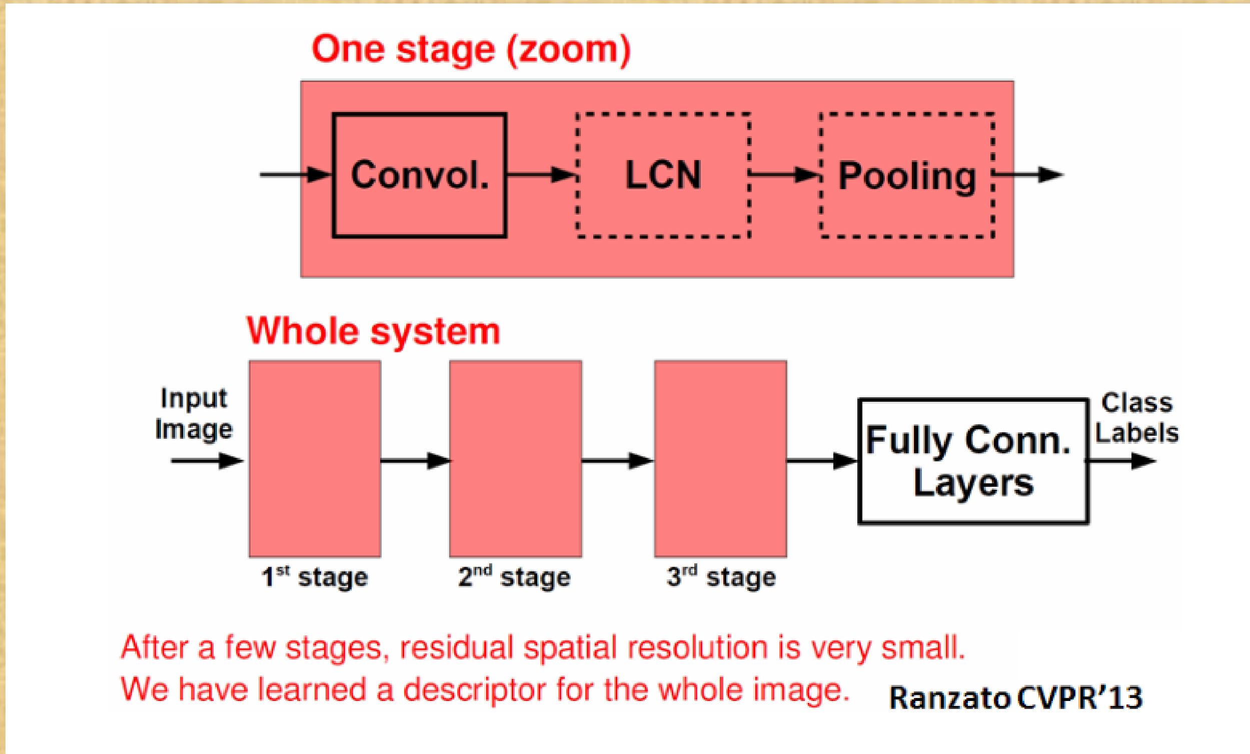
Convolutional Neural Network (CNN)

- Pooling
  - Max-pooling outputs the maximum value for each sub-region
  - The number of output maps is the same as input, but the resolution is reduced
  - Reduce the computational complexity for upper layers
  - Average pooling can also be applied



Convolutional Neural Network (CNN)

- Typical architecture of CNN
  - Convolutional layer increases the number of feature maps
  - Pooling layer decreases spatial resolution
  - LCN and pooling are optional at each stage



Convolutional Neural Network (CNN)

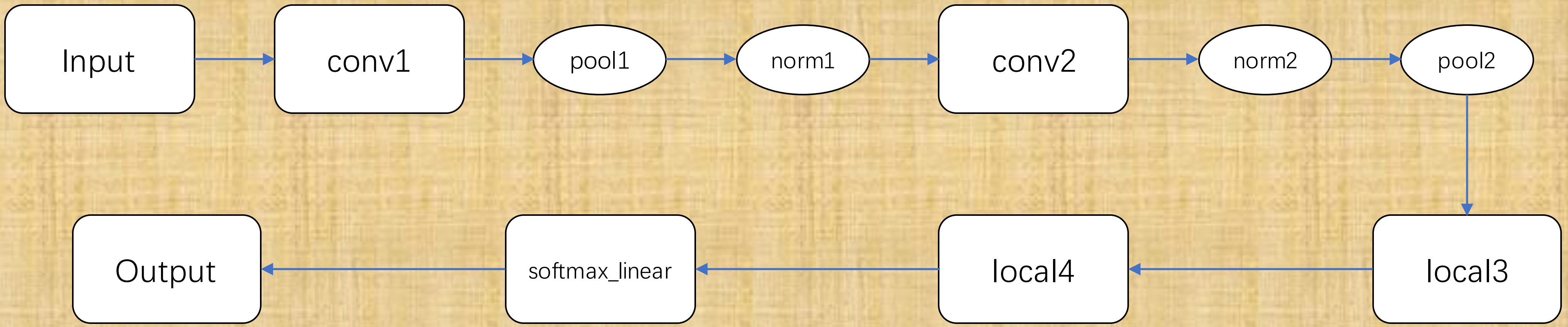
- Backpropagation on Convolution Neural Network
  - Calculate sensitivity (back propagate errors) $\delta = -\frac{\partial J}{\partial net}$ and update weights in the convolutional layer and pooling layer
  - Calculating sensitivity in the convolutional layer is the same as multilayer neural network

Convolutional Neural Network (CNN)

- Calculate sensitivities in the pooling layer
  - The input of a pooling layer l is the output feature map y^l of the previous convolutional layer. The output x^{l+1} of the pooling layer is the input of the next convolutional layer $l+1$
  - For max pooling, the sensitivity is propagated according to the corresponding indices built during max operation
  - If pooling regions are overlapped and one node in the input layer corresponds to multiple nodes in the output layer, the sensitivities are added
  - Average pooling

CNN Implementation via Tensorflow

- Model Architecture



CNN Implementation via Tensorflow

- Conv-Pooling-LRN structure implementation

```
# conv1
with tf.variable_scope('conv1') as scope:
  kernel = _variable_with_weight_decay('weights',
                                       shape=[5, 5, 3, 64],
                                       stddev=5e-2,
                                       wd=0.0)
  conv = tf.nn.conv2d(images, kernel, [1, 1, 1, 1], padding='SAME')
  biases = _variable_on_cpu('biases', [64], tf.constant_initializer(0.0))
  pre_activation = tf.nn.bias_add(conv, biases)
  conv1 = tf.nn.relu(pre_activation, name=scope.name)
  _activation_summary(conv1)

# pool1
pool1 = tf.nn.max_pool(conv1, ksize=[1, 3, 3, 1], strides=[1, 2, 2, 1],
                       padding='SAME', name='pool1')
# norm1
norm1 = tf.nn.lrn(pool1, 4, bias=1.0, alpha=0.001 / 9.0, beta=0.75,
                  name='norm1')
```

```
# conv2
with tf.variable_scope('conv2') as scope:
  kernel = _variable_with_weight_decay('weights',
                                       shape=[5, 5, 64, 64],
                                       stddev=5e-2,
                                       wd=0.0)
  conv = tf.nn.conv2d(norm1, kernel, [1, 1, 1, 1], padding='SAME')
  biases = _variable_on_cpu('biases', [64], tf.constant_initializer(0.1))
  pre_activation = tf.nn.bias_add(conv, biases)
  conv2 = tf.nn.relu(pre_activation, name=scope.name)
  _activation_summary(conv2)

# norm2
norm2 = tf.nn.lrn(conv2, 4, bias=1.0, alpha=0.001 / 9.0, beta=0.75,
                  name='norm2')
# pool2
pool2 = tf.nn.max_pool(norm2, ksize=[1, 3, 3, 1],
                       strides=[1, 2, 2, 1], padding='SAME', name='pool2')
```

CNN Implementation via Tensorflow

- Fully-connected layer with rectified linear activation
- Linear transformation to produce logits

```
# local3
with tf.variable_scope('local3') as scope:
  # Move everything into depth so we can perform a single matrix multiply.
  reshape = tf.reshape(pool2, [FLAGS.batch_size, -1])
  dim = reshape.get_shape()[1].value
  weights = _variable_with_weight_decay('weights', shape=[dim, 384],
                                        stddev=0.04, wd=0.004)
  biases = _variable_on_cpu('biases', [384], tf.constant_initializer(0.1))
  local3 = tf.nn.relu(tf.matmul(reshape, weights) + biases, name=scope.name)
  _activation_summary(local3)

# local4
with tf.variable_scope('local4') as scope:
  weights = _variable_with_weight_decay('weights', shape=[384, 192],
                                        stddev=0.04, wd=0.004)
  biases = _variable_on_cpu('biases', [192], tf.constant_initializer(0.1))
  local4 = tf.nn.relu(tf.matmul(local3, weights) + biases, name=scope.name)
  _activation_summary(local4)
```

```
# tf.nn.sparse_softmax_cross_entropy_with_logits accepts the unscaled logits
# and performs the softmax internally for efficiency.
with tf.variable_scope('softmax_linear') as scope:
  weights = _variable_with_weight_decay('weights', [192, NUM_CLASSES],
                                        stddev=1/192.0, wd=0.0)
  biases = _variable_on_cpu('biases', [NUM_CLASSES],
                            tf.constant_initializer(0.0))
  softmax_linear = tf.add(tf.matmul(local4, weights), biases, name=scope.name)
  _activation_summary(softmax_linear)

return softmax_linear
```

CNN Implementation via Tensorflow

- Objective function:
  - cross entropy loss
  - all weight decay terms

```
def loss(logits, labels):
  """Add L2Loss to all the trainable variables.

  Add summary for "Loss" and "Loss/avg".
  Args:
    logits: Logits from inference().
    labels: Labels from distorted_inputs or inputs(). 1-D tensor
            of shape [batch_size]

  Returns:
    Loss tensor of type float.
  """
  # Calculate the average cross entropy loss across the batch.
  labels = tf.cast(labels, tf.int64)
  cross_entropy = tf.nn.sparse_softmax_cross_entropy_with_logits(
      labels=labels, logits=logits, name='cross_entropy_per_example')
  cross_entropy_mean = tf.reduce_mean(cross_entropy, name='cross_entropy')
  tf.add_to_collection('losses', cross_entropy_mean)

  # The total loss is defined as the cross entropy loss plus all of the weight
  # decay terms (L2 loss).
  return tf.add_n(tf.get_collection('losses'), name='total_loss')
```

CNN Implementation via Tensorflow

- Optimization of trainable variables:

```
# Variables that affect learning rate.
num_batches_per_epoch = NUM_EXAMPLES_PER_EPOCH_FOR_TRAIN / FLAGS.batch_size
decay_steps = int(num_batches_per_epoch * NUM_EPOCHS_PER_DECAY)

# Decay the learning rate exponentially based on the number of steps.
lr = tf.train.exponential_decay(INITIAL_LEARNING_RATE,
                                global_step,
                                decay_steps,
                                LEARNING_RATE_DECAY_FACTOR,
                                staircase=True)
tf.summary.scalar('learning_rate', lr)

# Generate moving averages of all losses and associated summaries.
loss_averages_op = _add_loss_summaries(total_loss)

# Compute gradients.
with tf.control_dependencies([loss_averages_op]):
  opt = tf.train.GradientDescentOptimizer(lr)
  grads = opt.compute_gradients(total_loss)

# Apply gradients.
apply_gradient_op = opt.apply_gradients(grads, global_step=global_step)
```

```
# Add histograms for trainable variables.
for var in tf.trainable_variables():
  tf.summary.histogram(var.op.name, var)

# Add histograms for gradients.
for grad, var in grads:
  if grad is not None:
    tf.summary.histogram(var.op.name + '/gradients', grad)

# Track the moving averages of all trainable variables.
variable_averages = tf.train.ExponentialMovingAverage(
    MOVING_AVERAGE_DECAY, global_step)
variables_averages_op = variable_averages.apply(tf.trainable_variables())

with tf.control_dependencies([apply_gradient_op, variables_averages_op]):
  train_op = tf.no_op(name='train')

return train_op
```

CNN Implementation via Tensorflow

- Train the deep model via CPU implementation
- Code GitHub resource: https://github.com/tensorflow/models/tree/master/tutorials/image/cifar10

```python
def train():
  """Train CIFAR-10 for a number of steps."""
  with tf.Graph().as_default():
    global_step = tf.contrib.framework.get_or_create_global_step()

    # Get images and labels for CIFAR-10.
    images, labels = cifar10.distorted_inputs()

    # Build a Graph that computes the logits predictions from the
    # inference model.
    logits = cifar10.inference(images)

    # Calculate loss.
    loss = cifar10.loss(logits, labels)

    # Build a Graph that trains the model with one batch of examples and
    # updates the model parameters.
    train_op = cifar10.train(loss, global_step)
```

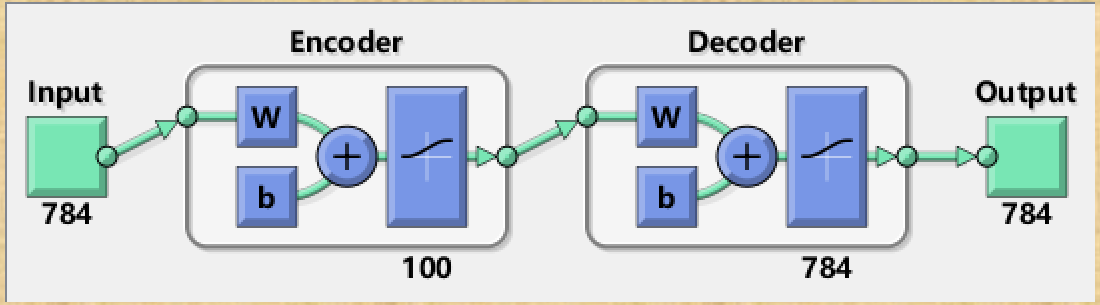
Auto-encoder

- So far, we have described the application of neural networks to supervised learning, in which we have labeled training examples.
- Now suppose we have only a set of unlabeled training examples.

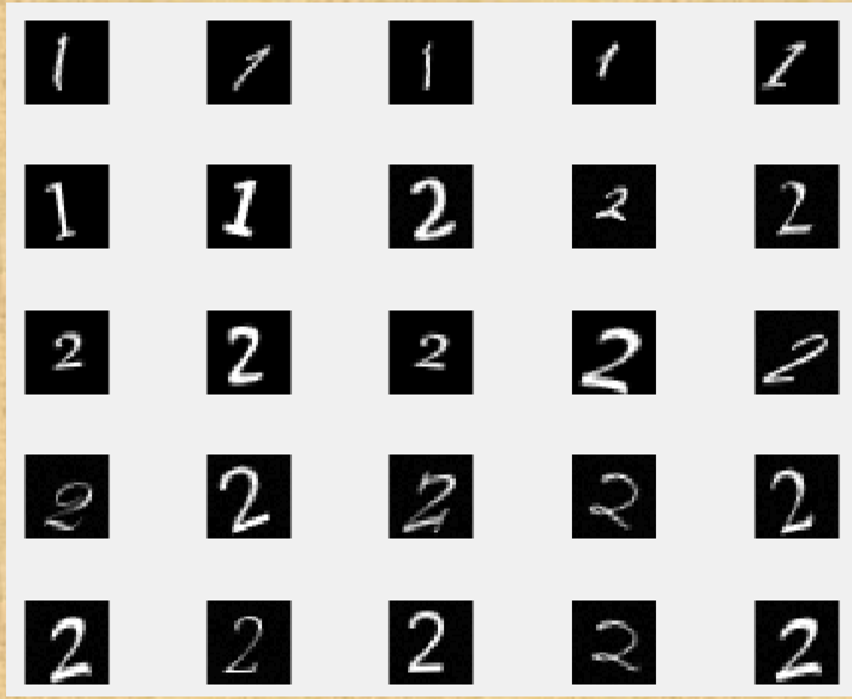
- An **autoencoder** neural network is an unsupervised learning algorithm that applies backpropagation, setting the target values to be equal to the inputs:

$$y^{(i)} = x^{(i)}.$$

Auto-encoder Implementation via Matlab



- Classify MNIST Dataset
  - 9 digits $(0\sim9)$
  - Input size: $28 \times 28 = 784$
  - Encoder size: 100
  - Decoder size: 784
  - Output size: 784



Auto-encoder Implementation via Matlab

- You can see that the features learned by the autoencoder represent curls and stroke patterns from the digit images
- These features are, not surprisingly, useful for such tasks as object recognition and other vision tasks.

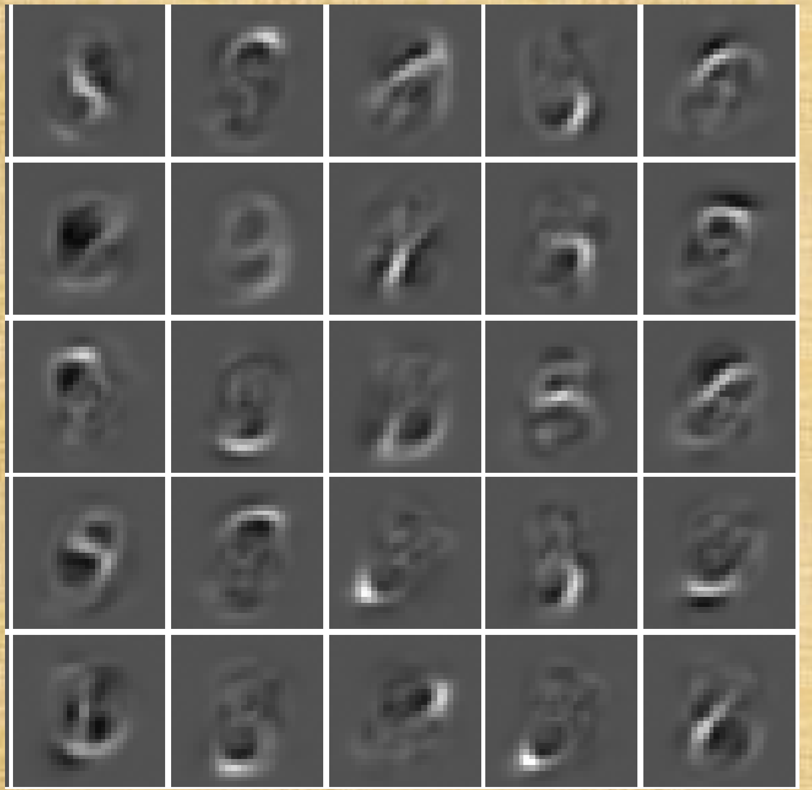


Image Classification Application

- Applications of Deep models in ImageNet Challenge
  - Introduction of ImageNet
  - Introduction of AlexNet model (Krizhevsky 2012)
  - Introduction of other different CNN structures (optional)

Image Classification Application

- What is ImageNet?
  - **ImageNet** is an image database organized according to the WordNet hierarchy (currently only the nouns), in which each node of the hierarchy is depicted by hundreds and thousands of images
  - http://www.image-net.org/

Image Classification Application

- CNN for object recognition on ImageNet challenge
  - Krizhevsky, Sutskever, and Hinton, NIPS 2012
  - Trained on ImageNet with two GPU. 2GB RAM on each GPU. 5GB of system memory
  - The first time deep model is shown to be effective on large scale computer vision task.
  - Training lasts for one week

Image Classification Application

- Model architecture-AlexNet Krizhevsky 2012

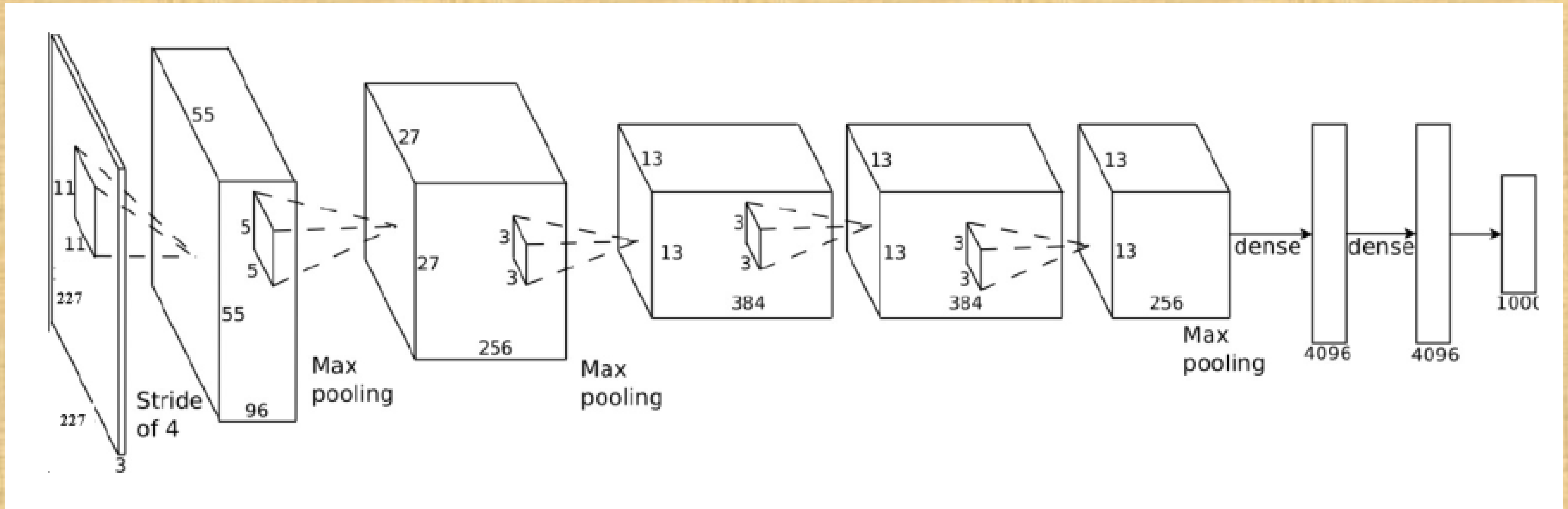


Image Classification Application

- Model architecture-AlexNet Krizhevsky 2012
  - 5 convolutional layers and 2 fully connected layers for learning features.
  - Max-pooling layers follow first, second, and fifth convolutional layers
  - The number of neurons in each layer is given by 253440, 186624, 64896, 64896, 43264, 4096, 4096, 1000
  - 650000 neurons, 60000000 parameters, and 630000000 connections

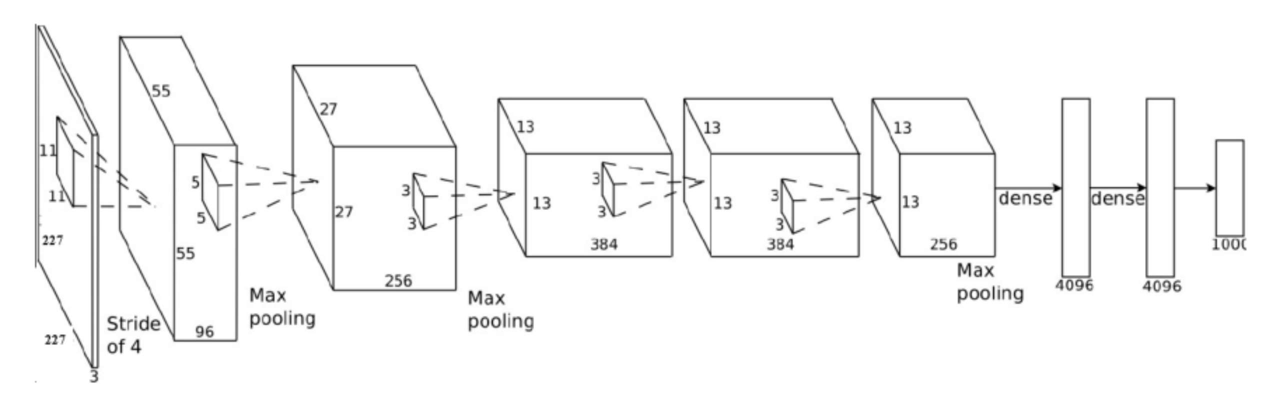


Image Classification Application

- Choice of activation function

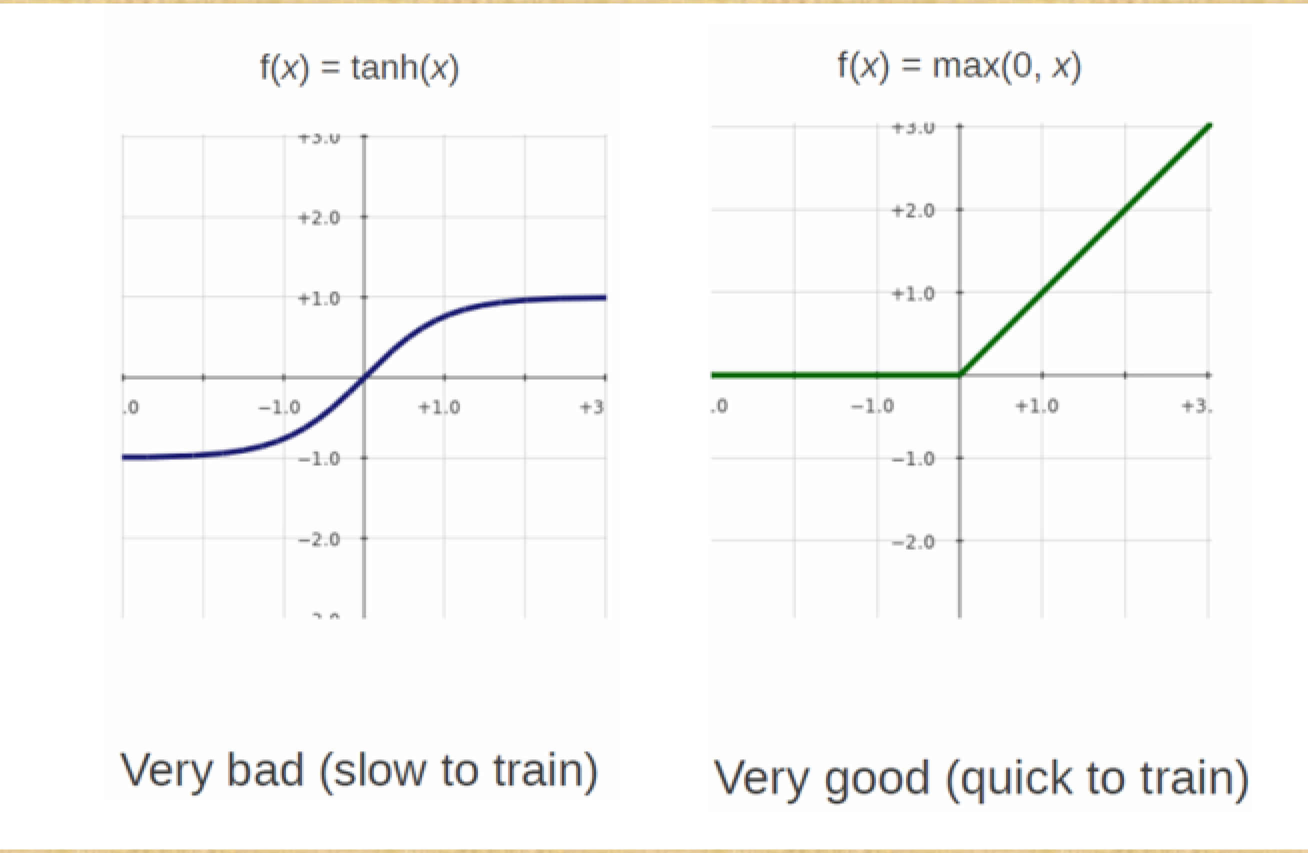


Image Classification Application

- Reducing Overfitting
  - What is overfitting?
- Useful Methods
  - Data augmentation
  - Dropout

Image Classification Application

- Data augmentation
  - The neural net has 60M real-valued parameters and 650,000 neurons
  - It overfits a lot. 224×224 image regions are randomly extracted from 256 images, and also their horizontal reflections

Image Classification Application

- Dropout
  - Independently set each hidden unit activity to zero with 0.5 probability
  - Do this in the two globally-connected hidden layers

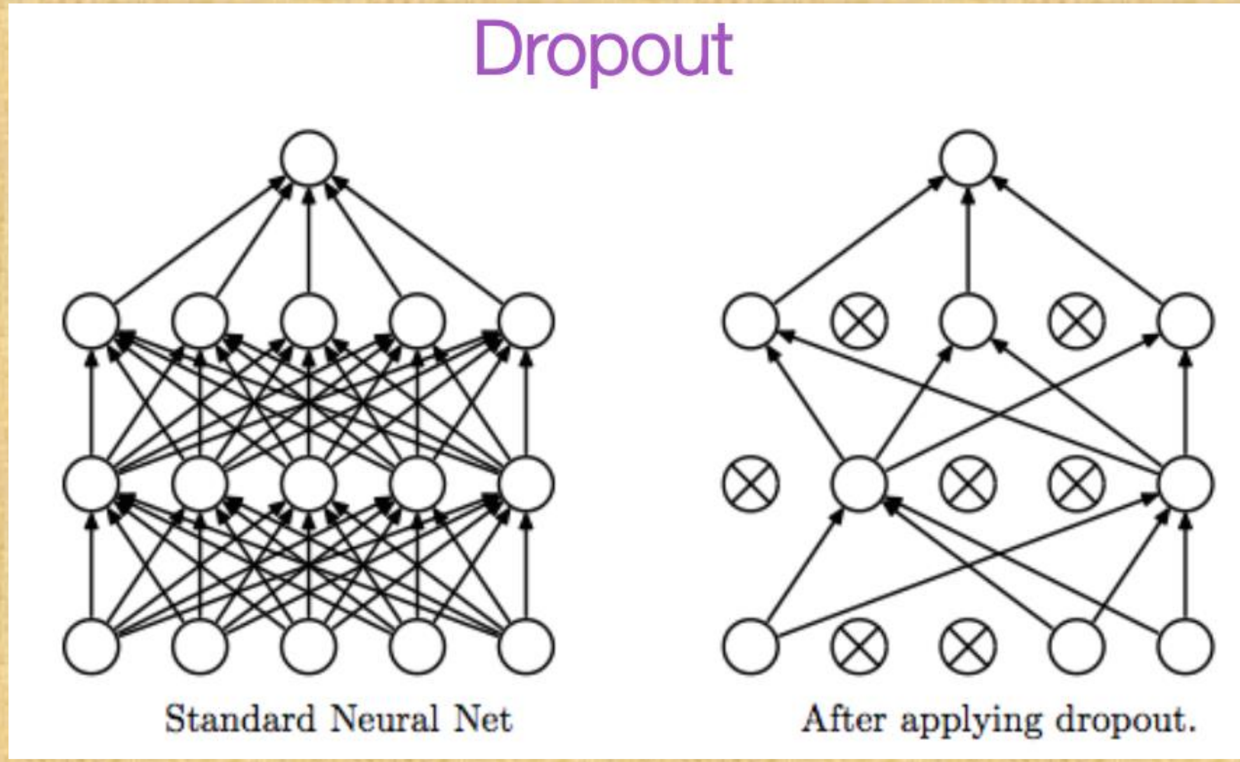


Image Classification Application

- Stochastic Gradient Descent Learning
  - Momentum Update

$$v_{i+1} = 0.9v_i - 0.0005\epsilon w_i - \epsilon \left\langle \frac{\partial L}{\partial w}|_{w_i} \right\rangle_{D_i}$$

$$w_{i+1} = w_i + v_{i+1}$$

Where 0.9 is momentum (damping parameter), $0.0005\epsilon w_i$ is weight decay, ϵ is learning rate (initialized with 0.01), and $\epsilon \left\langle \frac{\partial L}{\partial w}|_{w_i} \right\rangle_{D_i}$ is gradient of loss w.r.t weight averaged over batches (batch size:128)

Image Classification Application

- Results : ILSVRC-2010
  - Achieves top-1 and top-5 test set error rates of 37.5% and 17.0%
  - The best performance achieved during the ILSVRC-2010 competition was 47.1% and 28.2%
  - Shows the outperformance of deep learning to traditional methods

Model	Top-1	Top-5
Sparse coding [2]	*47.1%*	*28.2%*
SIFT + FVs [24]	*45.7%*	*25.7%*
CNN	**37.5%**	**17.0%**

Table 1: Comparison of results on ILSVRC-2010 test set. In *italics* are best results achieved by others.

Image Classification Application

- 96 learned low-level filters

Image Classification Application

- Classification result
  - The correct label is written under each image, and the probability assigned to the correct label is also shown with a red bar

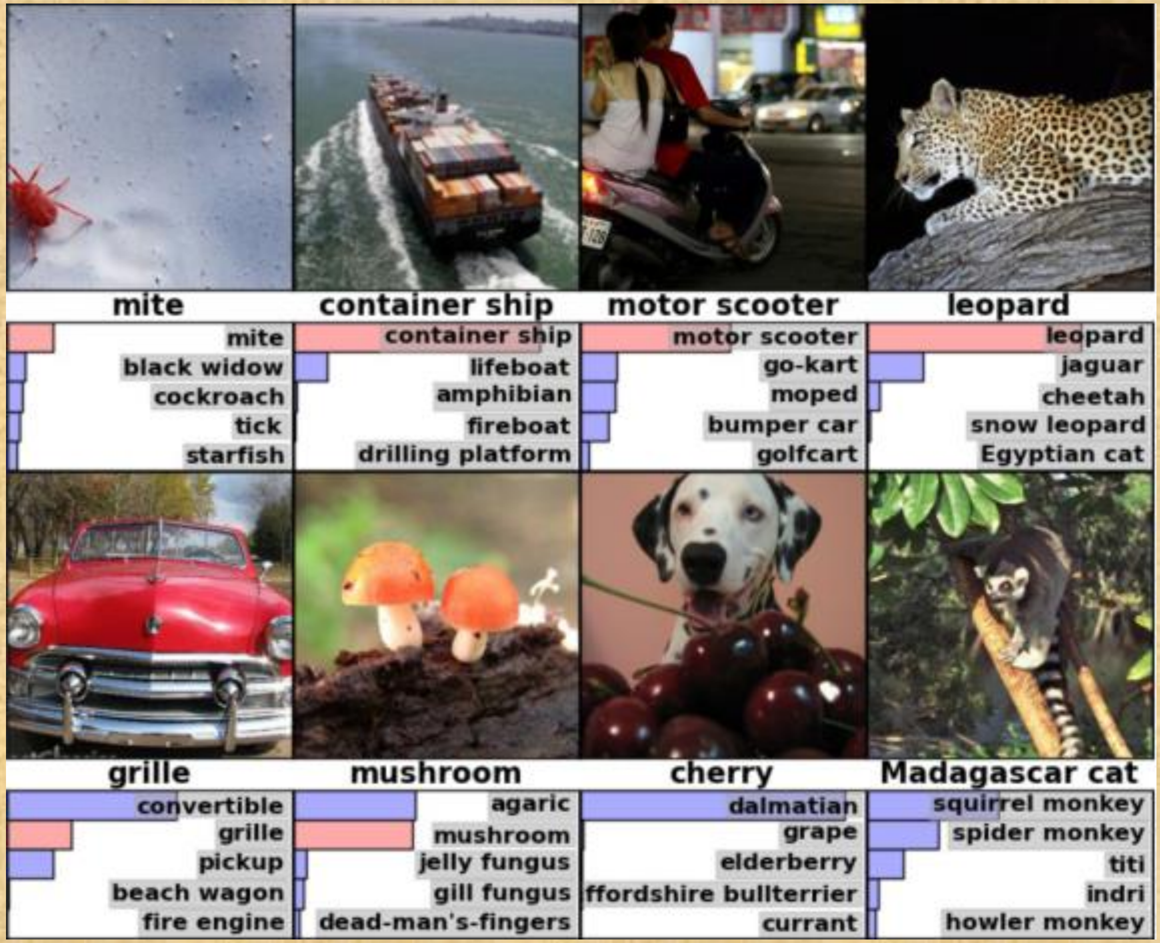


Image Classification Application

- Top hidden layer can be used as feature for retrieval

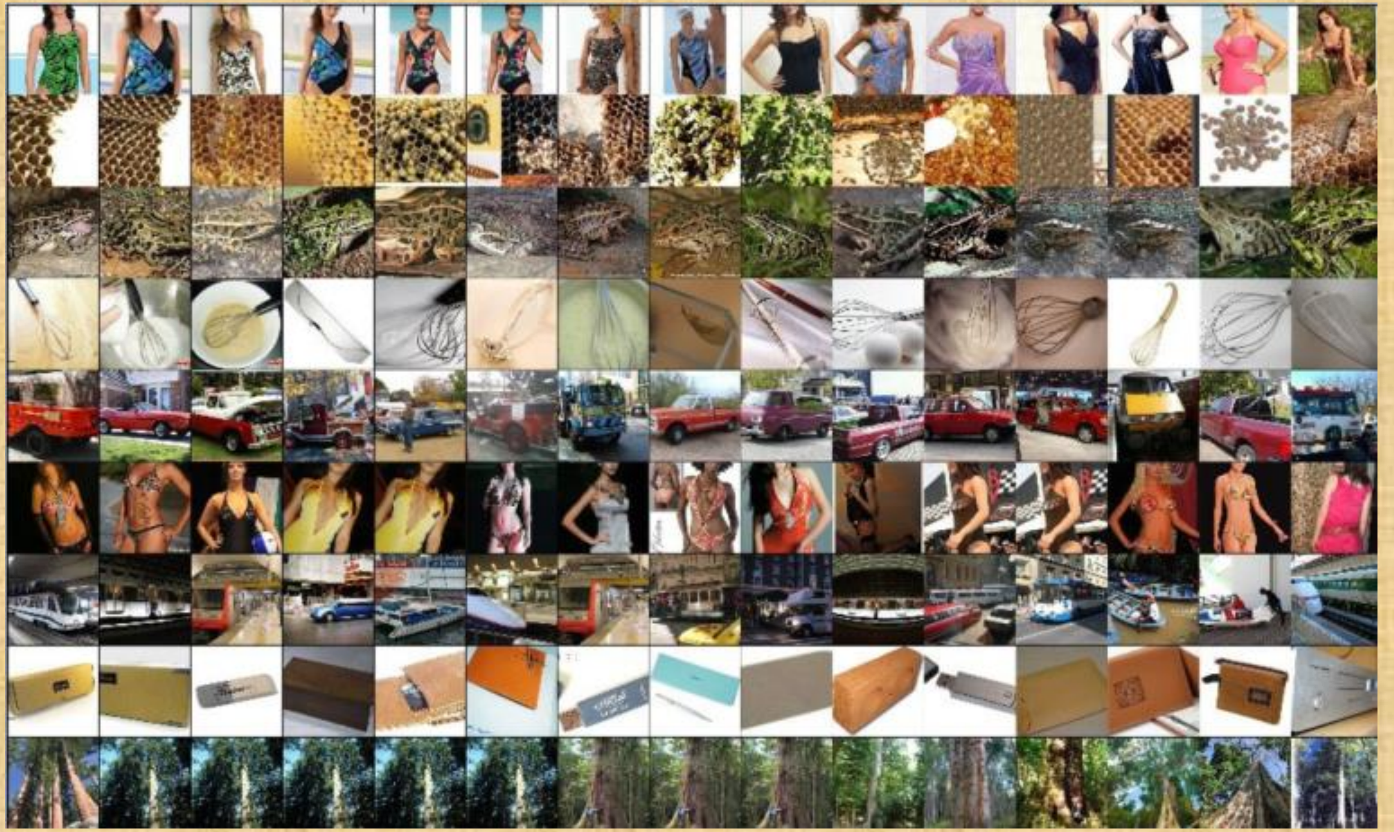


Image Classification Application

- Other different CNN structures for image classification
  - Clarifai
  - Overfeat
  - VGG
  - DeepImage of Baidu
  - Network-in-network
  - GoogLeNet
  - …

References

- Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.
- Marc'Aurelio Ranzato. " Large-scale visual recognition with deep learning. " *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 2013.

Thank you!