CS4487 - Machine Learning

Lecture 9b - Neural Networks, Deep Learning

Dr. Antoni B. Chan

Dept. of Computer Science, City University of Hong Kong

Outline

- History
- Perceptron
- **Multi-layer perceptron (MLP)**
- Convolutional neural network (CNN)
- Autoencoder (AE)

In [2]:
```
# use TensorFlow backend
%env KERAS_BACKEND=tensorflow
from keras.models import Sequential, Model
from keras.layers import Dense, Activation, Dropout, Conv2D, Flatten, Input
import keras
import tensorflow
import logging
logging.basicConfig()
import struct
```

```
env: KERAS_BACKEND=tensorflow

/anaconda3/lib/python3.5/importlib/_bootstrap.py:222: RuntimeWarning: numpy.
dtype size changed, may indicate binary incompatibility. Expected 96, got 88
  return f(*args, **kwds)
Using TensorFlow backend.
/anaconda3/lib/python3.5/importlib/_bootstrap.py:222: RuntimeWarning: numpy.
dtype size changed, may indicate binary incompatibility. Expected 96, got 88
  return f(*args, **kwds)
```

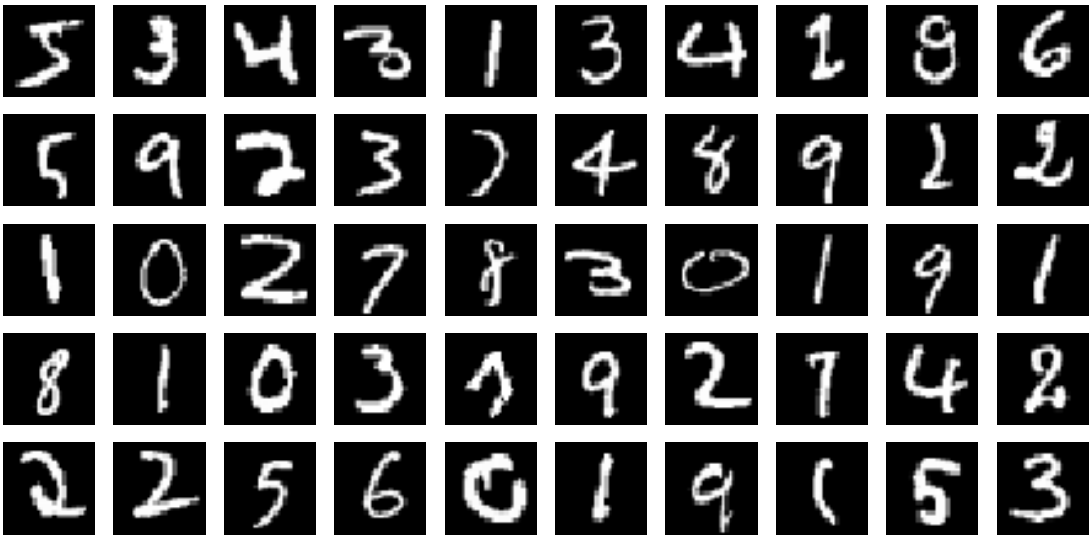
Example on MNIST Dataset

- Images are 28x28, digits 0-9
  - 6,000 for training
  - 10,000 for testing

In [7]:
```
n_train, nrow, ncol, trainimg = read_img('data/train-images.idx3-ubyte')
_, trainY = read_label('data/train-labels.idx1-ubyte')
n_test, _, _, testimg = read_img('data/t10k-images.idx3-ubyte')
_, testY = read_label('data/t10k-labels.idx1-ubyte')

# for demonstration we only use 10% of the training data
sample_index = range(0, trainimg.shape[0], 10)
trainimg  = trainimg[sample_index]
trainY    = trainY[sample_index]
print(trainimg.shape)
print(trainY.shape)
print(testimg.shape)
print(testY.shape)
```

```
(6000, 28, 28)
(6000,)
(10000, 28, 28)
(10000,)
```

In [8]:
```
# Example images
plt.figure(figsize=(8,4))
show_imgs(trainimg[0:50])
```



Pre-processing

- Reshape images into vectors
- map to [0,1], then subtract the mean

In [9]:
```
# Reshape the images to a vector
# and map the data to [0,1]
trainXraw = trainimg.reshape((len(trainimg), -1), order='C') / 255.0
testXraw = testimg.reshape((len(testimg), -1), order='C') / 255.0

# center the image data (but don't change variance)
scaler = preprocessing.StandardScaler(with_std=False)
trainX = scaler.fit_transform(trainXraw)
testX  = scaler.transform(testXraw)

# convert class labels to binary indicators
trainYb = keras.utils.np_utils.to_categorical(trainY)

print(trainX.shape)
print(trainYb.shape)
```

```
(6000, 784)
(6000, 10)
```

- Generate a fixed validation set
  - use vtrainX for training and validX for validation

In [10]:
```
# generate a fixed validation set using 10% of the training set
vtrainX, validX, vtrainYb, validYb = \
  model_selection.train_test_split(trainX, trainYb,
  train_size=0.9, test_size=0.1, random_state=4487)

# validation data
validset  = (validX, validYb)
```

MNIST - Logistic Regression (0-hidden layers)

- Training procedure
  - We specify the validation set so that it will be fixed when we change the `random_state` to randomly initialize the weights.
  - Train on the non-validation training data.
  - Use a larger batch size to speed up the algorithm

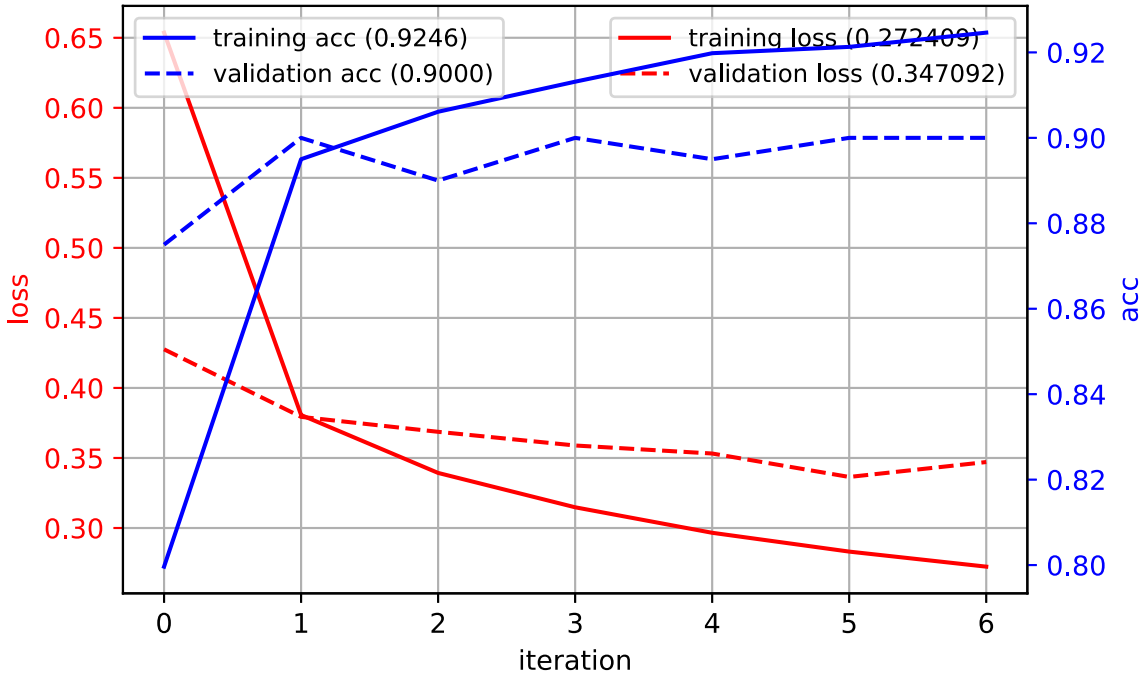
In [11]:

```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Dense(units=10, input_dim=784, activation='softmax'))

# early stopping criteria
earlystop = keras.callbacks.EarlyStopping(
               monitor='val_acc',             # use validation accuracy for stop
ping
               min_delta=0.0001, patience=5,
               verbose=1, mode='auto')
callbacks_list = [earlystop]

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.05, momentum=0.9, nesterov=True),
           metrics=['accuracy']  # also calculate accuracy during training
          )

history = nn.fit(vtrainX, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validset,  # specify the validation set
                 verbose=False)
```

```
Epoch 00007: early stopping
```

In [18]:
```
plot_history(history)

predY = nn.predict_classes(testX, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
test accuracy: 0.8921
```



- Examine the weights of the network
  - use `get_layer` to access indexed layer in the network
    - layer 0 is the input layer.
  - use `get_weights` to get the weights/biases for a layer.

In [19]:
```
nn.summary()
```

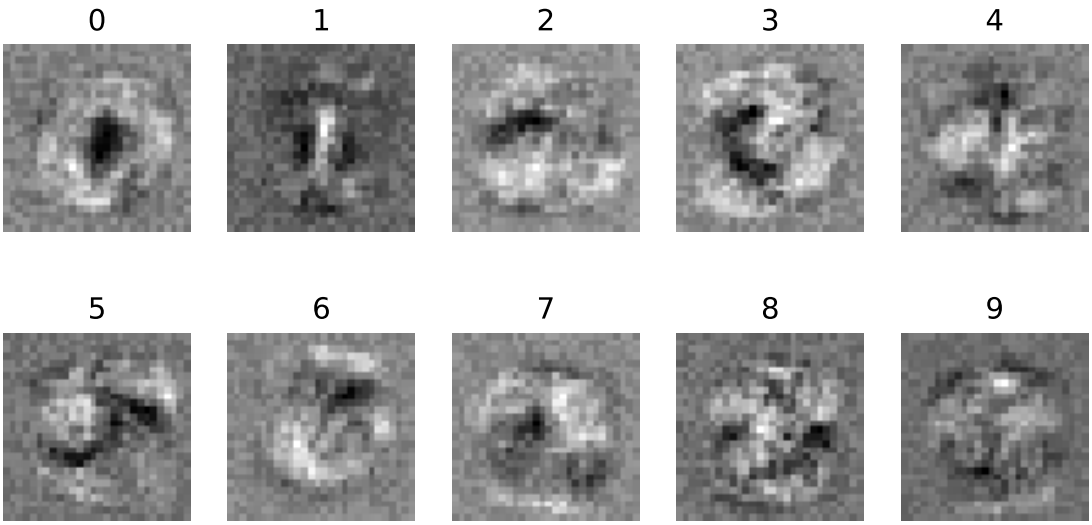
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_1 (Dense)              (None, 10)                7850
=================================================================
Total params: 7,850
Trainable params: 7,850
Non-trainable params: 0
_________________________________________________________________
```

In [22]:
```
params = nn.get_layer(index=0).get_weights()
print(params)
```

```
[array([[ 0.06149667, -0.00956881,  0.04494786, ..., -0.01983179,
        -0.01988732, -0.04903082],
       [-0.03783249,  0.05561111,  0.01096175, ...,  0.00689876,
        -0.03800327,  0.05169382],
       [ 0.0464403 , -0.06389185, -0.0054566 , ..., -0.08001423,
         0.00840039,  0.06919765],
       ...,
       [-0.08192953, -0.01071142, -0.08111438, ..., -0.00769493,
         0.02033912,  0.0334817 ],
       [ 0.02797209,  0.06162796,  0.04971624, ..., -0.07365877,
        -0.06210516,  0.04514118],
       [-0.0757691 , -0.0307025 ,  0.03168748, ...,  0.05234558,
         0.01123877, -0.05992332]], dtype=float32), array([-0.8677261 , -1.0
924444 ,  0.35359004,  0.4218637 , -0.5062293 ,
        0.7116781 , -0.44736755, -0.39708725,  1.2463356 ,  0.5773874 ],
      dtype=float32)]
```

- Reshape the weights into an image
  - input images that match the weights will have high response for that class.

In [23]:
```
W = params[0]
filter_list = [W[:,i].reshape((28,28)) for i in range(W.shape[1])]
plt.figure(figsize=(8,4))
show_imgs(filter_list, nc=5, titles="%d")
```



MNIST - 1-hidden layer

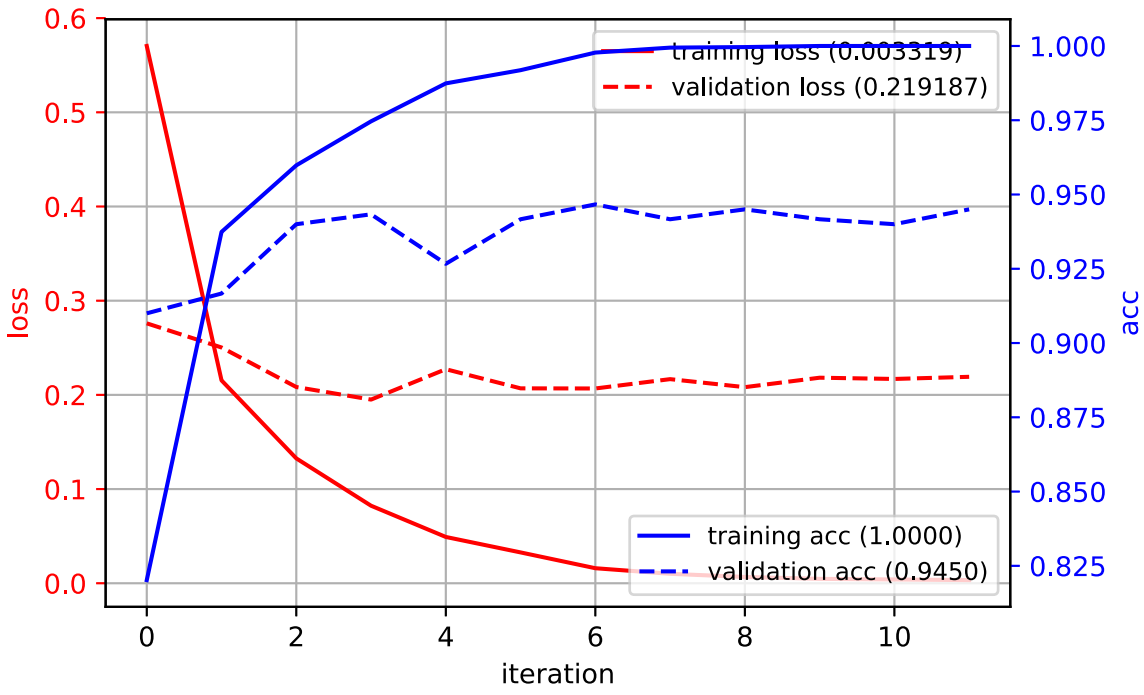
- Add 1 hidden layer with 50 ReLu nodes
  - each node is extracting a feature from the input image

In [24]:
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Dense(units=50, input_dim=784, activation='relu')) # hidden layer
nn.add(Dense(units=10, activation='softmax'))  # output layer

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.1, momentum=0.9, nesterov=True),
           metrics=['accuracy'])
history = nn.fit(vtrainX, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validset, verbose=False)
```

```
Epoch 00012: early stopping
```

In [25]:
```
plot_history(history)

predY = nn.predict_classes(testX, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
test accuracy: 0.9373
```

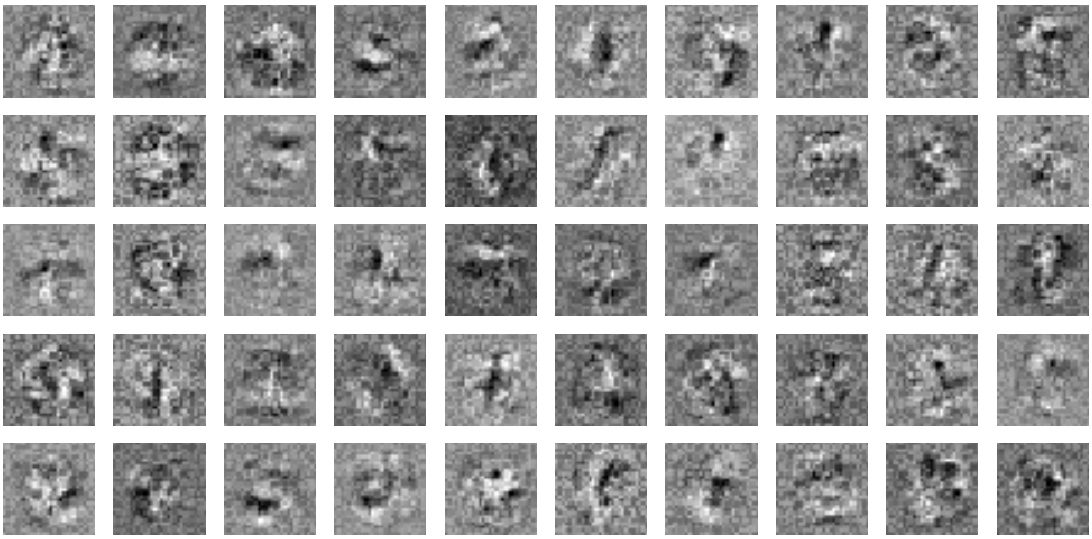


- Examine the weights of the hidden layer
  - $h_i = \sigma(\mathbf{w}_i^T \mathbf{x})$
  - each weight vector is a "pattern prototype" that the node will match
- The hidden nodes look for local structures:
  - oriented edges, curves, other local structures

In [26]:
```
nn.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (None, 50)                39250
_________________________________________________________________
dense_3 (Dense)              (None, 10)                510
=================================================================
Total params: 39,760
Trainable params: 39,760
Non-trainable params: 0
_________________________________________________________________
```

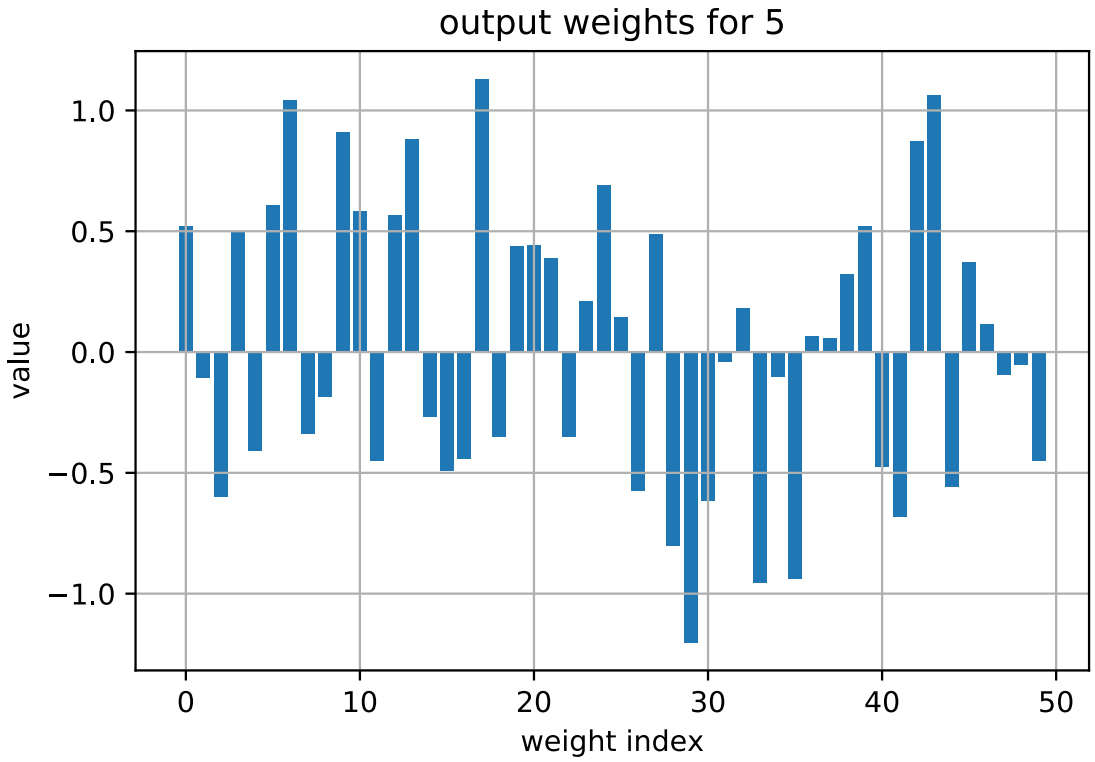
In [28]:
```
W = nn.get_layer(index=0).get_weights()[0]
filter_list = [W[:,i].reshape((28,28)) for i in range(W.shape[1])]
plt.figure(figsize=(8,4))
show_imgs(filter_list, nc=10)
```



- Examine the weights of the 2nd layer (output)
  - $y_j = \sigma(\mathbf{w}_j^T \mathbf{h})$
  - recall the hidden-layer outputs h are always non-negative.
    - positive value in $\mathbf{w}_j$ -> class j should have j-th pattern
    - negative value in $\mathbf{w}_j$ -> class j shouldn't have j-th pattern

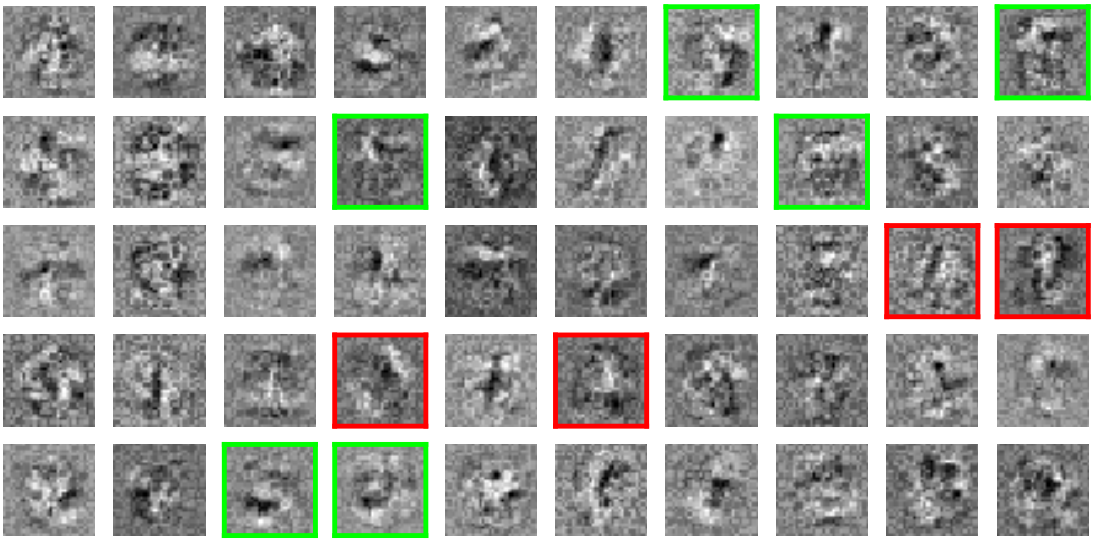
In [31]:

```
W = nn.get_layer(index=1).get_weights()[0]
d = 5
plt.figure()
plt.bar(arange(0,W.shape[0]),W[:,d]); plt.grid(True);
plt.xlabel('weight index'); plt.ylabel('value')
plt.title('output weights for {}'.format(d));
```



- For "5", finds local image parts that correspond to 5
  - should have (green boxes):
    - horizontal line at top
    - semicircle on the botoom
  - shouldn't have (red boxes):
    - vertical line in top-right
    - verticle line in the middle

In [32]:
```
plt.figure(figsize=(8,4))
show_imgs(filter_list, nc=10,
          highlight_green=(W[:,d]>0.75), # positive weights are green
          highlight_red=(W[:,d]<-0.75))  # negative weights are red
```



---

1 Hidden layer with more nodes

- hidden layer with 200 nodes

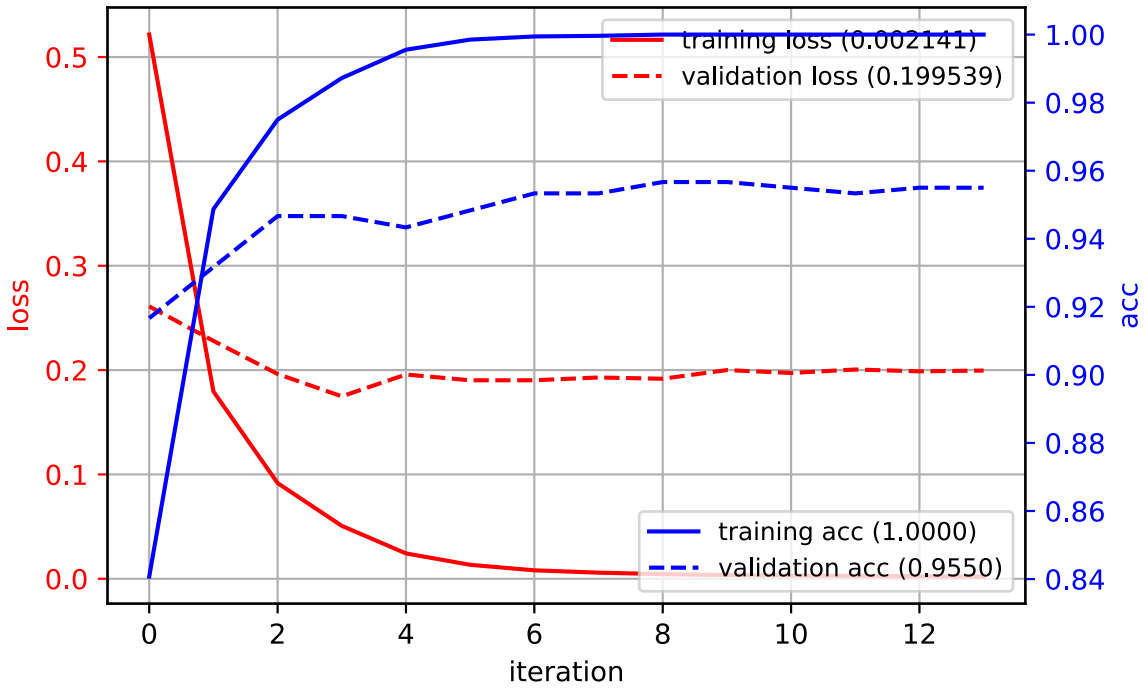
In [33]:
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Dense(units=200, input_dim=784, activation='relu'))
nn.add(Dense(units=10, activation='softmax'))

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.1, momentum=0.9, nesterov=True),
           metrics=['accuracy'])
history = nn.fit(vtrainX, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validset, verbose=False)
```

```
Epoch 00014: early stopping
```

In [34]:

```
nn.summary()

plot_history(history)

predY = nn.predict_classes(testX, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy: ", acc)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 200)               157000
_________________________________________________________________
dense_5 (Dense)              (None, 10)                2010
=================================================================
Total params: 159,010
Trainable params: 159,010
Non-trainable params: 0
_________________________________________________________________
test accuracy:  0.9434
```



- hidden layer with 1000 nodes

In [35]:

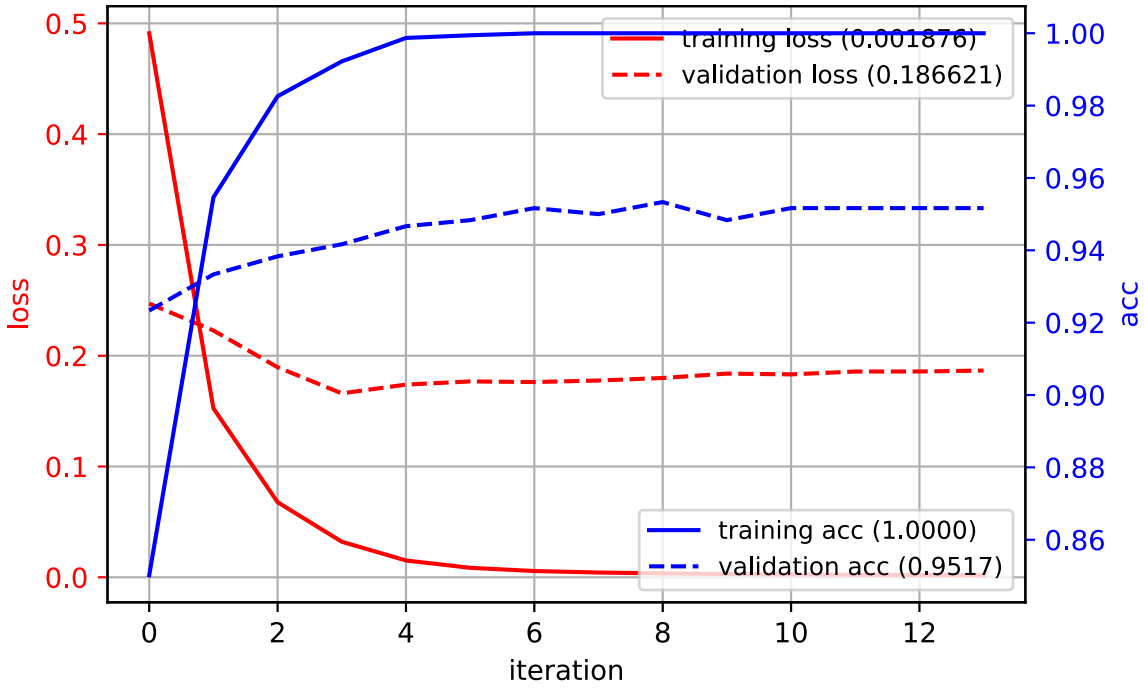
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Dense(units=1000, input_dim=784, activation='relu'))
nn.add(Dense(units=10, activation='softmax'))

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.1, momentum=0.9, nesterov=True),
          metrics=['accuracy'])
history = nn.fit(vtrainX, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validset, verbose=False)
```

```
Epoch 00014: early stopping
```

In [36]:

```
nn.summary()
plot_history(history)

predY = nn.predict_classes(testX, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_6 (Dense)              (None, 1000)              785000
_________________________________________________________________
dense_7 (Dense)              (None, 10)                10010
=================================================================
Total params: 795,010
Trainable params: 795,010
Non-trainable params: 0
_________________________________________________________________
test accuracy: 0.9454
```



- 2 hidden layers
  - input (28x28) -> 500 nodes -> 500 nodes -> output
  - Slightly better

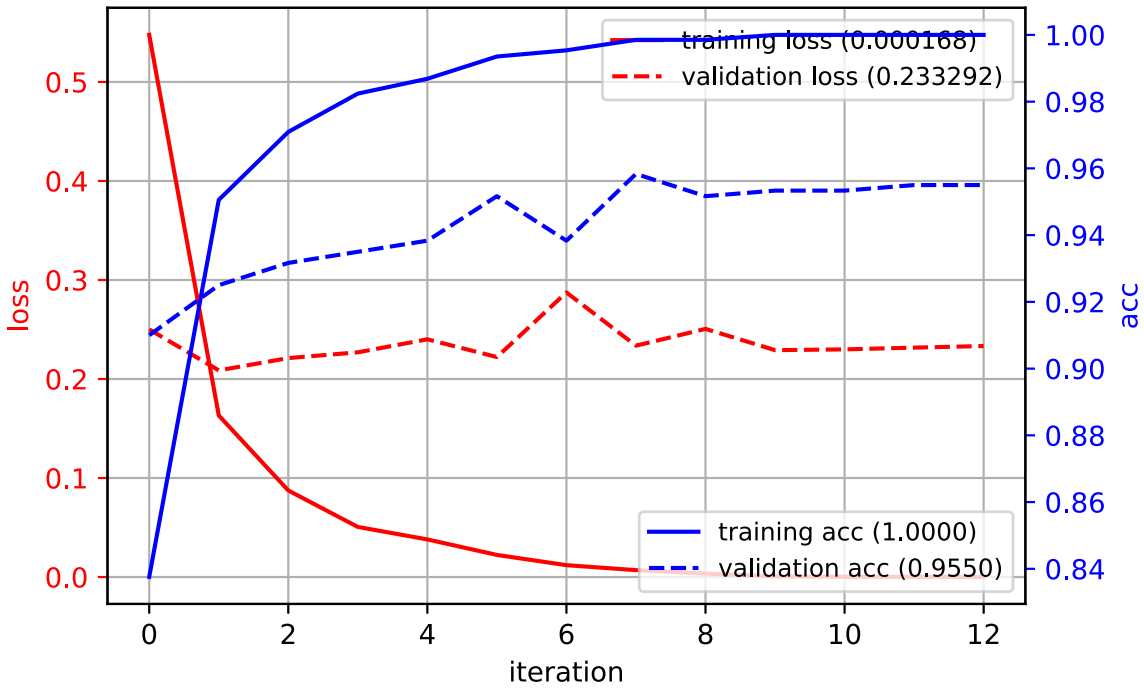
In [37]:

```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Dense(units=500, input_dim=784, activation='relu'))
nn.add(Dense(units=500, activation='relu'))
nn.add(Dense(units=10, activation='softmax'))

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.1, momentum=0.9, nesterov=True),
          metrics=['accuracy'])
history = nn.fit(vtrainX, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validset, verbose=False)
```

```
Epoch 00013: early stopping
```

In [38]:
```
nn.summary()
plot_history(history)

predY = nn.predict_classes(testX, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 500)               392500
_________________________________________________________________
dense_9 (Dense)              (None, 500)               250500
_________________________________________________________________
dense_10 (Dense)             (None, 10)                5010
=================================================================
Total params: 648,010
Trainable params: 648,010
Non-trainable params: 0
_________________________________________________________________
test accuracy: 0.9517
```

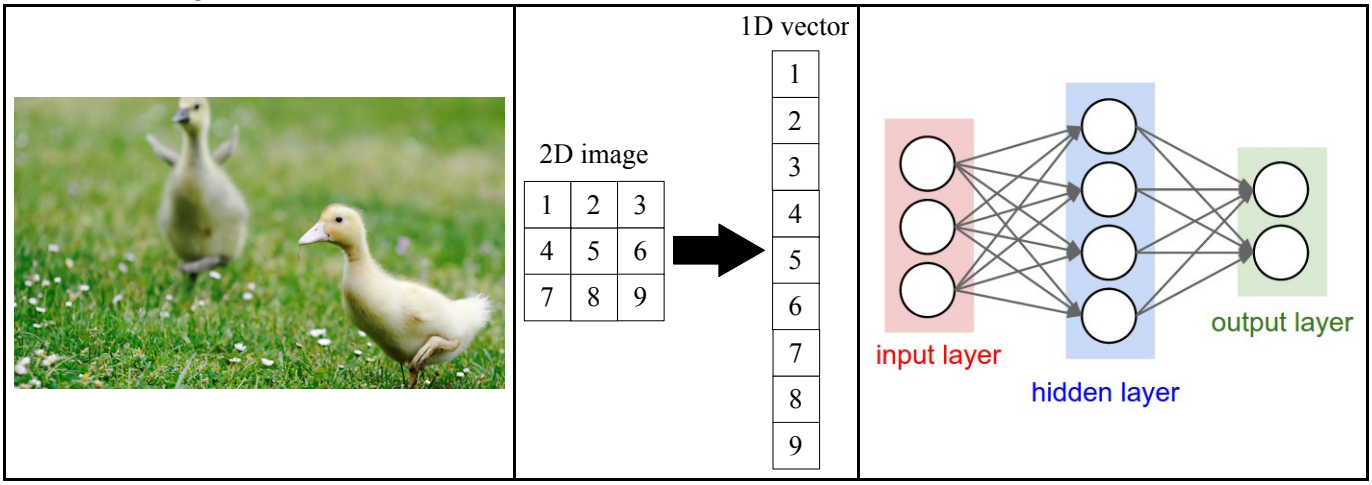


Outline

- History
- Perceptron
- Multi-layer perceptron (MLP)
- **Convolutional neural network (CNN)**
- Autoencoder (AE)

Image Inputs and Neural Networks

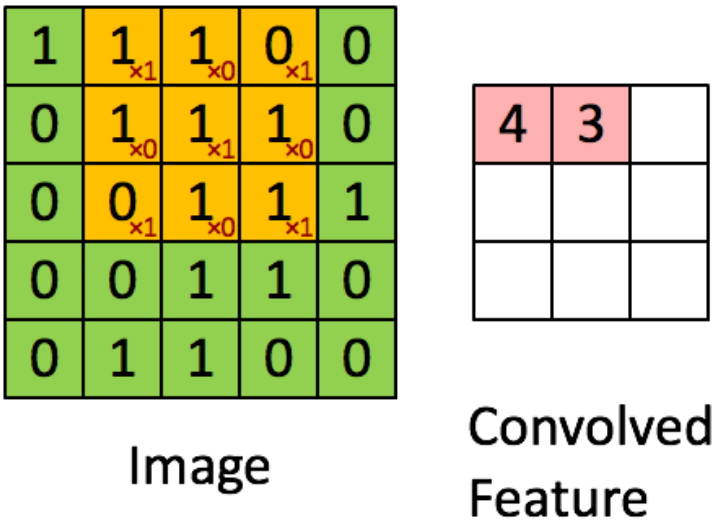
- In the MLP, each node takes inputs from all other nodes in the previous layer.
  - For image input, we transform the image into a vector, which is the input into the MLP.



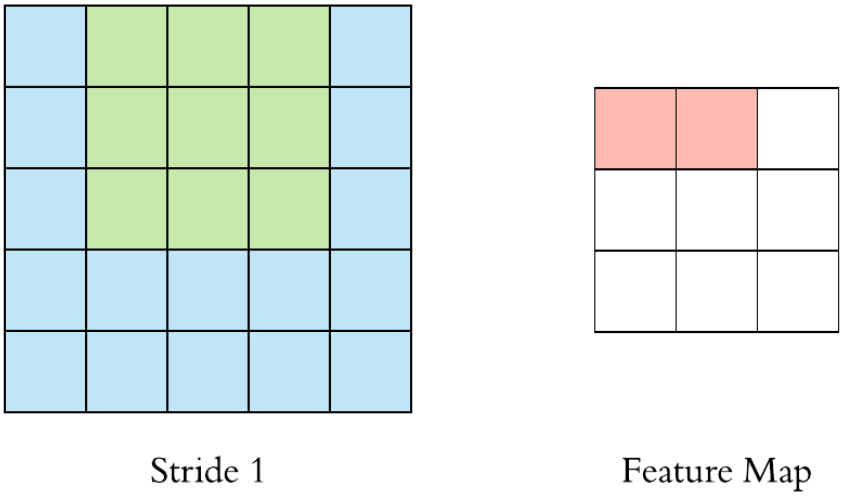
- **Problem:** This ignores the spatial relationship between pixels in the image.
  - Images contain local structures
    - groups of neighboring pixels correspond to visual structures (edges, corners, texture).
    - pixels far from each other are typically not correlated.

Convolutional Neural Network (CNN)

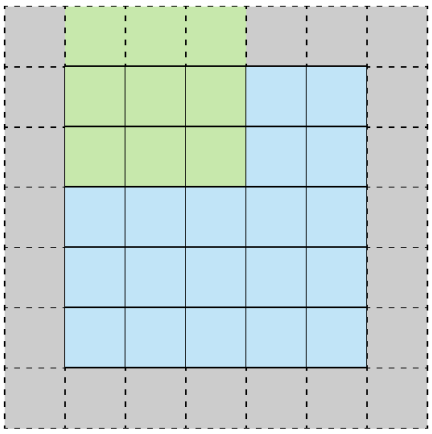
- Use the spatial structure of the image
- 2D convolution filter
  - the weights $\mathbf{W}$ form a 2D filter template
  - filter response: $h = f(\sum_{x,y} W_{x,y} P_{x,y})$
    - $\mathbf{P}$ is an image patch with the same size as $\mathbf{W}$.
- Convolution feature map
  - pass a sliding window over the image, and apply filter to get a *feature map*.



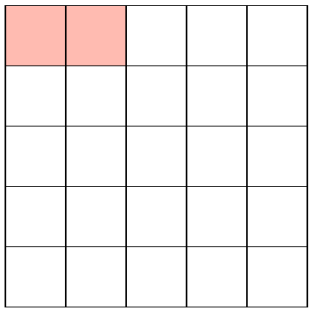
- Convolution modes
  - **"valid"** mode - only compute feature where convolution filter has valid image values.
    - size of feature map is reduced.



- Convolution modes
  - **"same"** mode - zero-pad the border of the image
    - feature map is the same size as the input image.

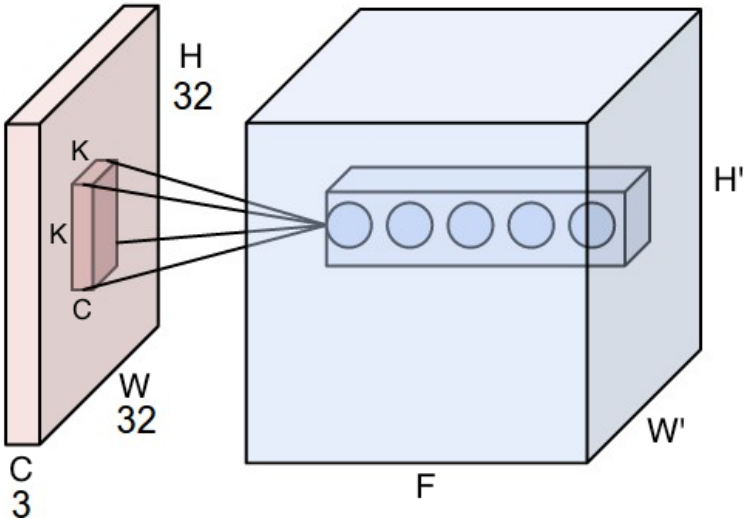


Stride 1 with Padding

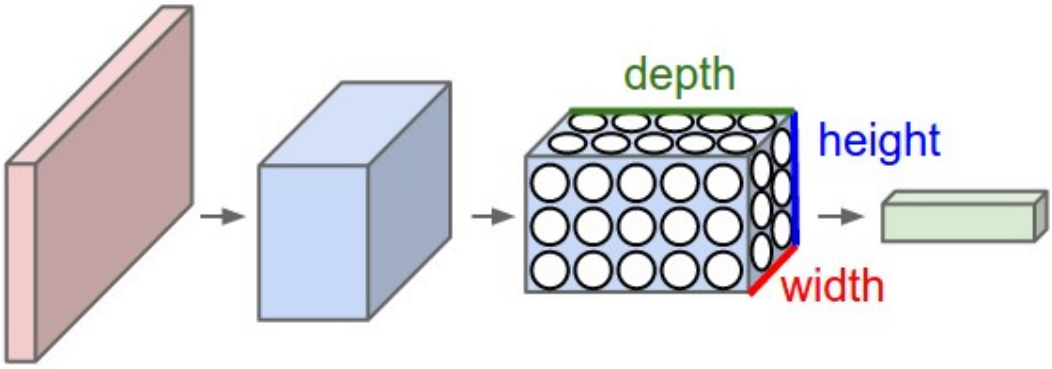


Feature Map

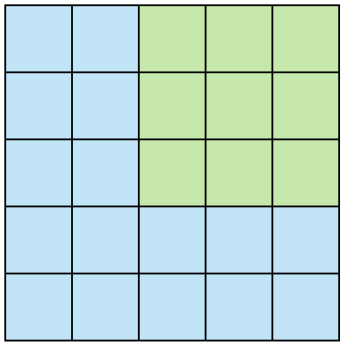
- Convolutional layer
  - **Input:** HxW image with C channels
    - For example, in the first layer, C=3 for RGB channels.
    - defines a 3D volume: C x H x W
  - **Features:** apply F convolution filters to get F feature maps.
    - Uses 3D convolution filters: weight volume is C x K x K
    - K is the spatial extent of the filter
  - **Output:** a feature map with F channels
    - defines a 3D volume: F x H' x W'



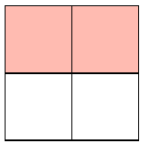
- Convolutional Neural Network
  - Concatenate several convolutional layers.
  - From layer to layer
    - spatial resolution decreases
    - number of feature maps increases
  - Can extract high-level features in the final layers



- Spatial sub-sampling
  - reduce the feature map size by subsampling feature maps between convolutional layers
    - *stride* for convolution filter - step size when moving the windows across the image.

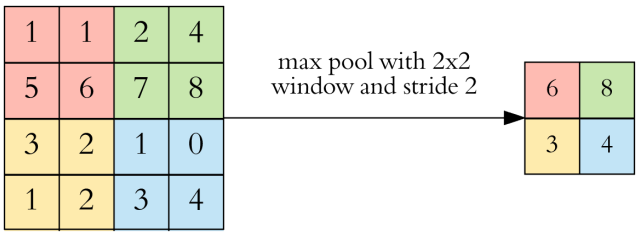


Stride 2

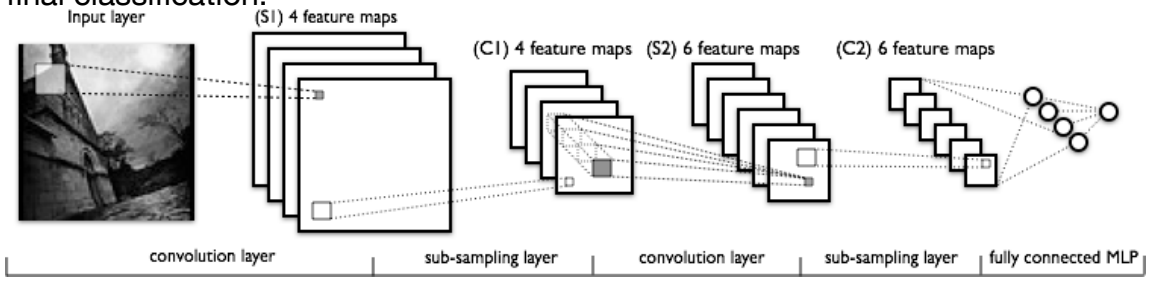


Feature Map

    - *max-pooling* - use the maximum over the pooling window
      - gathers features together, makes it robust to small changes in configuration of features

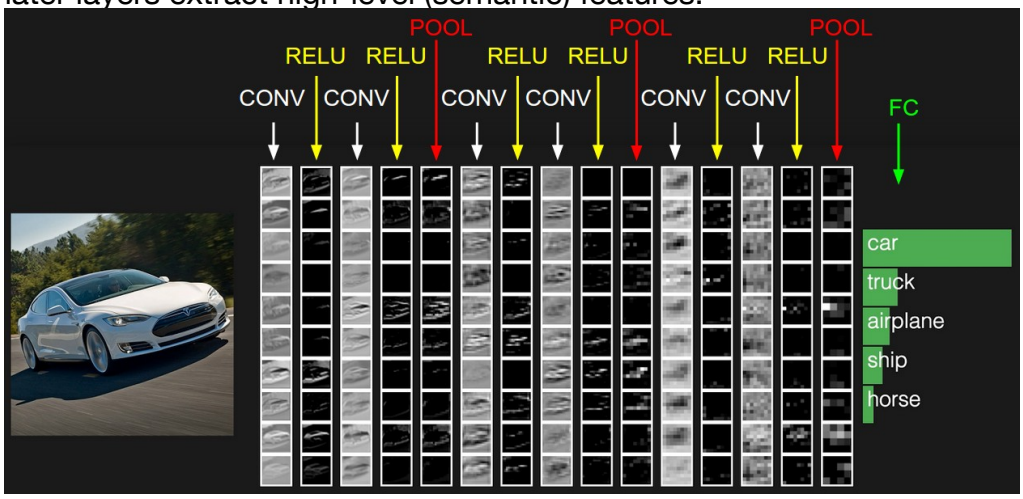


- Fully-connected MLP
  - after several convolutional layers, input the feature map into an MLP to get the final classification.



Example

- Object classification
  - Each layer shows its feature maps for the example image.
    - early layers extract low-level (visual) features
    - later layers extract high-level (semantic) features.



Advantages of Convolution Layers

- The convolutional filters extract the same features throughout the image.
  - Good when the object can appear in different locations of the image.
- Pooling makes it robust to changes in feature configuration, and translation of the object.
- The number of parameters is small compared to Dense (Fully-connected) layer
  - Example: input is C x H x W, and output is F x H x W
    - Number of MLP parameters: (CHW+1) x (FHW)
    - Number of CNN parameters: (CKK+1) x (FKK)

Example on MNIST

- Pre-processing
  - scale to [0,1]
  - 4-D tensor: (sample, channel, height, width)
    - channel = 1 (grayscale)
  - create training/validation sets

In [40]:
```
# scale to 0-1
trainI = (trainimg.reshape((6000,1,28,28)) / 255.0)
testI  = (testimg.reshape((10000,1,28,28)) / 255.0)
print(trainI.shape)
print(testI.shape)
```

```
(6000, 1, 28, 28)
(10000, 1, 28, 28)
```

- Generate fixed training and validation sets

In [41]:
```
# generate fixed validation set of 10% of the training set
vtrainI, validI, vtrainYb, validYb = \
  model_selection.train_test_split(trainI, trainYb,
  train_size=0.9, test_size=0.1, random_state=4487)

validsetI = (validI, validYb)
```

Shallow CNN Architecture

- Architecture
  - 1 Convolution layer
    - 1x5x5 kernel, 10 features
    - *stride* = 2 (step-size between sliding windows)
    - No pooling here since the image input is small (28x28)
    - Input: 1x28x28 (grayscale image) -> Output: 10x14x14
  - 1 fully-connected layer (MLP), 50 nodes
    - Input: 10x14x14=1960 -> Output: 50
  - Classification output node

In [42]:

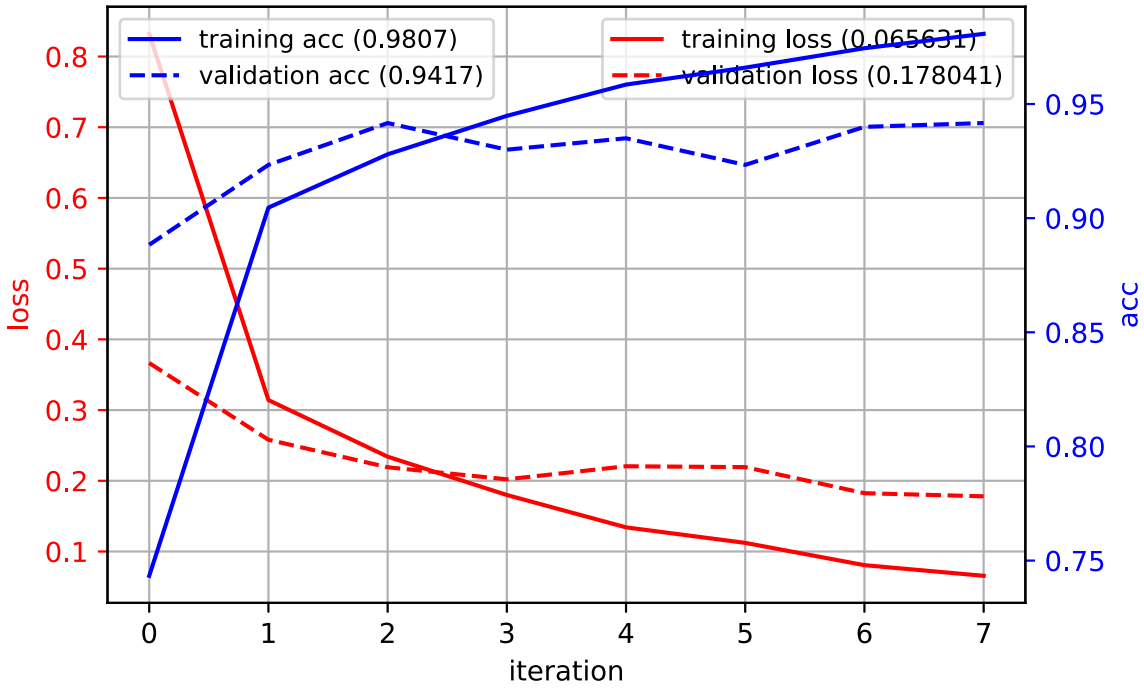
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Conv2D(10, (5,5),        # channel, kerne size
              strides=(2,2),    # stride
              activation='relu',
              padding='same',   # convolution padding
              data_format='channels_first', # using channel-first format
              input_shape=(1,28,28)))
nn.add(Flatten())   # flatten the feature map into a vector to apply Dense layer
s
nn.add(Dense(units=50, activation='relu'))
nn.add(Dense(units=10, activation='softmax'))

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.02, momentum=0.9, nesterov=True),
          metrics=['accuracy'])
history = nn.fit(vtrainI, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validsetI, verbose=False)
```

```
Epoch 00008: early stopping
```

In [43]:

```
nn.summary()

plot_history(history)

predY = nn.predict_classes(testI, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

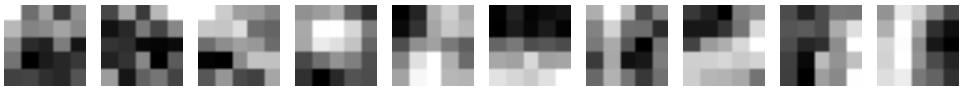
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 10, 14, 14)        260
_________________________________________________________________
flatten_1 (Flatten)          (None, 1960)              0
_________________________________________________________________
dense_11 (Dense)             (None, 50)                98050
_________________________________________________________________
dense_12 (Dense)             (None, 10)                510
=================================================================
Total params: 98,820
Trainable params: 98,820
Non-trainable params: 0
_________________________________________________________________
test accuracy: 0.9449
```



- Visualize the convolutional filters
  - filters are looking for local stroke features
    - corners, edges, lines

In [46]:
```
W = nn.get_layer(index=0).get_weights()[0]
print(W.shape)
flist = [squeeze(W[:,:,:,c]) for c in range(10)]
show_imgs(flist)
```

```
(5, 5, 1, 10)
```



Handling the Image Border

- How to handle the border of the image input when doing convolution?
- Two options:
  - "same" - zero-padding around the image border, so that the filter can be applied to all pixels in the image.
  - "valid" - only do convolution where there is valid image - reduces the image size slightly around the border
- (Usually "same" is better since it looks at structures around border)

Deep CNN Architecture

- Deep Architecture
  - 3 Convolutional layers
    - 1x5x5 kernel, stride 2, 10 features
      - output feature map is 10x14x14
    - 10x3x3 kernel, stride 2, 40 features
      - output feature map is 40x7x7
    - 40x3x3 kernel, stride 1, 80 features
      - output feature map is 80x7x7
      - set stride as 1 to avoid reducing the feature map too much)
  - 1 fully-connected layer
    - 50 nodes
      - input: 80x7x7=3920 -> output: 50
  - Classification output node

In [47]:

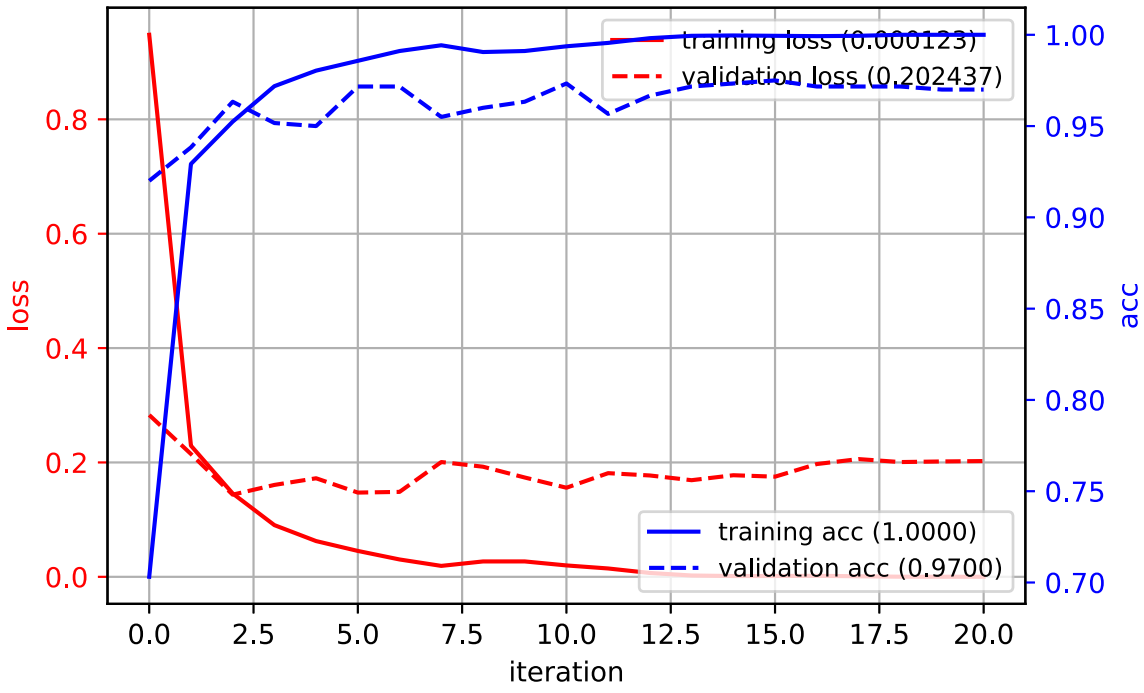
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Conv2D(10, (5,5), strides=(2,2),
              activation='relu', input_shape=(1,28,28),
              padding='same', data_format='channels_first'))
nn.add(Conv2D(40, (5,5), strides=(2,2), activation='relu',
              padding='same', data_format='channels_first'))
nn.add(Conv2D(80, (5,5), strides=(1,1), activation='relu',
              padding='same', data_format='channels_first'))
nn.add(Flatten())
nn.add(Dense(units=50, activation='relu'))
nn.add(Dense(units=10, activation='softmax'))

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.02, momentum=0.9, nesterov=True),
          metrics=['accuracy'])
history = nn.fit(vtrainI, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validsetI, verbose=False)
```

```
Epoch 00021: early stopping
```

In [48]:

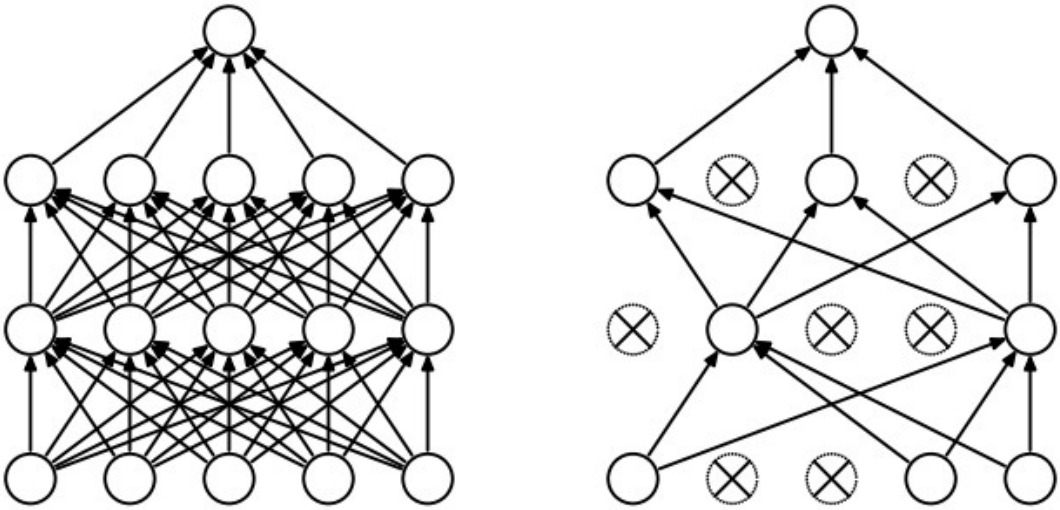
```
nn.summary()
plot_history(history)

predY = nn.predict_classes(testI, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy: ", acc)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 10, 14, 14)        260
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 40, 7, 7)          10040
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 80, 7, 7)          80080
_________________________________________________________________
flatten_2 (Flatten)          (None, 3920)              0
_________________________________________________________________
dense_13 (Dense)             (None, 50)                196050
_________________________________________________________________
dense_14 (Dense)             (None, 10)                510
=================================================================
Total params: 286,940
Trainable params: 286,940
Non-trainable params: 0
_________________________________________________________________
test accuracy:  0.9687
```



Regularization with "Dropout"

- During training, randomly "drop out" each node with probability p
  - a dropped-out node is not used for calculating the prediction or weight updating.
  - trains a reduced network in each iteration.



(a) Standard Neural Net

(b) After applying dropout.

- During test time, use all the nodes for prediction and scale output by p.
  - Similar to creating an ensemble of networks, and then averaging the predictions.
- Prevents overfitting
  - also improves the training time.

- Dropout is implemented as a layer.
- Example:
  - apply dropout layer after last feature layer and 1st dense layer.
  - accuracy improves

In [49]:

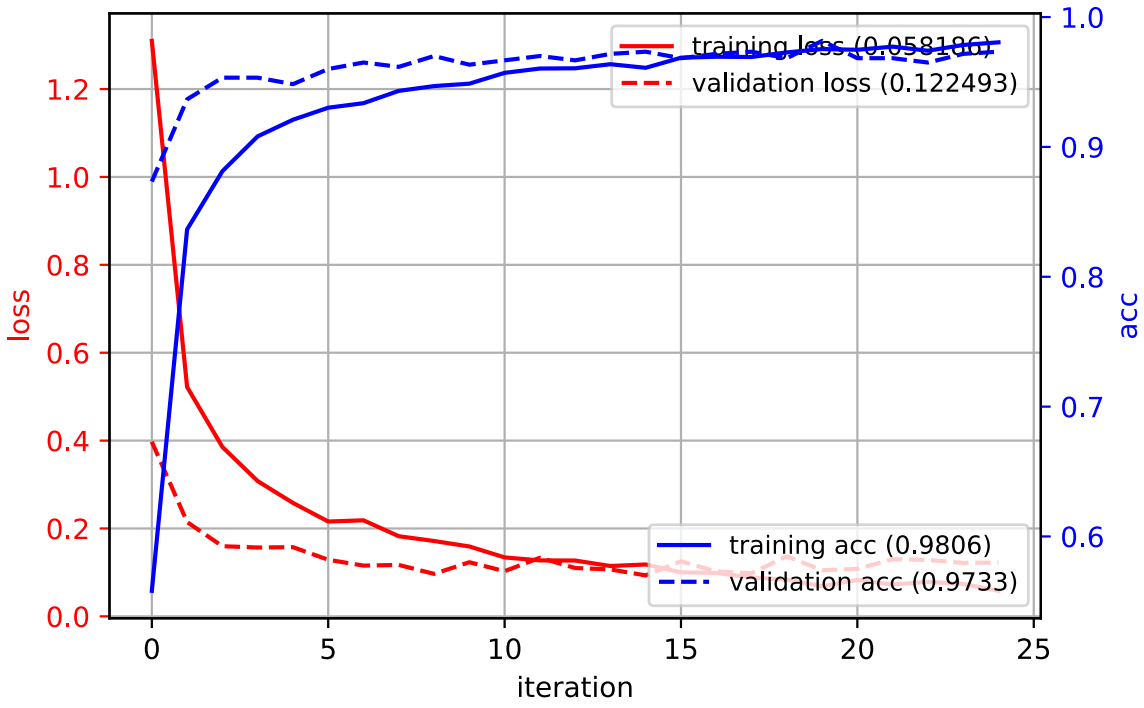
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Conv2D(10, (5,5), strides=(2,2), activation='relu',
              input_shape=(1,28,28),
              padding='same', data_format='channels_first'))
nn.add(Conv2D(40, (5,5), strides=(2,2), activation='relu',
              padding='same', data_format='channels_first'))
nn.add(Conv2D(80, (5,5), strides=(1,1), activation='relu',
              padding='same',  data_format='channels_first'))
nn.add(Dropout(rate=0.5, seed=44))   # dropout layer! (need to specify the seed)
nn.add(Flatten())
nn.add(Dense(units=50, activation='relu'))
nn.add(Dropout(rate=0.5, seed=45))   # dropout layer!
nn.add(Dense(units=10, activation='softmax'))

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.02, momentum=0.9, nesterov=True),
          metrics=['accuracy'])
history = nn.fit(vtrainI, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validsetI, verbose=False)
```

```
Epoch 00025: early stopping
```

In [50]:

```
nn.summary()
plot_history(history)

predY = nn.predict_classes(testI, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_5 (Conv2D)            (None, 10, 14, 14)        260
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 40, 7, 7)          10040
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 80, 7, 7)          80080
_________________________________________________________________
dropout_1 (Dropout)          (None, 80, 7, 7)          0
_________________________________________________________________
flatten_3 (Flatten)          (None, 3920)              0
_________________________________________________________________
dense_15 (Dense)             (None, 50)                196050
_________________________________________________________________
dropout_2 (Dropout)          (None, 50)                0
_________________________________________________________________
dense_16 (Dense)             (None, 10)                510
=================================================================
Total params: 286,940
Trainable params: 286,940
Non-trainable params: 0
_________________________________________________________________
test accuracy: 0.9726
```



Regularization with Weight Decay

- Another way to regularize the network is to use "weight decay"
  - Add a penalty term to the loss function
    - larger weights impose higher penalty
    - $L = Loss + \alpha \sum_i w_i^2$

- Apply regularizers on selected later layers.
  - About the same accuracy

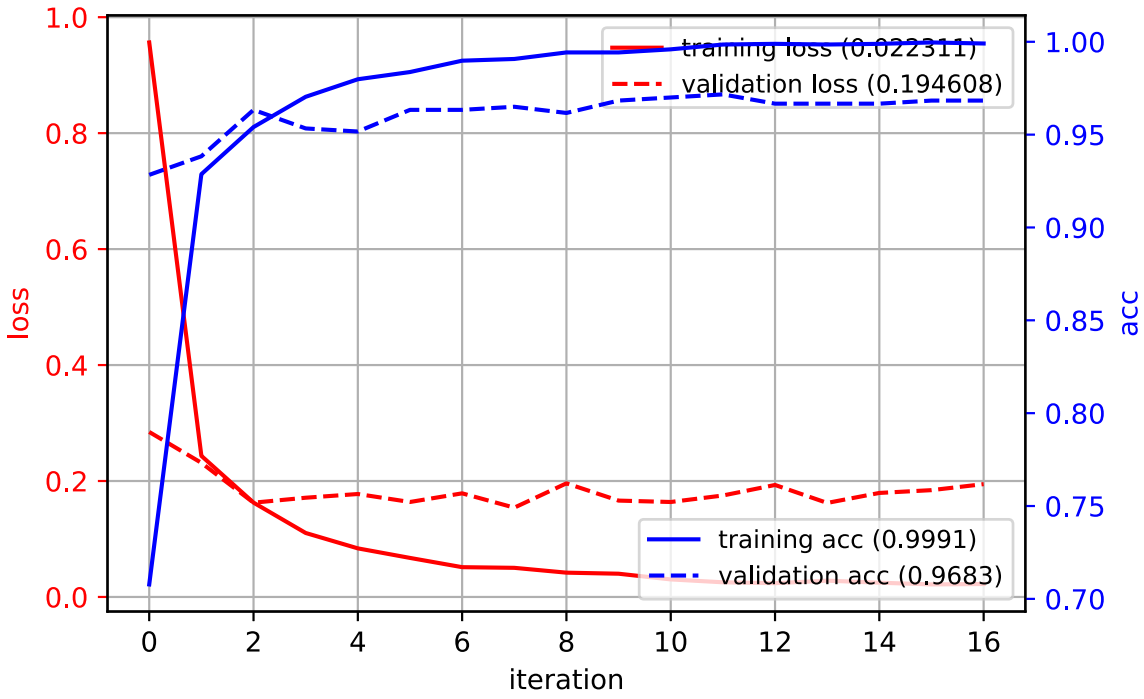
In [51]:
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Conv2D(10, (5,5), strides=(2,2), activation='relu',
              input_shape=(1,28,28),
              padding='same', data_format='channels_first'))
nn.add(Conv2D(40, (5,5), strides=(2,2), activation='relu',
              padding='same', data_format='channels_first'))
nn.add(Conv2D(80, (5,5), strides=(1,1), activation='relu',
              kernel_regularizer=keras.regularizers.l2(0.0001),  # L2 regularize
r
              padding='same', data_format='channels_first'))
nn.add(Flatten())
nn.add(Dense(units=50, activation='relu',
             kernel_regularizer=keras.regularizers.l2(0.0001))) # L2 regularizer
nn.add(Dense(units=10, activation='softmax'))

# compile and fit the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.02, momentum=0.9, nesterov=True),
          metrics=['accuracy'])
history = nn.fit(vtrainI, vtrainYb, epochs=100, batch_size=50,
                 callbacks=callbacks_list,
                 validation_data=validsetI, verbose=False)
```

```
Epoch 00017: early stopping
```

In [53]:

```
plot_history(history)

predY = nn.predict_classes(testI, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
test accuracy: 0.9637
```



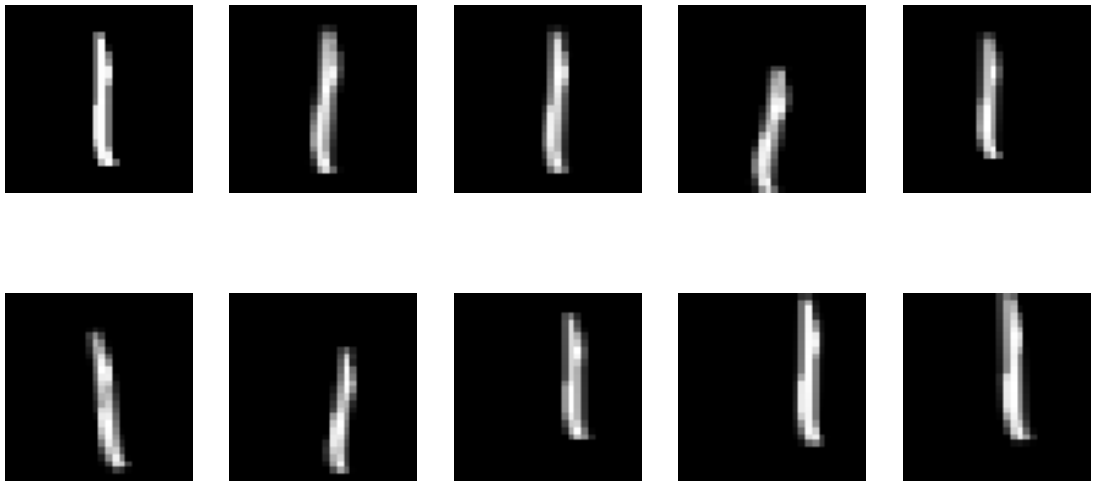
Data augmentation

- artificially permute the data to increase the dataset size
  - goal: make the network invariant to the permutations
  - examples: translate image, flip image, add pixel noise, rotate image, deform image, etc.

In [54]:
```
from keras.preprocessing.image import ImageDataGenerator

# build the data augmenter
datagen = ImageDataGenerator(
    rotation_range=10,          # image rotation
    width_shift_range=0.2,      # image shifting
    height_shift_range=0.2,     # image shifting
    shear_range=0.1,            # shear transformation
    zoom_range=0.1,             # zooming
    data_format='channels_first')

# fit (required for some normalization augmentations)
datagen.fit(vtrainI)
```

- Example of original (top-left) and augmented data

In [56]:
```
plt.figure(figsize=(8,4))
show_imgs(imgs, nc=5)
```



- Train with `fit_generator`
  - passes data through the generator first
  - runs generator and fit in parallel

In [57]:

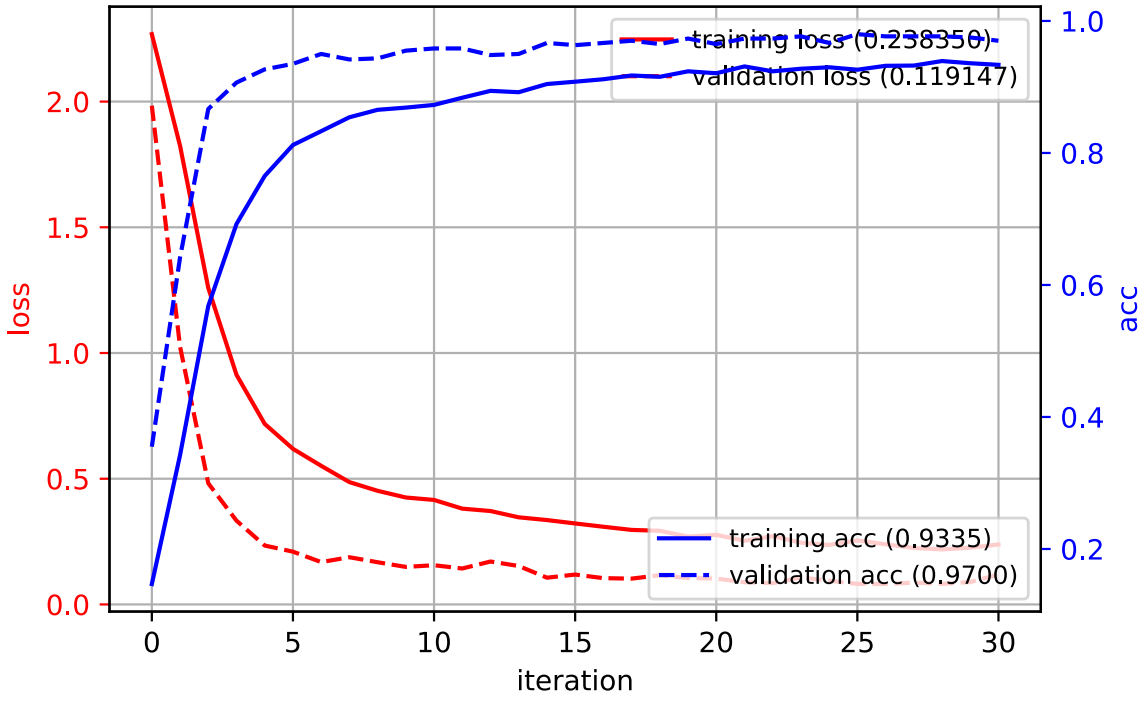
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Conv2D(10, (5,5), strides=(2,2), activation='relu',
              input_shape=(1,28,28),
              padding='same', data_format='channels_first'))
nn.add(Conv2D(40, (5,5), strides=(2,2), activation='relu',
              padding='same', data_format='channels_first'))
nn.add(Conv2D(80, (5,5), strides=(1,1), activation='relu',
              padding='same',  data_format='channels_first'))
nn.add(Dropout(rate=0.5, seed=44))
nn.add(Flatten())
nn.add(Dense(units=50, activation='relu'))
nn.add(Dropout(rate=0.5, seed=45))
nn.add(Dense(units=10, activation='softmax'))

# compile the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.02, momentum=0.9, nesterov=True),
          metrics=['accuracy'])

# pass data through augmentor and fit
# runs data-generator and fit in parallel
history = nn.fit_generator(
            datagen.flow(vtrainI, vtrainYb, batch_size=50),  # data from generat
or
            steps_per_epoch=len(vtrainI)/50,    # should be number of batches pe
r epoch
            epochs=100,
            callbacks=callbacks_list,
            validation_data=validsetI, verbose=False)
```

```
Epoch 00031: early stopping
```

- data augmentation increases accuracy.

In [58]:
```
plot_history(history)

predY = nn.predict_classes(testI, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
test accuracy: 0.9807
```



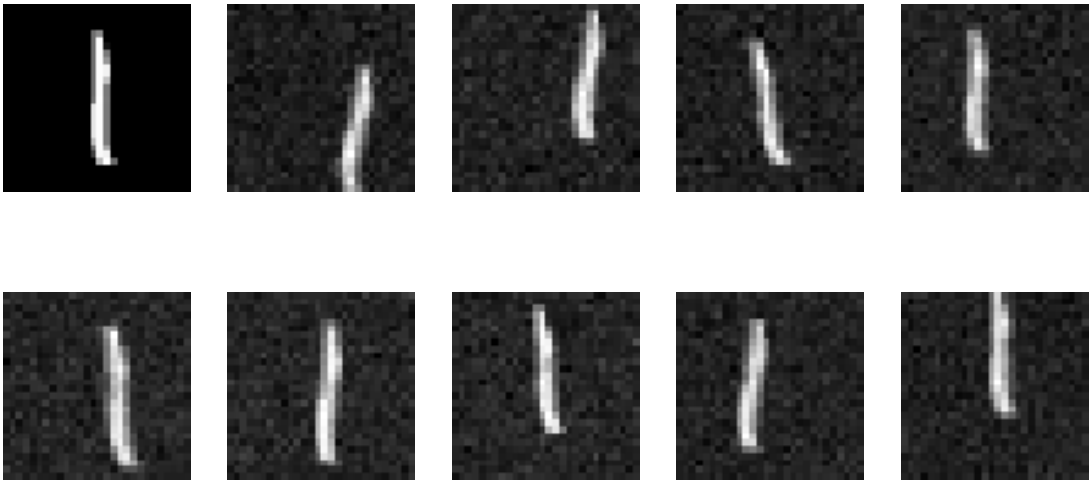
Data augmentation with noise

- Also add per-pixel noise to the image for data augmentation.
  - define a function to add noise
  - set it as the `preprocessing_function`

In [59]:
```
def add_gauss_noise(X, sigma2=0.05):
    # add Gaussian noise with zero mean, and variance sigma2
    return X + random.normal(0, sigma2, X.shape)

# build the data augmenter
datagen = ImageDataGenerator(
    rotation_range=10,          # image rotation
    width_shift_range=0.2,      # image shifting
    height_shift_range=0.2,     # image shifting
    shear_range=0.1,            # shear transformation
    zoom_range=0.1,             # zooming
    preprocessing_function=add_gauss_noise,
    data_format='channels_first')

# fit (required for some normalization augmentations)
datagen.fit(vtrainI)
```

- Example: original image (top-left) and augmented data

In [61]:
```
plt.figure(figsize=(8,4))
show_imgs(imgs, nc=5)
```



- Train with augmented data: transformations and per-pixel noise
  - the dataset changes each epoch, so validation error will change a lot.
  - we disable early stopping and just let it run for 100 epochs.

In [62]:

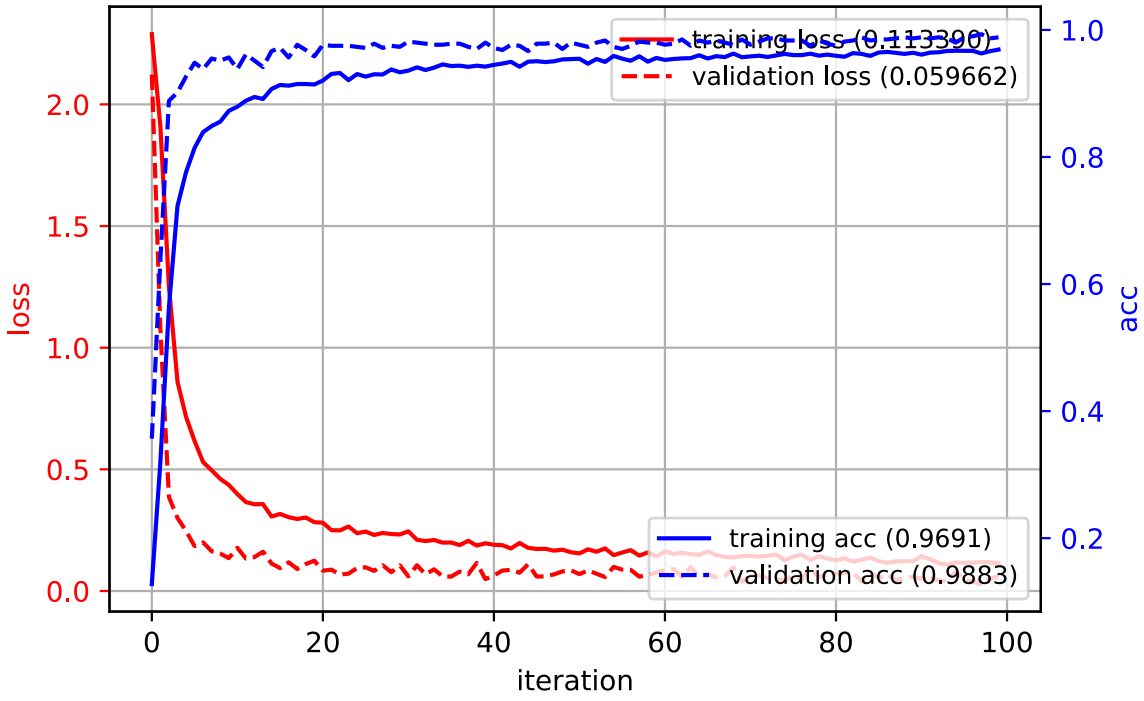
```
# initialize random seed
random.seed(4487); tensorflow.set_random_seed(4487)

# build the network
nn = Sequential()
nn.add(Conv2D(10, (5,5), strides=(2,2), activation='relu',
              input_shape=(1,28,28),
              padding='same', data_format='channels_first'))
nn.add(Conv2D(40, (5,5), strides=(2,2), activation='relu',
              padding='same', data_format='channels_first'))
nn.add(Conv2D(80, (5,5), strides=(1,1), activation='relu',
              padding='same',  data_format='channels_first'))
nn.add(Dropout(rate=0.5, seed=44))
nn.add(Flatten())
nn.add(Dense(units=50, activation='relu'))
nn.add(Dropout(rate=0.5, seed=45))
nn.add(Dense(units=10, activation='softmax'))

# compile the network
nn.compile(loss=keras.losses.categorical_crossentropy,
           optimizer=keras.optimizers.SGD(lr=0.02, momentum=0.9, nesterov=True),
          metrics=['accuracy'])

# pass data through augmentor and fit
# runs data-generator and fit in parallel
history = nn.fit_generator(
            datagen.flow(vtrainI, vtrainYb, batch_size=50),  # data from generat
or
            steps_per_epoch=len(vtrainI)/50,    # should be number of batches pe
r epoch
            epochs=100,
            validation_data=validsetI, verbose=False)
```

- Results improved!

In [63]:

```
plot_history(history)

predY = nn.predict_classes(testI, verbose=False)
acc = metrics.accuracy_score(testY, predY)
print("test accuracy:", acc)
```

```
test accuracy: 0.9851
```



Comparison on MNIST

- For image data, CNN works better and has less parameters.

Type	No.Layers	Architecture	No.Parameters	Test Accuracy
LR	1	output(10)	7,850	0.8890
MLP	2	ReLu(50), output(10)	39,760	0.9373
MLP	2	Relu(200), output(10)	159,010	0.9431
MLP	2	Relu(1000), output(10)	795,010	0.9453
MLP	3	ReLu(500), Relu(500), output(10)	648,010	0.9523
CNN	3	Conv(10x5x5), ReLu(50), output(10)	98,820	0.9537
CNN	5	Conv(10x5x5), Conv(50x3x3), Conv(80x3x3), ReLu(50), output(10)	286,940	0.9693
CNN (w/ dropout)	5	Conv(10x5x5), Conv(50x3x3), Conv(80x3x3), ReLu(50), output(10)	286,940	0.9756
CNN (w/ dropout, data-augmentation)	5	Conv(10x5x5), Conv(50x3x3), Conv(80x3x3), ReLu(50), output(10)	286,940	0.9843
CNN (w/ dropout, data-augmentation, noise)	5	Conv(10x5x5), Conv(50x3x3), Conv(80x3x3), ReLu(50), output(10)	286,940	0.9911

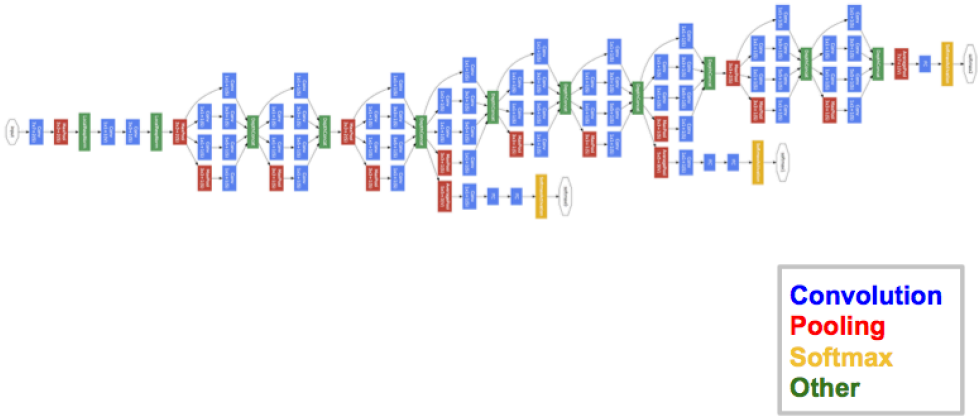
Summary

- **Different types of neural networks**
  - *Perceptron* - single node (similar to logistic regression)
  - *Multi-layer perceptron (MLP)* - collection of perceptrons in layers
    - also called *Fully-connected layer*
  - *Convolutional neural network (CNN)* - convolution filters for extracting local image features
- **Training**
  - optimize loss function using stochastic gradient descent

- **Advantages**
  - lots of parameters - large capacity to learn from large amounts of data
- **Disadvantages**
  - lots of parameters - easy to overfit data
    - need to regularize parameters (dropout, L2)
    - need to monitor the training process
  - sensitive to initialization, learning rate, training algorithm.

Other things

- **Improving speed**
  - parallelize computations using GPU (Nvidia+CUDA)
- **Initialization**
  - the resulting network is still sensitive to initialization.
    - Solution: train several networks and combine them as an ensemble.
- **Training problems**
  - For very deep networks, the "vanishing gradient" problem can hinder convergence
    - Solution 1: "pre-train" parts of the network, then combine the parts and train the network as a whole to "fine-tune" it.
    - Solution 2: add auxiliary tasks in the middle layers to provide a stronger supervision signal.



Installing NN packages

- Keras - https://keras.io (https://keras.io)
  - Easy-to-use front-end for deep learning
  - Installation: https://keras.io/#installation (https://keras.io/#installation)
    - Also need to install a backend: Tensorflow or Theano.
      - Defaults to Tensorflow. To switch to Theano, see here (https://keras.io/backend/#switching-from-one-backend-to-another).
    - Might also need to install "np_utils".
  - API Documentation: https://keras.io/layers/core/ (https://keras.io/layers/core/)
- Tensorflow - https://www.tensorflow.org (https://www.tensorflow.org)
  - Google's NN engine
  - Installation: https://www.tensorflow.org/install/ (https://www.tensorflow.org/install/)
- Theano - http://deeplearning.net/software/theano/ (http://deeplearning.net/software/theano/)
  - powerful NN engine
  - Installation: http://deeplearning.net/software/theano/install.html (http://deeplearning.net/software/theano/install.html)
    - for Mac, need to install Xcode and run it to get C++ compiler.
- Installation tips:
  - Use Anaconda installer
  - Tensorflow has GPU and non-GPU versions
    - `tensorflow` vs `tensorflow-gpu`

References

- History:
  - http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning/ (http://www.andreykurenkov.com/writing/a-brief-history-of-neural-nets-and-deep-learning/)
- Keras tutorials:
  - https://elitedatascience.com/keras-tutorial-deep-learning-in-python (https://elitedatascience.com/keras-tutorial-deep-learning-in-python)
  - https://blog.keras.io (https://blog.keras.io)
- Online courses::
  - http://cs231n.github.io/neural-networks-1/ (http://cs231n.github.io/neural-networks-1/)
  - http://cs231n.github.io/convolutional-networks/ (http://cs231n.github.io/convolutional-networks/)