### STAT562 Lecture 18 Convolutional Neural Network

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#### Convolutional Neural Networks

Convolutional neural network (CNN) is an advanced architectures of artificial neural network (ANN) and it is specifically used in image classification.

- Similar to ordinary Neural Networks: they are made up of hidden layers and units that have learnable weights.
- Convolutional neural network has two specialized types of hidden layers, called convolution layers and pooling layers.
- Convolution layers search for instances of small patterns in the image
- Pooling layers downsample these instances of patterns to select a prominent subset.

## Convolution layer

A convolution layer is made up of a large number of convolution filters (activation units).

- A filter is a I<sub>1</sub> x I<sub>2</sub> array of weights that is operated to the original image data.
- The operation is called convolution, which basically repeatedly multiplying matrix elements to every I<sub>1</sub> x I<sub>2</sub> submatrix of the original image and then adding up.

$$\text{Original Image} = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \\ j & k & l \end{bmatrix}.$$

Now consider a  $2 \times 2$  filter of the form

$$\text{Convolution Filter} = \begin{bmatrix} \alpha & \beta \\ \gamma & \delta \end{bmatrix}.$$

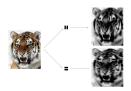
When we convolve the image with the filter, we get the result<sup>8</sup>

$$\label{eq:Convolved Image} \text{Convolved Image} = \begin{bmatrix} a\alpha + b\beta + d\gamma + e\delta & b\alpha + c\beta + e\gamma + f\delta \\ d\alpha + e\beta + g\gamma + h\delta & e\alpha + f\beta + h\gamma + i\delta \\ g\alpha + h\beta + j\gamma + k\delta & h\alpha + i\beta + k\gamma + l\delta \end{bmatrix}.$$



# Convolution layer, Cont.

- If a sub-matrix of the original image resembles the convolution filter, then it will have a large value in the convolved image; otherwise, it will have a small value.
- Thus, the convolved image highlights regions of the original image that resemble the convolution filter.
- We can think of the original image as the input layer in a convolutional neural network, and the convolved images as the units in the first hidden layer.



# More details on colored Image Data

- Format of input data:  $W \times H$  colored (RGB) pixels per image. Each color channel (red, green, and blue), is a 2-d ( $W \times H$ ) array (called feature map). The dimension of input image is  $W \times H \times 3$ .
- A single convolution filter will also have three channels, one per color, with potentially different filter weights.
- The results of the three convolutions are summed to form a 2-d output feature map (color is not passed on to subsequent layers).
- ▶ The dimension of output activations in the 1st convolution layer is  $W_1 \times H_1 \times K$ , where K is the number of filters.

# Depth, stride and zero-padding

Three hyperparameters control the size of the output in each convolution layer: depth, stride and zero-padding.

- ► The depth (K) of the output volume is the number of filters we would like to use.
- ► The stride (usually S = 1 or 2) defined how we slide the filter. When the stride is 1 then we move the filters one pixel at a time. When the stride is 2 then the filters jump 2 pixels at a time.
- Zero-padding (P) is the amount of 0 added to the outside of the feature map, which allows us to control or preserve the spatial size of the input volume.

#### Detector layer

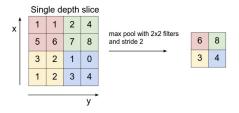
We apply the ReLU activation function to the convolved image from the convolution layer.

- This step is often viewed as a separate layer in CNN, called detector layer or ReLU layer.
- This layer simply threshold at zero and dimension of the information is unchanged.

### **Pooling Layers**

A pooling layer condense a large image into a smaller summary image. The layer reduce the amount of parameters and computation in the network, and hence to also control overfitting.

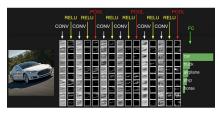
- The Pooling layer operates independently on every slice of the input, using the MAX operation.
- ▶ The most common form is a max pooling of size 2 x 2, taking a max over 4 numbers (little 2 x 2 region).
- This reduces the size of the image by a factor of two in each direction, discarding 75%.



#### Architecture of a Convolutional Neural Network

In a convolutional Neural Network, the convolve-then-pool sequence is often repeated several times

- Each subsequent convolutional layer is similar to the first, with number of channels same as the number of filters from previous convolution layer.
- Since the feature maps are reduced in size after each pool layer, we usually increase the number of filters in the next convolve layer to compensate.
- Sometimes we repeat several convolve layers before a pool layer.



### Fully-connected layer

After a set of convolve-then-pool, each channel feature map down to just a few pixels in each dimension.

- We "flattened" the feature maps by treating each of the pixels as separate units.
- We then feed those into a fully connected layer just as one in a regular ANN.
- The output is fed into the output layer, which is has softmax activation for image classes.

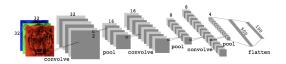


FIGURE 10.8. Architecture of a deep CNN for the CITAR100 classification task. Convolution layers are interspersed with 2 × 2 max-pool layers, which reduce the size by a factor of 2 in both dimensions.

# Sequential Input data and RNN

#### Many data sources are sequential in nature:

- Documents such as book, articles, and tweets. The sequence of words in a document needs to be exploited in tasks such as topic classification, and language translation.
- Time series of temperature, rainfall, wind speed, air quality, and so on.
- Financial time series, where we track market indices, trading volumes, stock and bond prices
- ▶ Recorded speech, musical recordings, and other sound recordings.

# Structure of Simple Recurrent Neural Networks

- ▶ Input: a sequence  $X = \{X_1 \cdots X_L\}$
- ▶ Sequence of hidden layers:  $A = \{A_1 \cdots A_L\}$
- ▶ The network processes the input sequence *X* sequentially.
- At each step, the network updates the activations  $A_l$  in the hidden layer, taking as input the vector  $X_l$  and the activation vector  $A_{l-1}$  from the previous step.
- ▶ Then  $A_l$  feeds into the output layer and produces a prediction  $O_l$ .

Note here  $O_L$  is the final output. Intermediate outputs  $O_l$  are not used.

