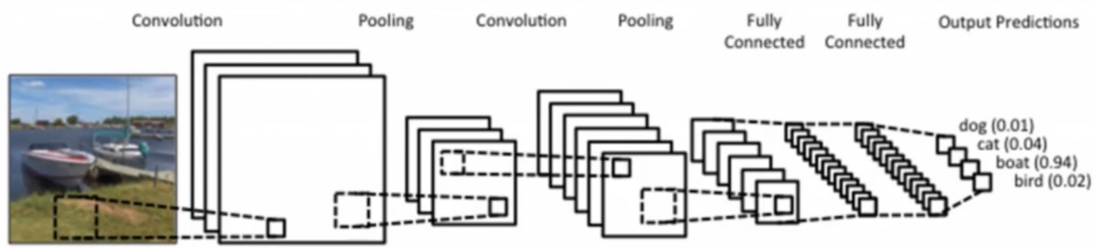
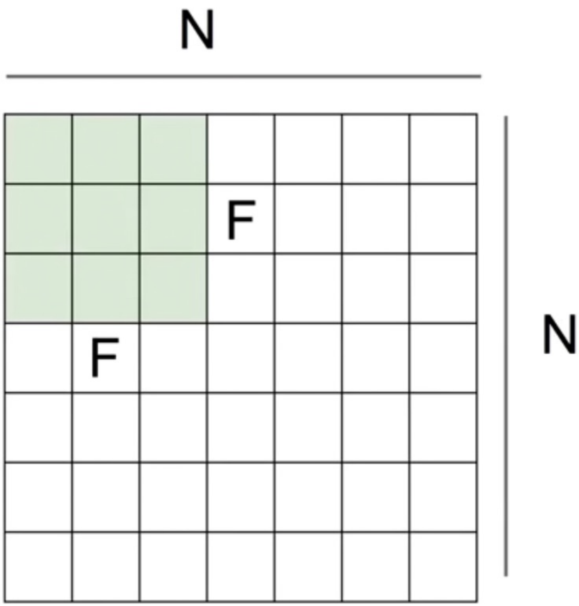
4주차 머신러닝 발표

김찬원

Convolutional Neural Network

- Most widely used for image classification.
- Generally, it consists of convolution layer, pooling layer and fully-connected layer.
- Convolution, Pooling layer – feature extraction
- Fully-connected layer – classification





Output size:

(N - F) / stride + 1

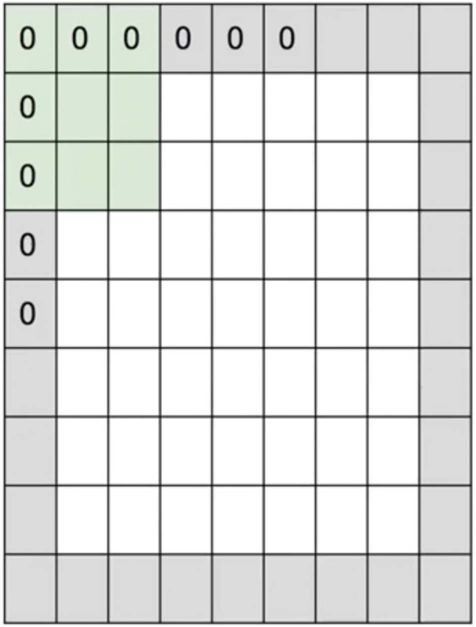
e.g. N = 7, F = 3:

stride 1 => (7 - 3)/1 + 1 = 5

stride 2 => (7 - 3)/2 + 1 = 3

stride 3 => (7 - 3)/3 + 1 = 2.33 :\

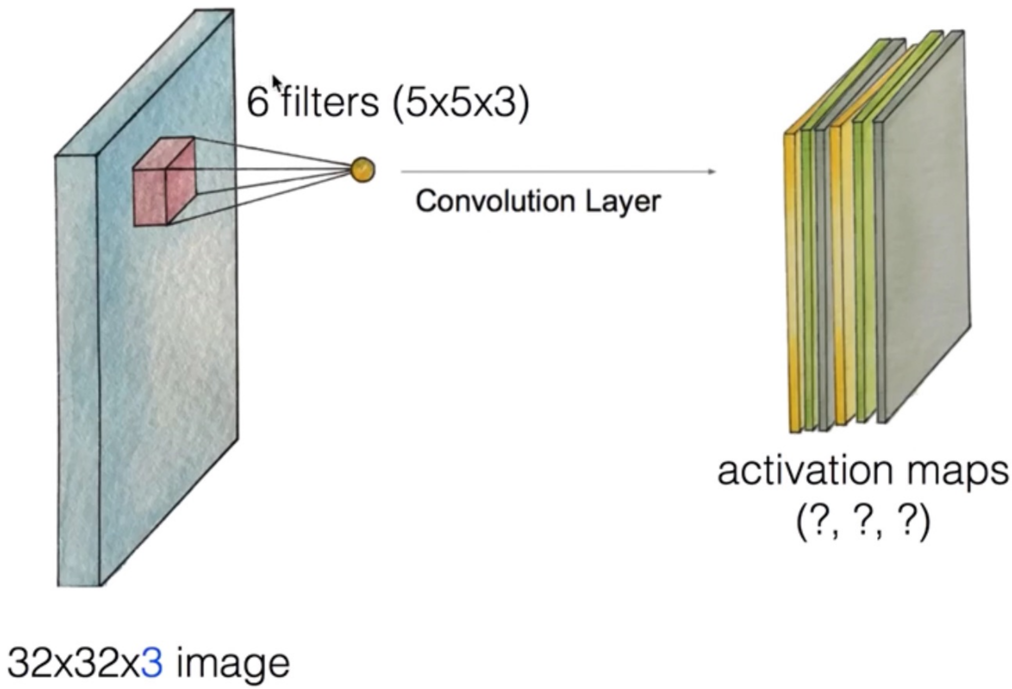
In practice: Common to zero pad the border



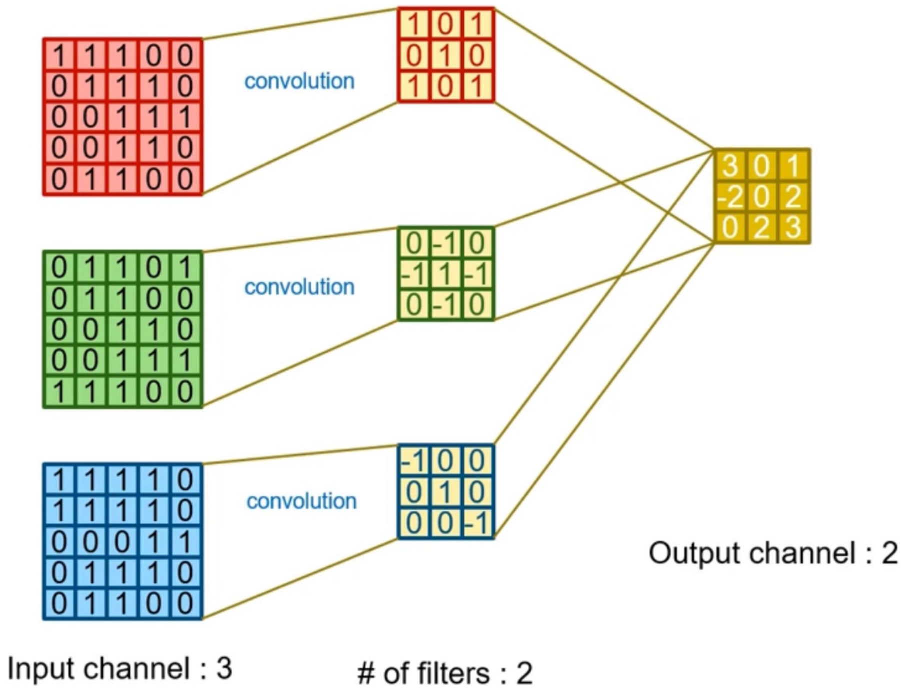
e.g. input 7x7
3x3 filter, applied with **stride 1**
pad with 1 pixel border => what is the output?

7x7 output!
in general, common to see CONV layers with stride 1, filters of size FxF, and zero-padding with (F-1)/2. (will preserve size spatially)
e.g. F = 3 => zero pad with 1
F = 5 => zero pad with 2
F = 7 => zero pad with 3

Swiping the entire image

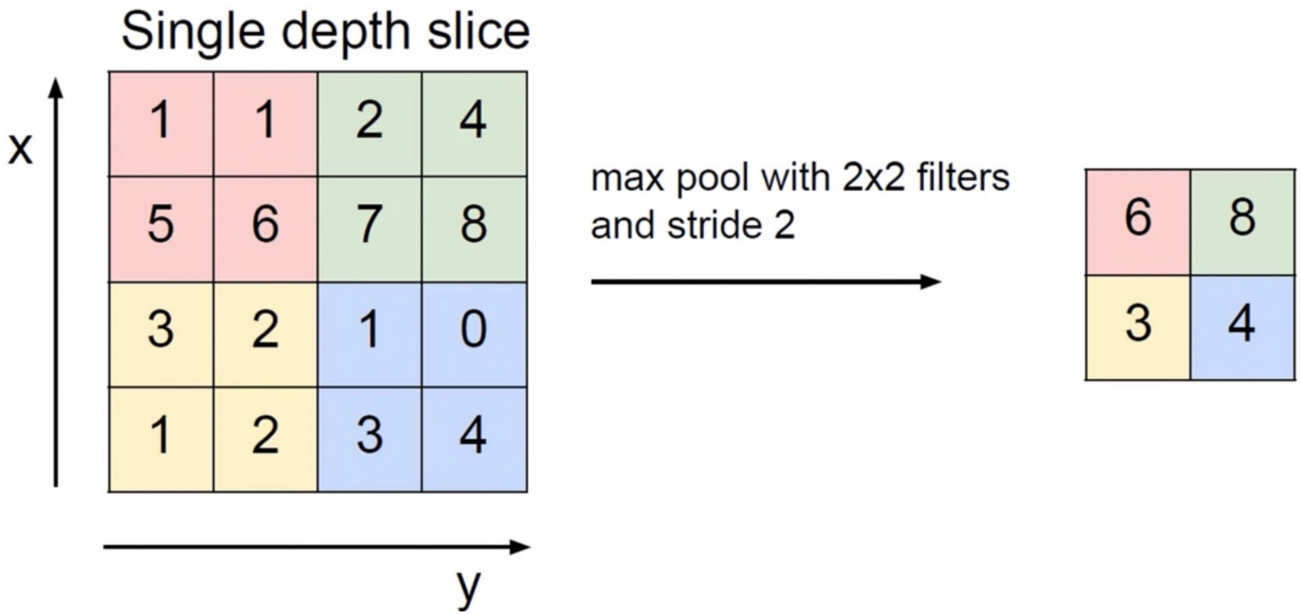


2D Convolution Layer
– Multi Channel, Many Filters

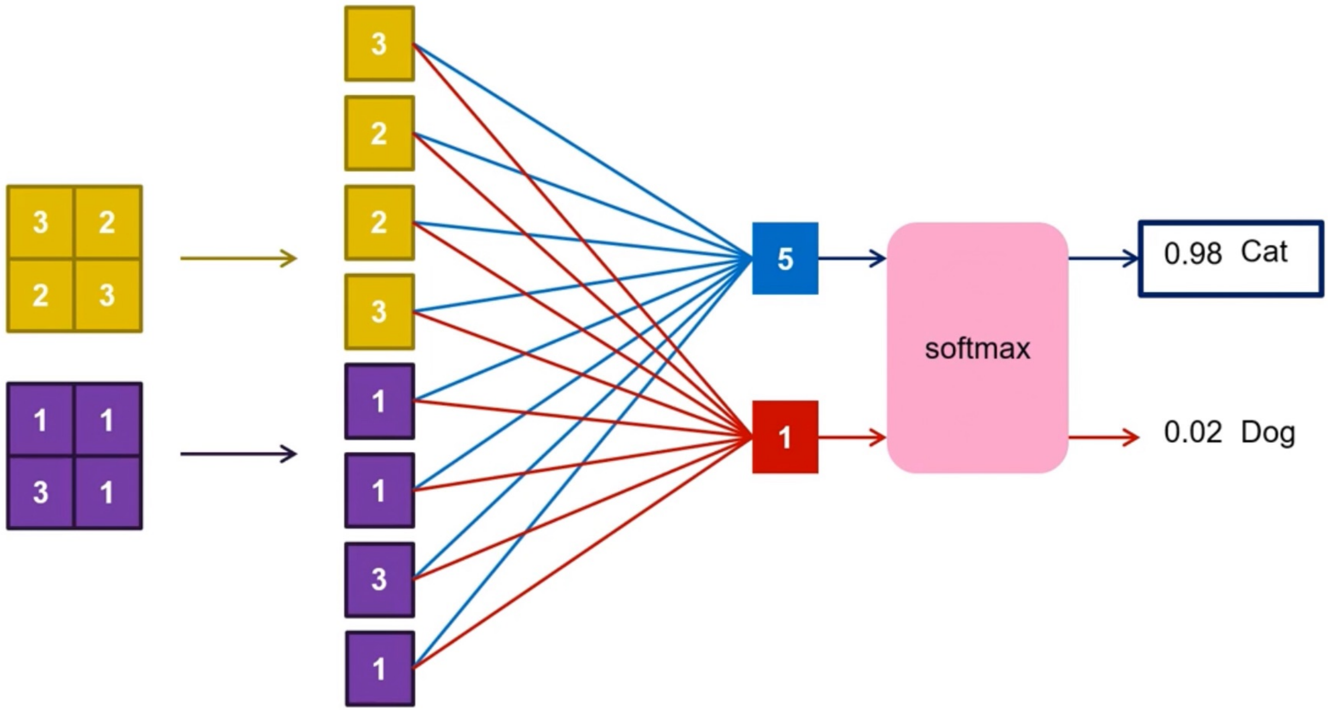


Pooling

- Max Pooling or Average Pooling

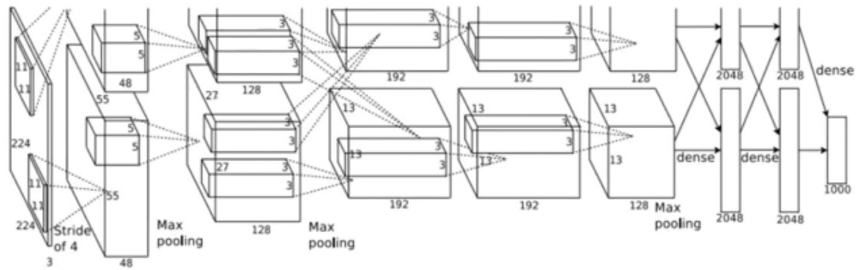


Fully Connected(Dense) Layer



Case Study: AlexNet

[Krizhevsky et al. 2012]



Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10
manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

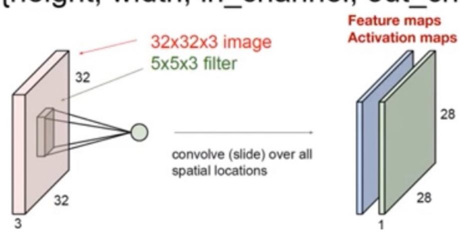
tf.keras.layers.Conv2D

- `filters`: Integer, the dimensionality of the output space (i.e. the number of output filters in the convolution).
- `kernel_size`: An integer or tuple/list of 2 integers, specifying the height and width of the 2D convolution window. Can be a single integer to specify the same value for all spatial dimensions.
- `strides`: An integer or tuple/list of 2 integers, specifying the strides of the convolution along the height and width. Can be a single integer to specify the same value for all spatial dimensions. Specifying any stride value != 1 is incompatible with specifying any `dilation_rate` value != 1.
- `padding`: one of `"valid"` or `"same"` (case-insensitive).
- `data_format`: A string, one of `channels_last` (default) or `channels_first`. The ordering of the dimensions in the inputs. `channels_last` corresponds to inputs with shape `(batch, height, width, channels)` while `channels_first` corresponds to inputs with shape `(batch, channels, height, width)`. It defaults to the `image_data_format` value found in your Keras config file at `~/.keras/keras.json`. If you never set it, then it will be "channels_last".

tf.keras.layers.Conv2D

- `activation` : Activation function to use. If you don't specify anything, no activation is applied (ie. "linear" activation: `a(x) = x`).
- `use_bias` : Boolean, whether the layer uses a bias vector.
- `kernel_initializer` : Initializer for the `kernel` weights matrix.
- `bias_initializer` : Initializer for the bias vector.
- `kernel_regularizer` : Regularizer function applied to the `kernel` weights matrix.
- `bias_regularizer` : Regularizer function applied to the bias vector.

kernel dimension : {height, width, in_channel, out_channel}
Ex) {5, 5, 3, 2}



NN Implementation Flow in TensorFlow

1. Set hyper parameters – learning rate, training epochs, batch size, etc.
2. Make a data pipelining – use tf.data
3. Build a neural network model – use tf.keras sequential APIs
4. Define a loss function – cross entropy
5. Calculate a gradient – use tf.GradientTape
6. Select an optimizer – Adam optimizer
7. Define a metric for model's performance – accuracy
8. (optional) Make a checkpoint for saving
9. Train and Validate a neural network model