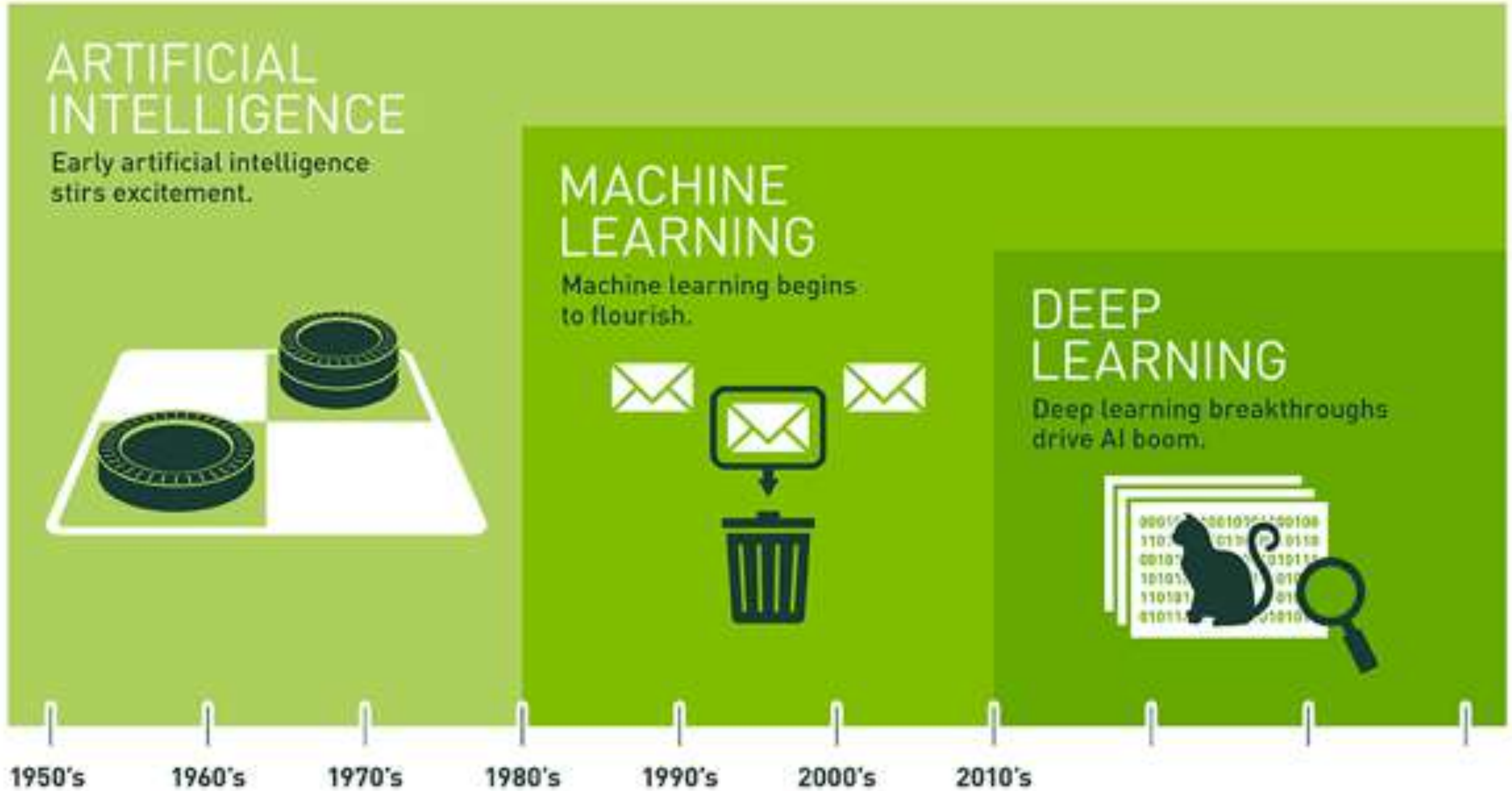
NUS-ISS
Pattern Recognition using
Machine Learning System

The rise of machine-learned features

by Dr. Tan Jen Hong

The AI time line

A broad overview

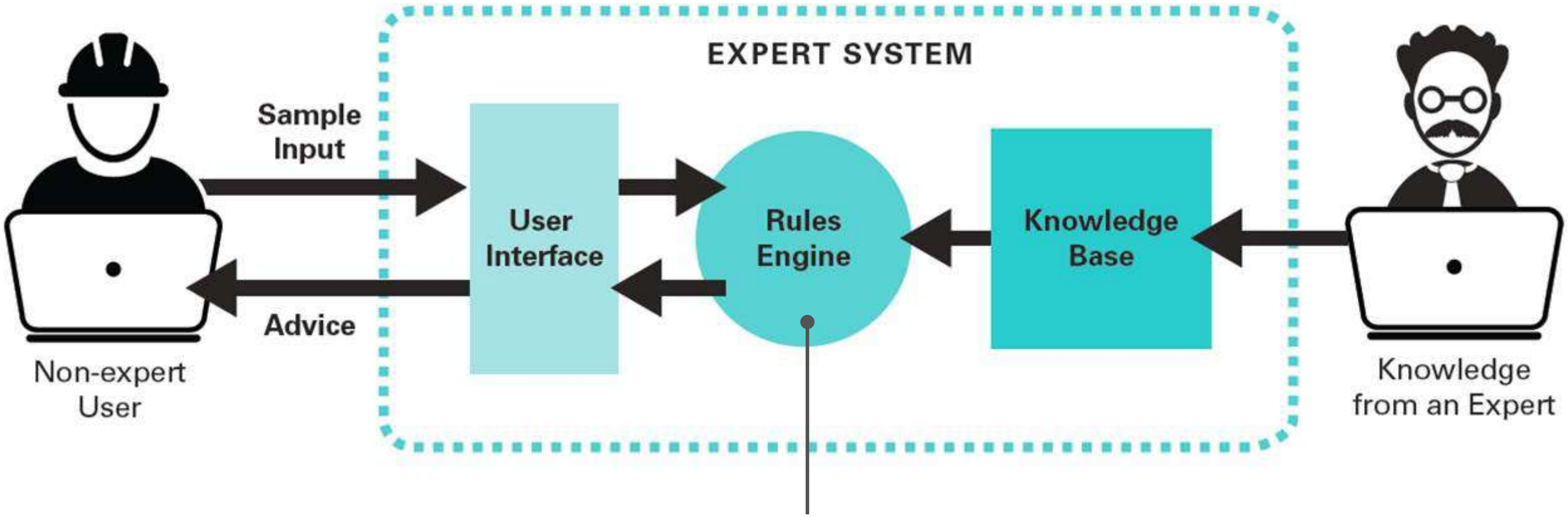


Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

Source: https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

The AI time line

The starting point ...

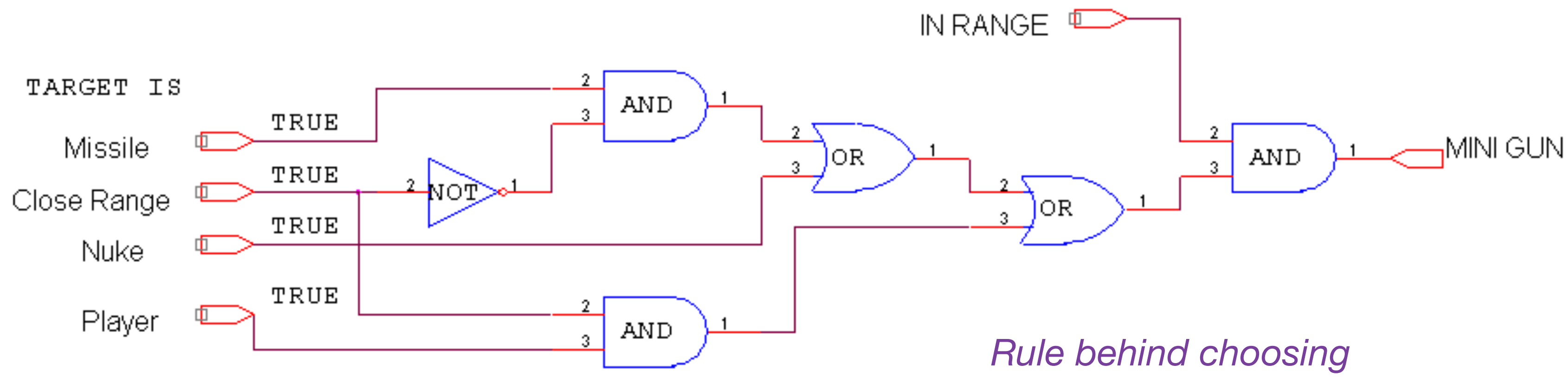


a series of
if-then-else
rules

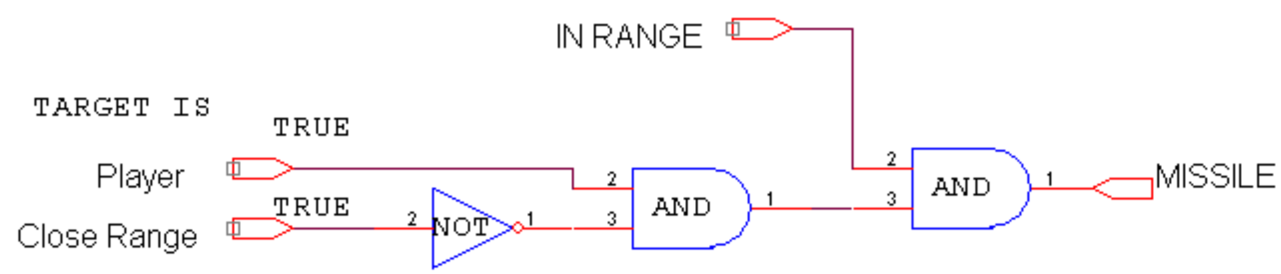
Source: https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

Expert system

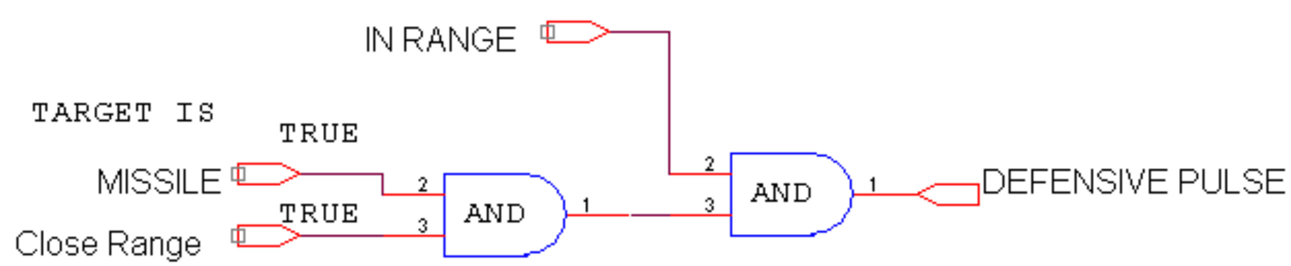
Example: Arriving decision to choose a weapon at any time by the expert system



Rule behind choosing mini gun



Rule behind choosing missile



Rule behind choosing defensive pulse

Source: https://wiki.bath.ac.uk/display/BISAI/Expert+System+in+a+Gaming+Enviroment

Expert system

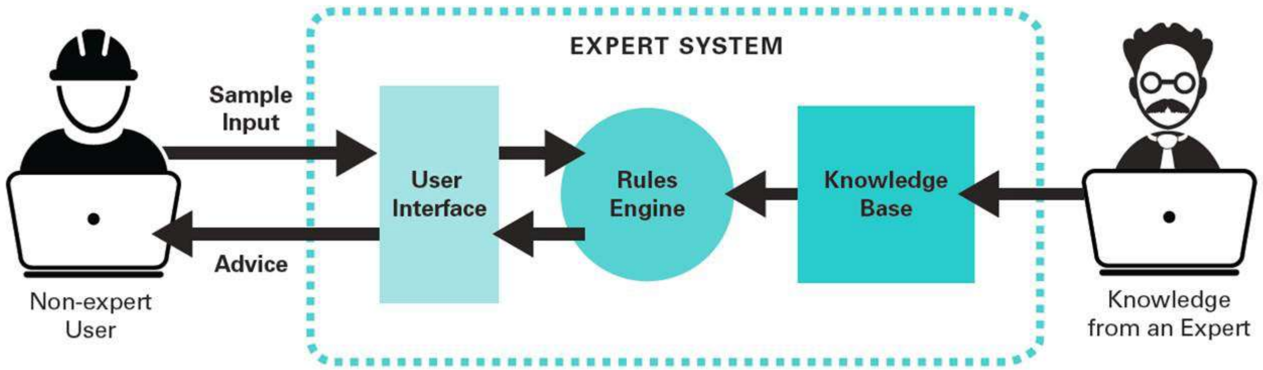
Rules to determine ...
a yacht?

Source: https://yachtharbour.com/news/venus-spotted-in-mallorca-1887?src=news_view_page_bar

Expert system

The limitations

- Expensive and time consuming! Experts are never cheap
- Bad in handling sophisticated sensory inputs (like signals, images)
- Possible to make dumb decision since it just goes through rules; no common sense in the system
- System not easy to be updated



Source: https://blogs.nvidia.com/blog/2016/07/29/whats-difference-artificial-intelligence-machine-learning-deep-learning-ai/

Features + classifier

A new solution to the rescue

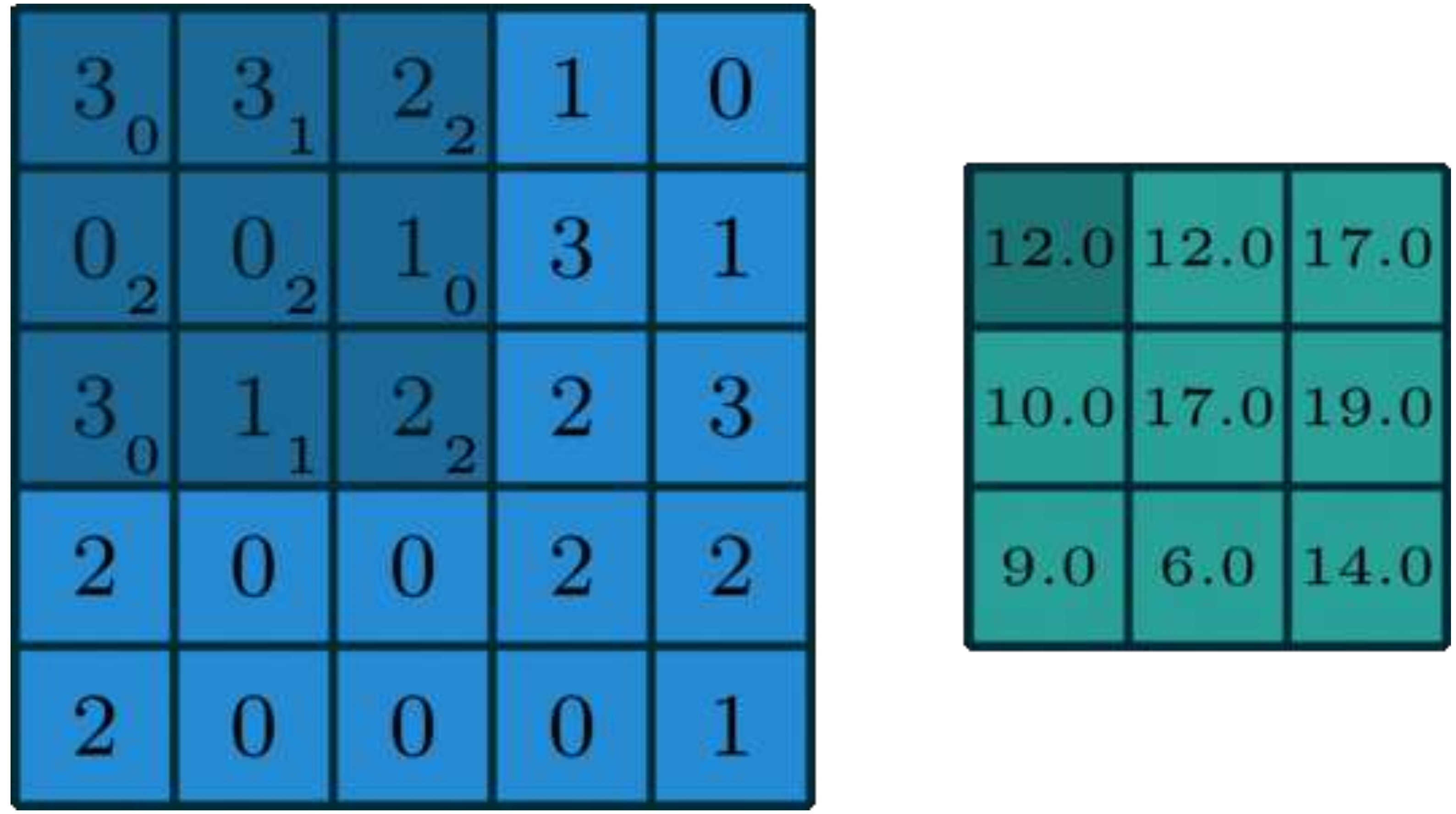
- Feature: a number or a vector that describes something about the input
- Classifer figures out (by itself) the underlying pattern between features and output
- This is where the 'learning' happens

Source: https://verhaert.com/difference-machine-learning-deep-learning/

Filtering ..... or feature extraction

Filtering

It's all about convolution



Source: https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

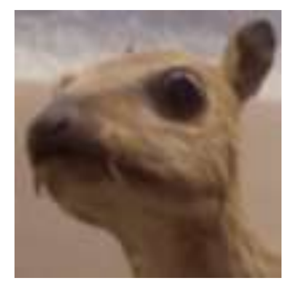
Filtering

What filtering can do ....

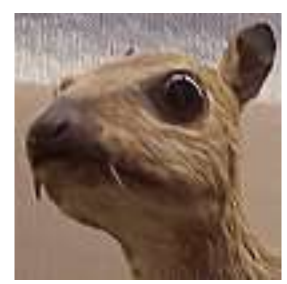
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$$

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$$



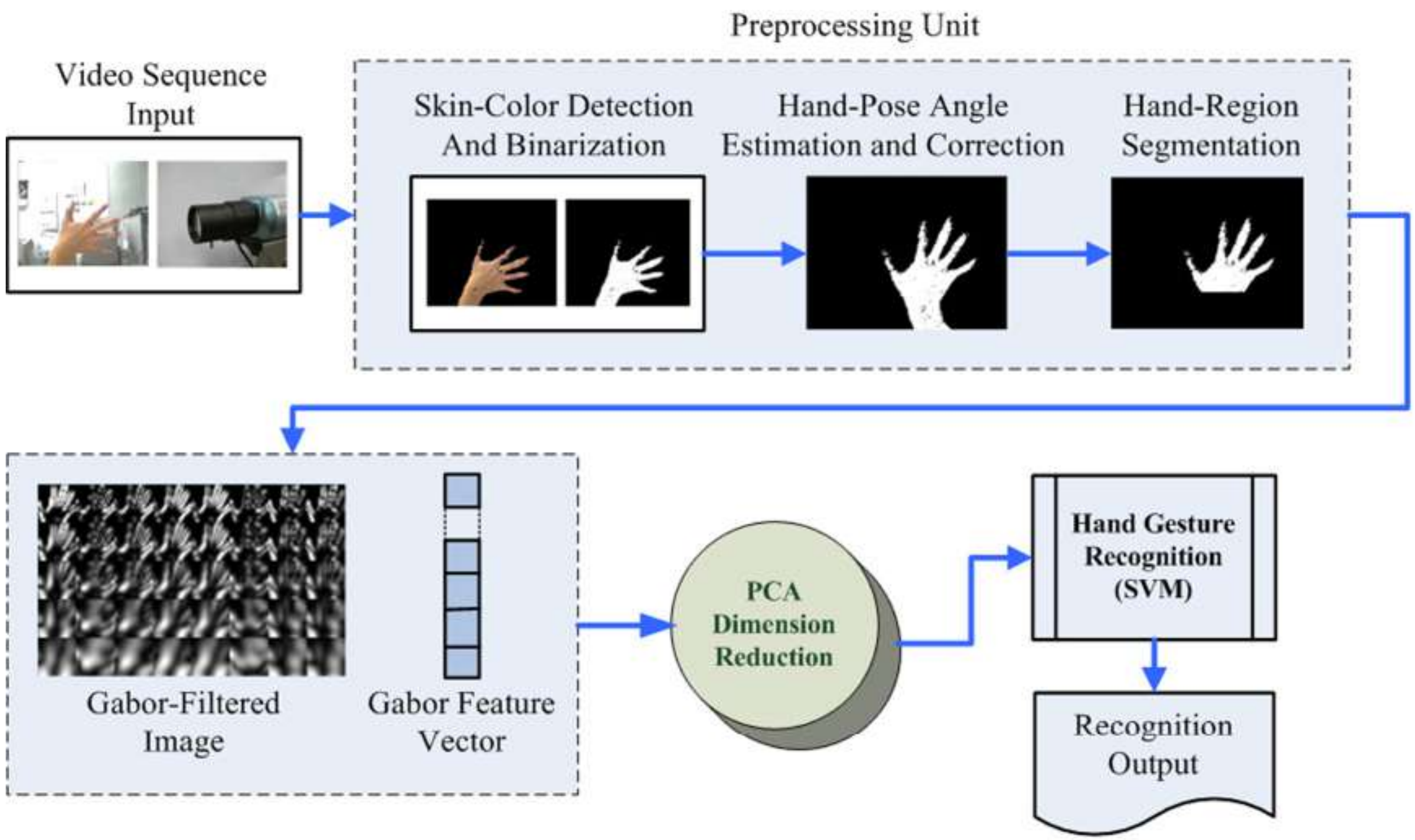
$$\frac{1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & 36 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$



$$\frac{-1}{256}\begin{bmatrix} 1 & 4 & 6 & 4 & 1 \\ 4 & 16 & 24 & 16 & 4 \\ 6 & 24 & -476 & 24 & 6 \\ 4 & 16 & 24 & 16 & 4 \\ 1 & 4 & 6 & 4 & 1 \end{bmatrix}$$

Source: https://en.wikipedia.org/wiki/Kernel_(image_processing)

Features + classifier
Gabor filtering



Source: https://doi.org/10.1016/j.eswa.2010.11.016

Features + classifier

Conclusion?

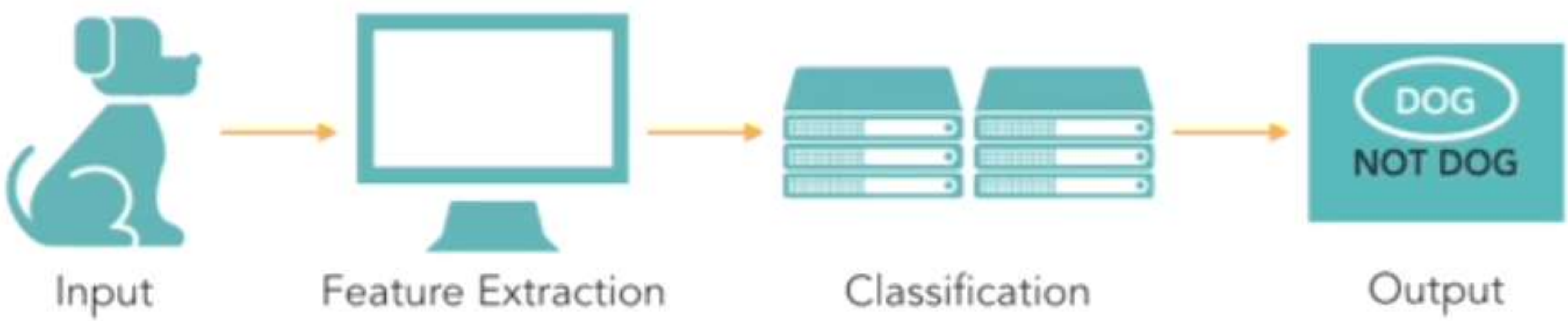
- We need to design features manually, through much trial and error, with luck
- Classifiers used are generic (like SVM)

Source: https://verhaert.com/difference-machine-learning-deep-learning/

Features + classifier

Conclusion?

- Progress in recognition accuracy powered by better features
- Plethora hand-crafted features proposed and used, such as HOG, SIFT, LBP and etc...
- But what next? Come out more new features? Better classifiers?



Source: https://www.guru99.com/machine-learning-vs-deep-learning.html

Learning the features

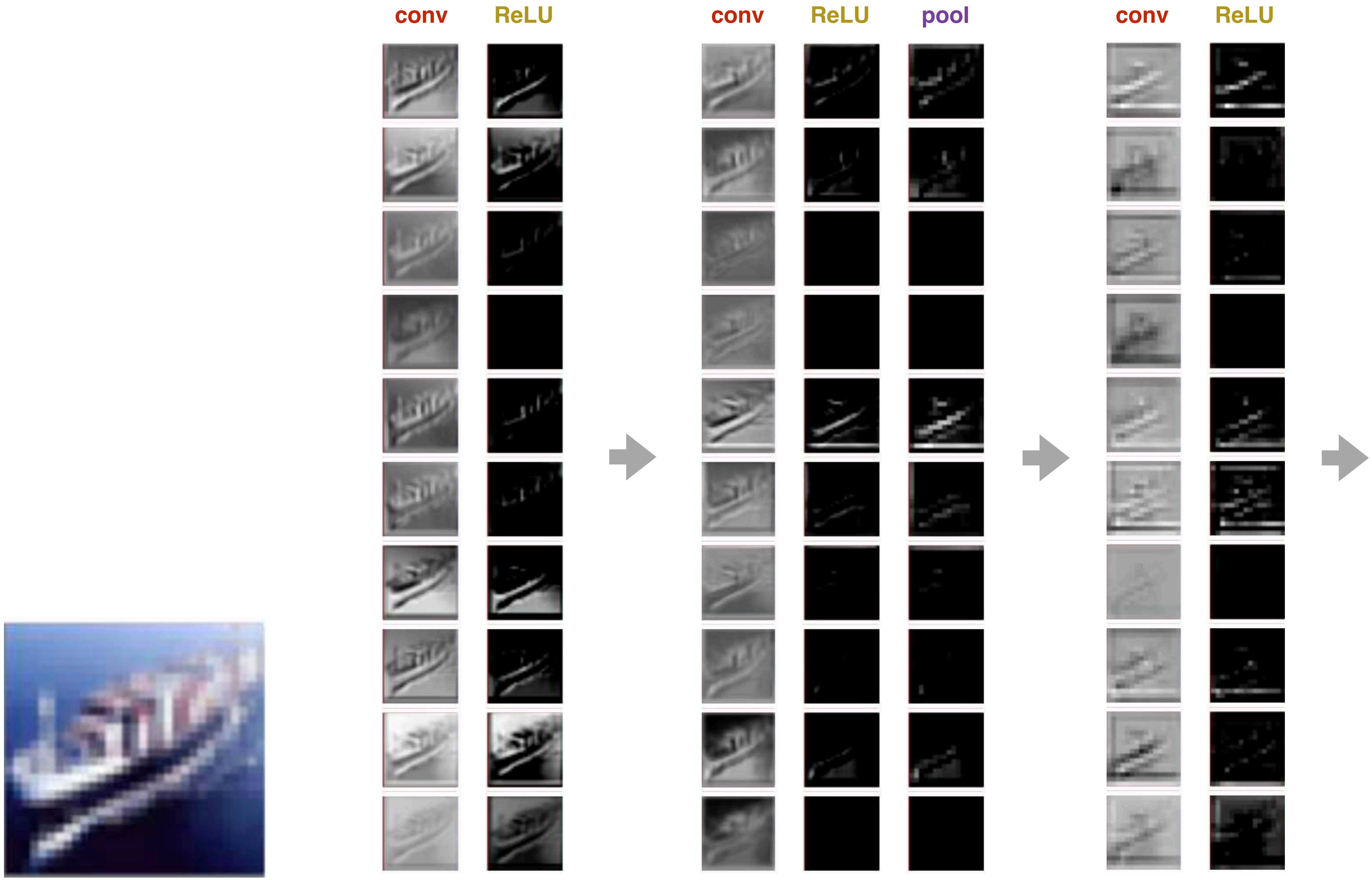
Better performance?

- Instead of we deciding the features, get algorithm to learn the most appropriate features by itself?
- Series of feature extractors?
- All the way from pixels to classifier, layer by layer?
- Train all the layers together?

Source: https://www.guru99.com/machine-learning-vs-deep-learning.html

Deep in action

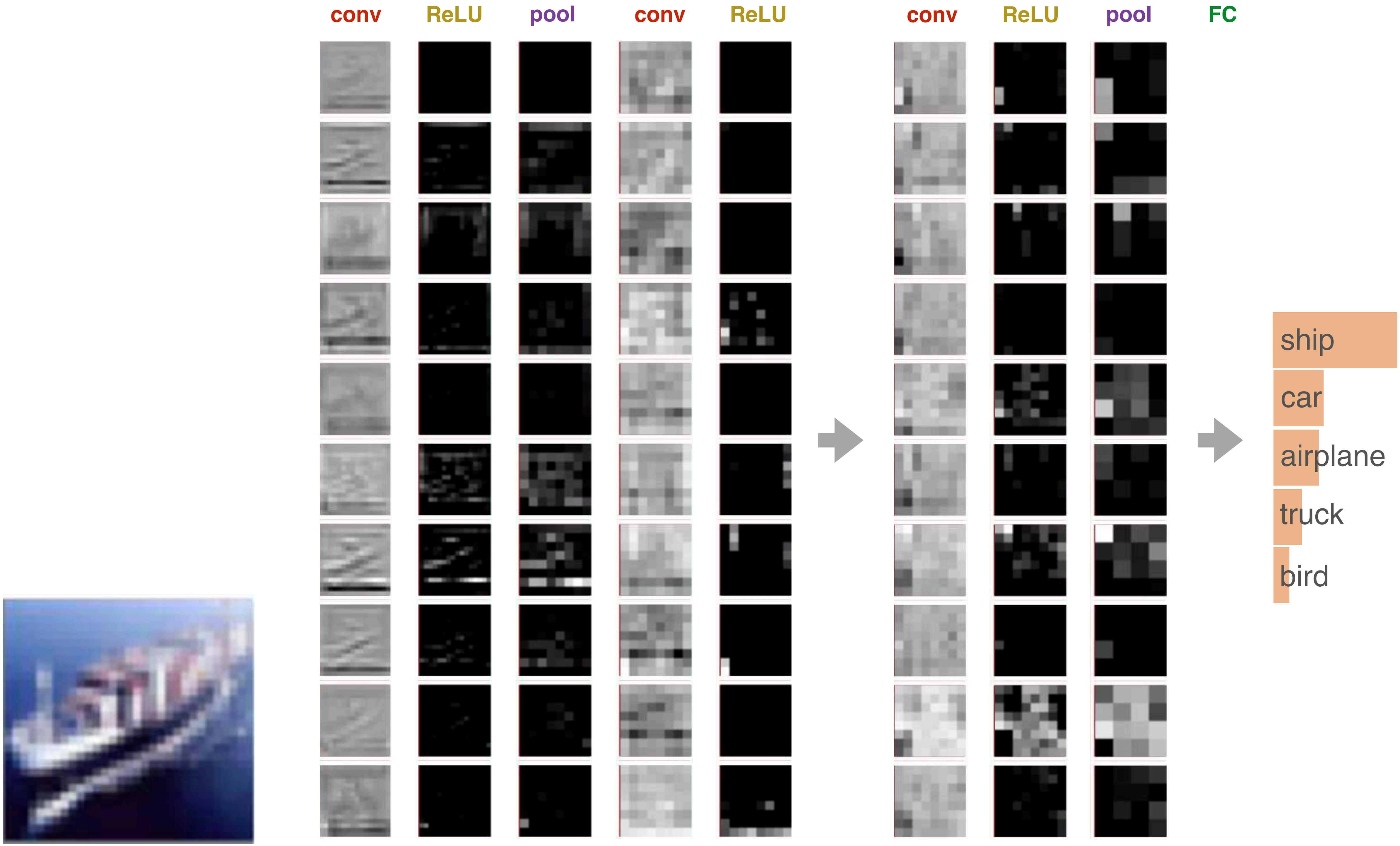
Part 1



Source: http://cs231n.stanford.edu

Deep in action

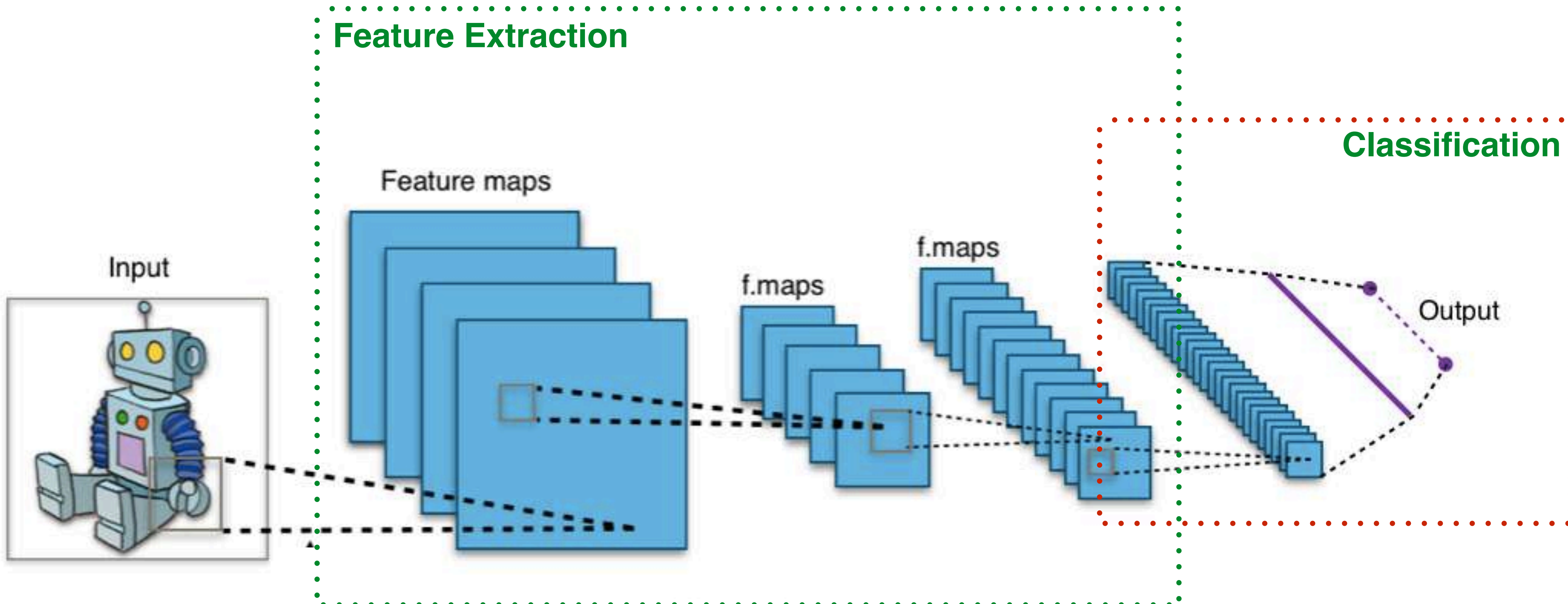
Part 2



Source: http://cs231n.stanford.edu

Learning the features

The idea behind convnet



Source: https://commons.wikimedia.org/wiki/File:Typical_cnn.png

From then on …

ILSVRC 2012

Rank	Error - 5	Algorithm	Team
1	0.153	Deep convolutional neural network	University of Toronto
2	0.262	Features + Fisher vectors + linear classifiers	ISI
3	0.270	Features + Fisher vectors + SVM	Oxford VGG
4	0.271	Not specified	XRCE/INRIA
5	0.300	Dense SIFT + colour SIFT + Fisher vectors + SVM	University of Amsterdam

Source: http://www.image-net.org/challenges/LSVRC/2012/results.html

From then on …

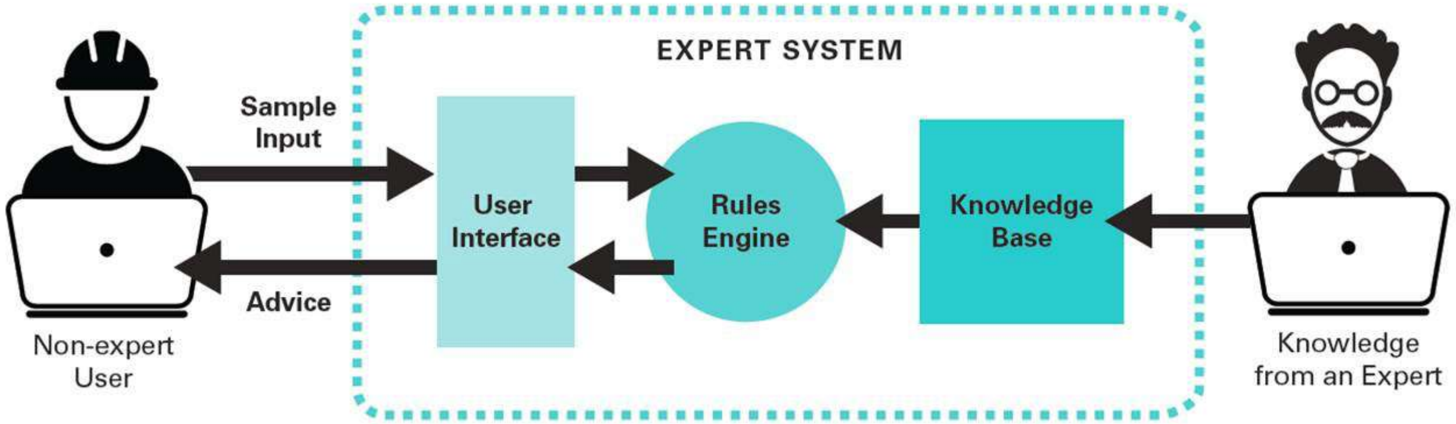
ILSVRC 2013

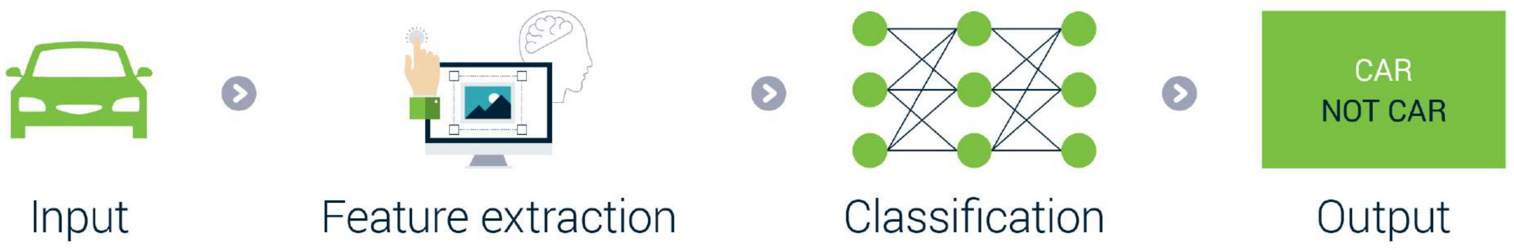
Rank	Error - 5	Algorithm	Team
1	0.117	Deep convolutional neural network	Clarifai
2	0.129	Deep convolutional neural network	NUS
3	0.135	Deep convolutional neural network	ZF
4	0.136	Deep convolutional neural network	Andrew Howard
5	0.142	Deep convolutional neural network	NYU

Source: http://www.image-net.org/challenges/LSVRC/2012/results.html

The progress

So far





Comparison

Machine learning vs deep learning

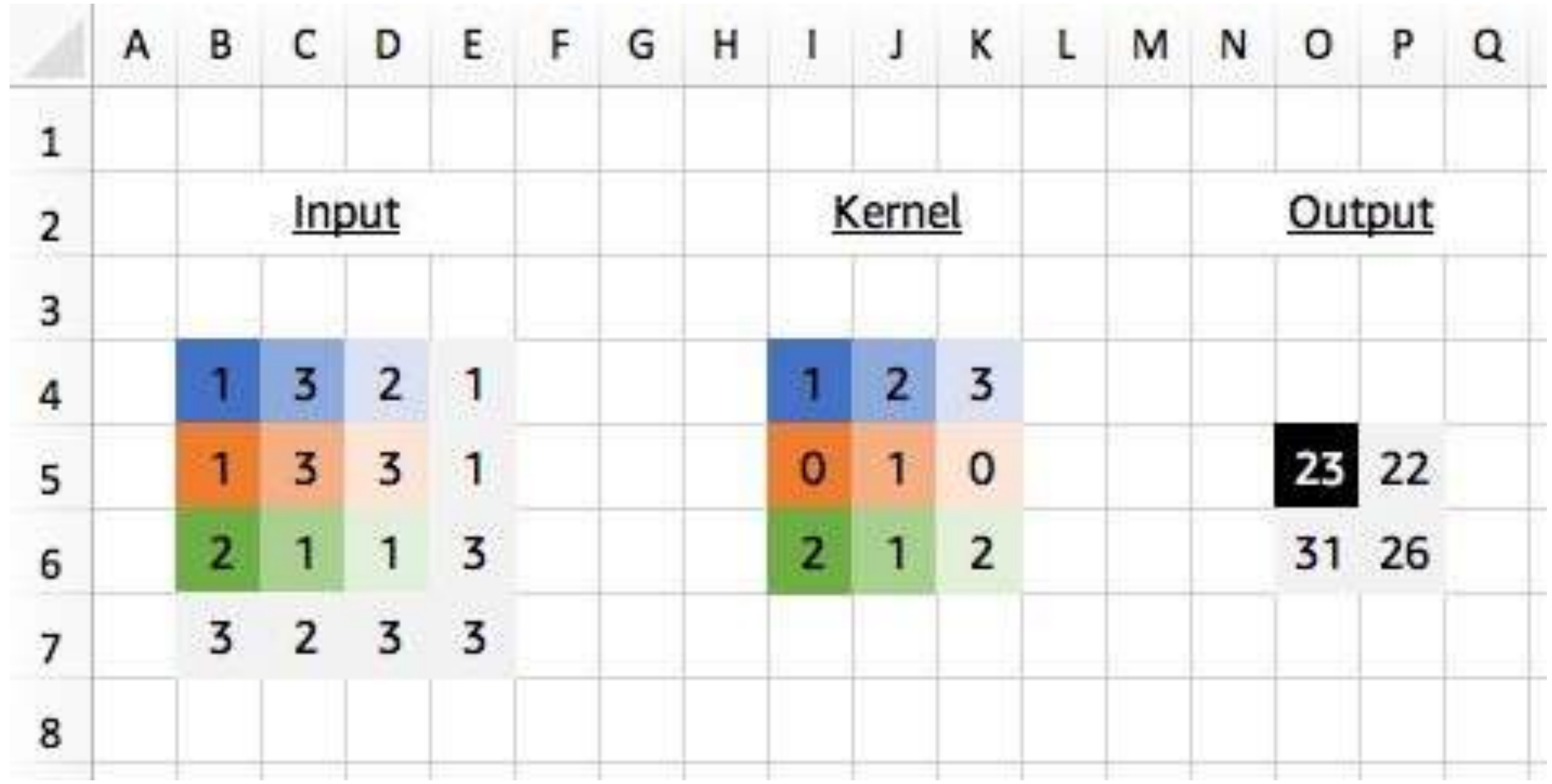
	Machine learning	Deep learning
Data dependencies	Excellent performances on a small/medium dataset	Excellent performance on a big dataset
Hardware dependencies	Work on a low-end machine	Requires powerful machine
Feature engineering	Need to understand the features that represent the data	No need to understand the learned features
Execution time	From few minutes to hours	Up to weeks
Interpretability	Possible for some (logistic, decision tree); some not possible (SVM, XGBoost)	Difficult to impossible

Source: https://www.guru99.com/machine-learning-vs-deep-learning.html

Components in deep learning

2D convolution

The original



Source: https://medium.com/apache-mxnet/convolutions-explained-with-ms-excel-465d6649831c

2D convolution

The padded

Input

0	0	0	0	0	0
0	1	3	2	1	0
0	1	3	3	1	0
0	2	1	1	3	0
0	3	2	3	3	0
0	0	0	0	0	0

Kernel

1	2	3
0	1	0
2	1	2

Output

8	14	13	8
16	23	22	10
20	31	26	17
10	9	15	10

Source: https://medium.com/apache-mxnet/convolutions-explained-with-ms-excel-465d6649831c

2D convolution

Determine the output size

Output size   input size   padding size   filter size

$$M_r = \left\lfloor \frac{W_r + P_r - F_r}{S_r} \right\rfloor + 1$$

row   stride length

$$M_c = \left\lfloor \frac{W_c + P_c - F_c}{S_c} \right\rfloor + 1$$

column

- M_r, M_c: Output size in rows and columns respectively
- W_r, W_c: Input size in rows and columns respectively
- F_r, F_c: Filter size in rows and columns respectively
- P_r, P_c: Amount of zero-padding in rows and columns respectively
- S_r, S_c: Stride in in rows and columns respectively

Example

Calculate the output size

- Assume we have an input of size 128 x 128 (row x column) going into a 2D convolution layer

- The filter / kernel size for the layer is 7 x 7, and the stride is 2 x 2, no padding is applied, calculate the output size of the 2D convolution

$$M_r = \left\lfloor \frac{W_r + P_r - F_r}{S_r} \right\rfloor + 1$$

Output size (M_r), row (r), input size (W_r), padding size (P_r), filter size (F_r), stride length (S_r)

$$M_c = \left\lfloor \frac{W_c + P_c - F_c}{S_c} \right\rfloor + 1$$

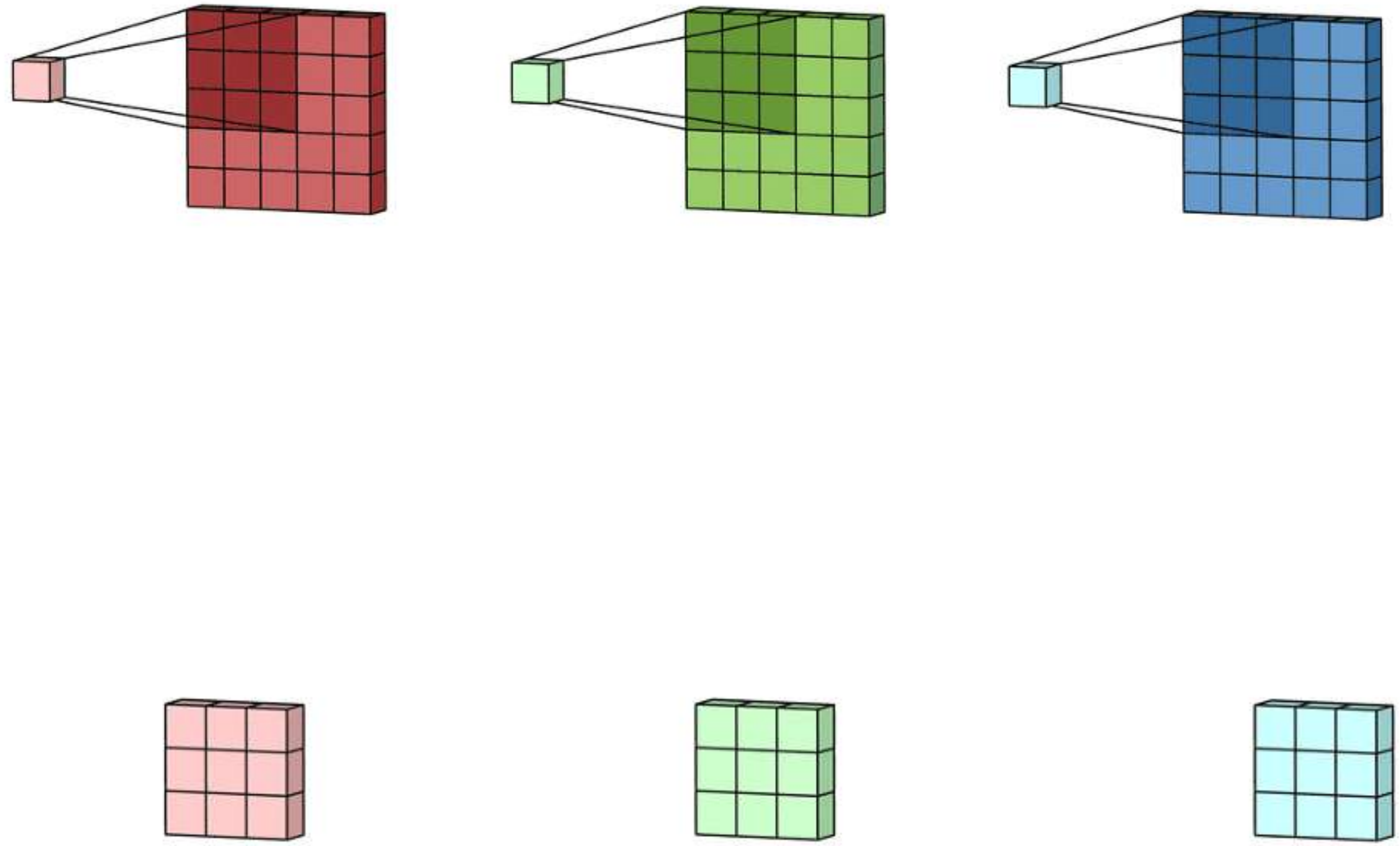
column (c)

$$M_r = M_c = \left\lfloor \frac{128 + 0 - 7}{2} \right\rfloor + 1$$

$$= \left\lfloor \frac{121}{2} \right\rfloor + 1$$

$$= 61$$

2D convolution
Multi-channel



Source: https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1

2D convolution

Multi-channel

Input

1	0	1	0	2
1	1	3	2	1
1	1	0	1	1
2	3	2	1	3
0	2	0	1	0

1	0	0	1	0
2	0	1	2	0
3	1	1	3	0
0	3	0	3	2
1	0	3	2	1

2	0	1	2	1
3	3	1	3	2
2	1	1	1	0
3	1	3	2	0
1	1	2	1	1

Kernel

0	1	0
0	0	2
0	1	0

2	1	0
0	0	0
0	3	0

1	0	0
1	0	0
0	0	2

Intermediate Output

7	5	3
4	7	5
7	2	8

5	3	10
13	1	13
7	12	11

7	5	2
11	8	2
9	4	6

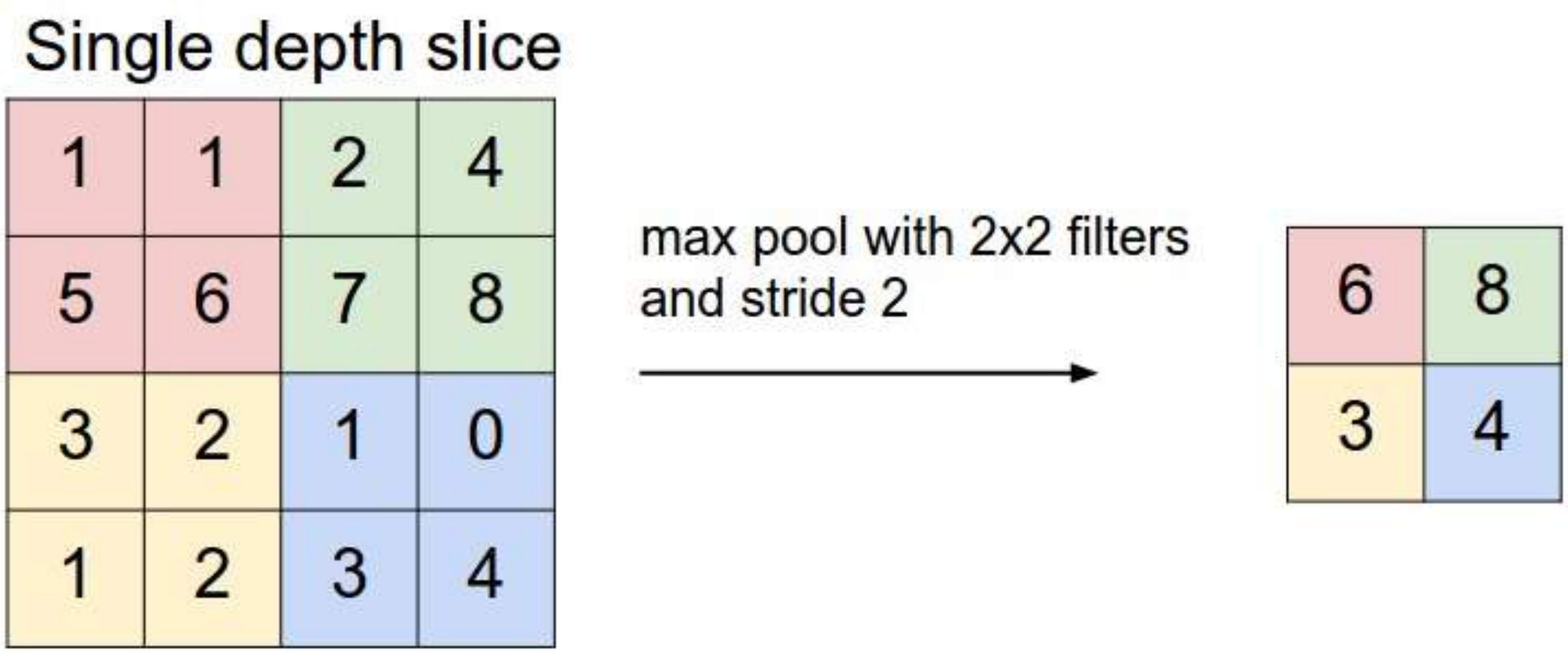
Output

19	13	15
28	16	20
23	18	25

Source: https://medium.com/apache-mxnet/convolutions-explained-with-ms-excel-465d6649831c

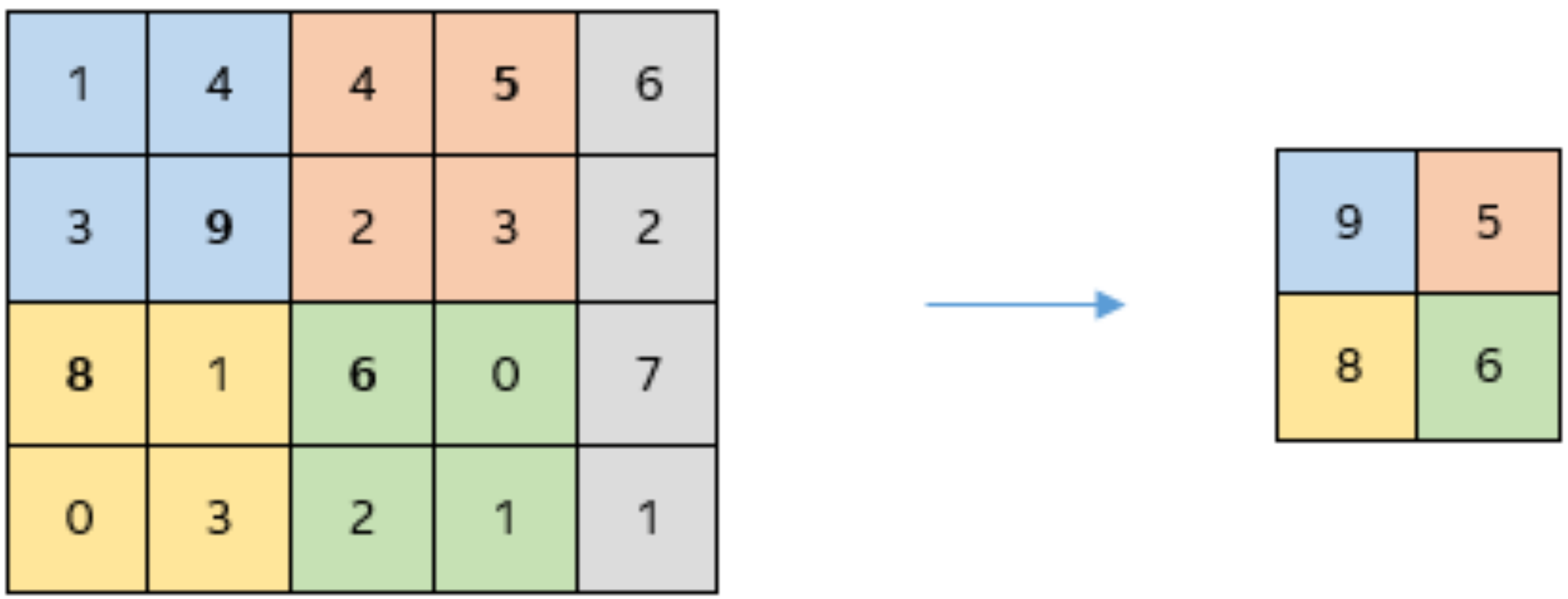
Max pooling

The original



Source: http://cs231n.github.io/convolutional-networks/

Max pooling
With situation



Source: https://software.intel.com/en-us/daal-programming-guide-2d-max-pooling-forward-layer

Maxpooling

Determine the output size

$$\underset{\text{row}}{\overset{\text{Output size}}{M_r}} = \left\lfloor \frac{\overset{\text{input size}}{W_r} - \overset{\text{filter size}}{F_r}}{\underset{\text{stride length}}{S_r}} \right\rfloor + 1$$

$$\underset{\text{column}}{M_c} = \left\lfloor \frac{W_c - F_c}{S_c} \right\rfloor + 1$$

- M_r, M_c: Output size in rows and columns respectively
- W_r, W_c: Input size in rows and columns respectively
- F_r, F_c: Filter size in rows and columns respectively
- S_r, S_c: Stride in rows and columns respectively

Maxpooling

Determine the output size

Output size   input size   filter size

$$M_r = \left\lfloor \frac{W_r - F_r}{S_r} \right\rfloor + 1$$

row   stride length

$$M_c = \left\lfloor \frac{W_c - F_c}{S_c} \right\rfloor + 1$$

column

- Assume we have an input of size 61 x 61 (row x column) going into a 2D pooling layer

- The kernel size for the layer is 4 x 4, and the stride is 2 x 2, calculate the output size of the 2D pooling layer

$$M_r = M_c = \left\lfloor \frac{61 - 4}{2} \right\rfloor + 1$$

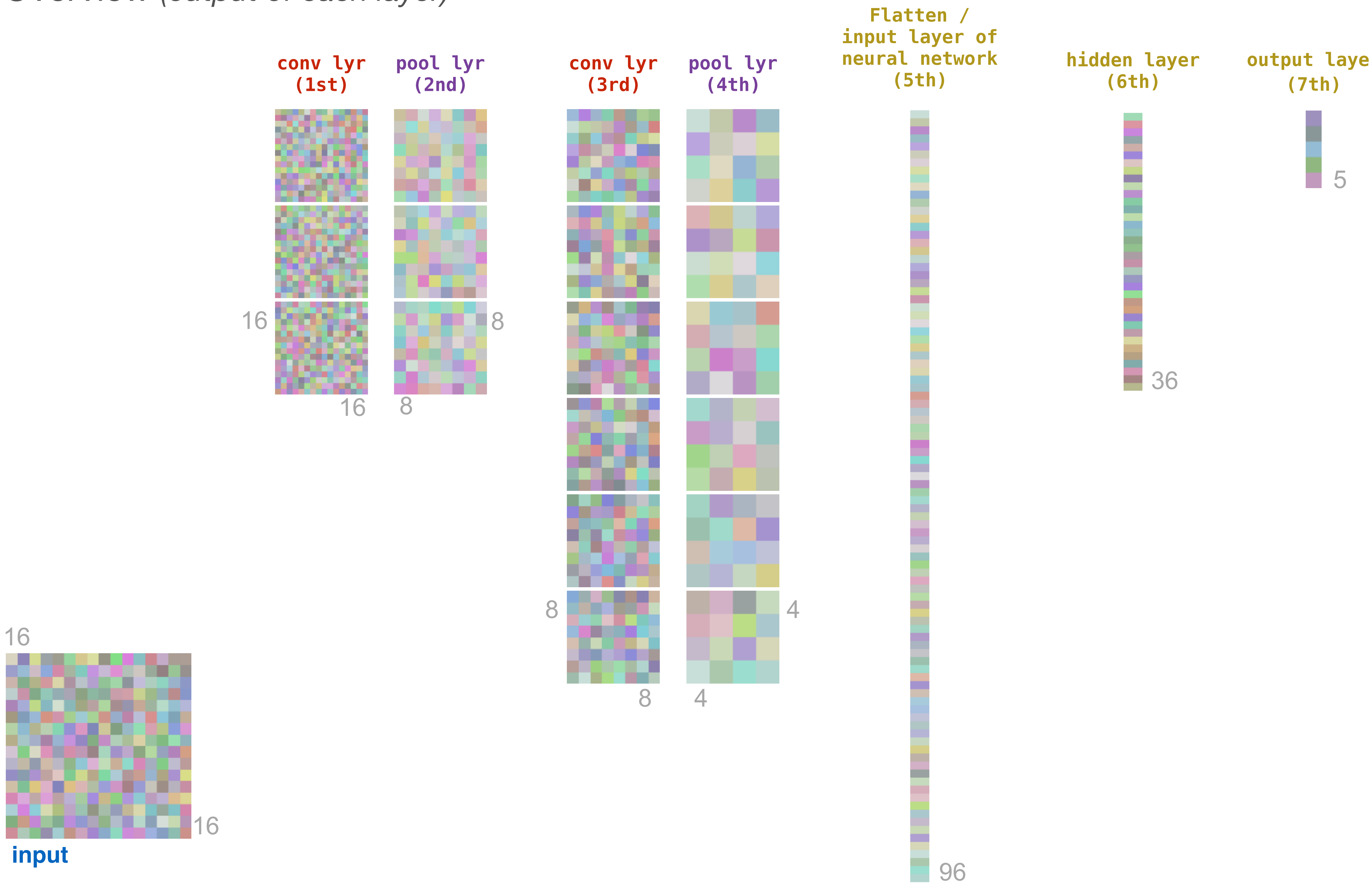
$$= \left\lfloor \frac{57}{2} \right\rfloor + 1$$

$$= \lfloor 28.5 \rfloor + 1 = 29$$

Time for exercise!

Convolutional neural network

Overview *(output of each layer)*

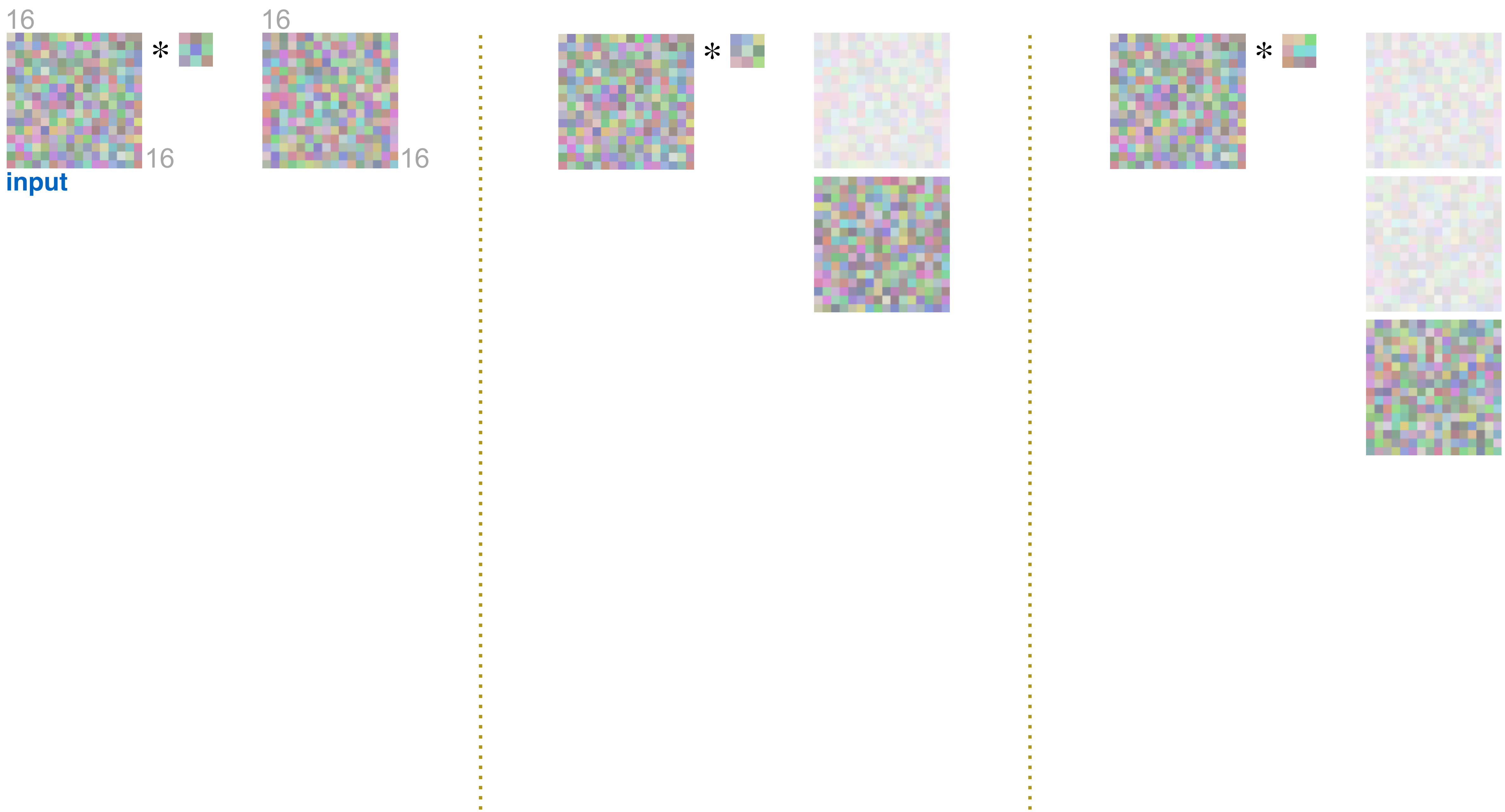


prumls/m2.3/v1.0

The making of ...

The first convolutional layer (part 1)

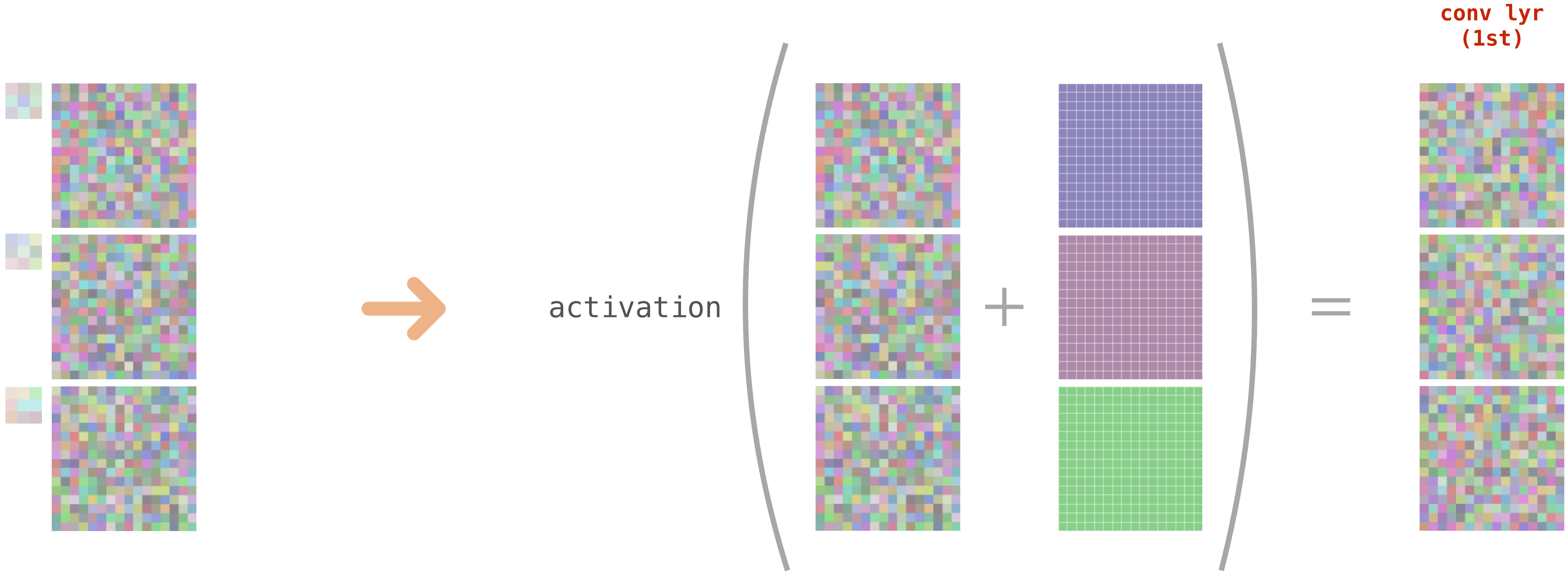
- Performs 3 separate 2D convolutions (with padding) to generate 3 intermediate outputs



The making of ...

The first convolutional layer (part 2)

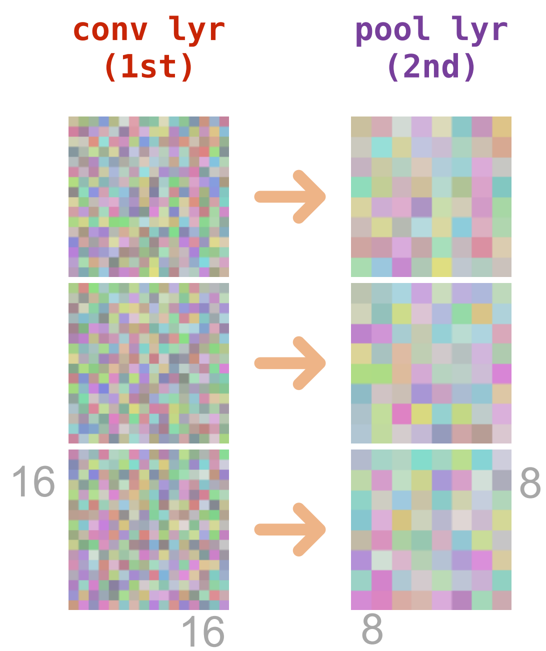
- Add bias to each convolution output, and apply activation function to get the final output for the convolutional layer

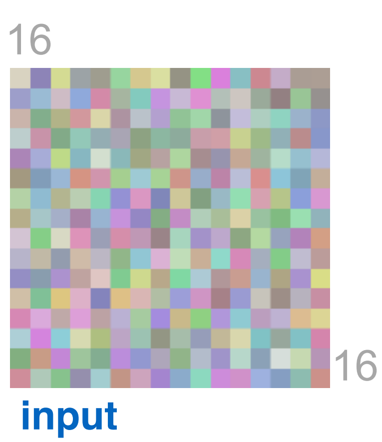


The making of ....

The pooling layer

- Apply 2 x 2 max-pooling (stride 2) on the outputs from the first convolutional layer





The making of ...

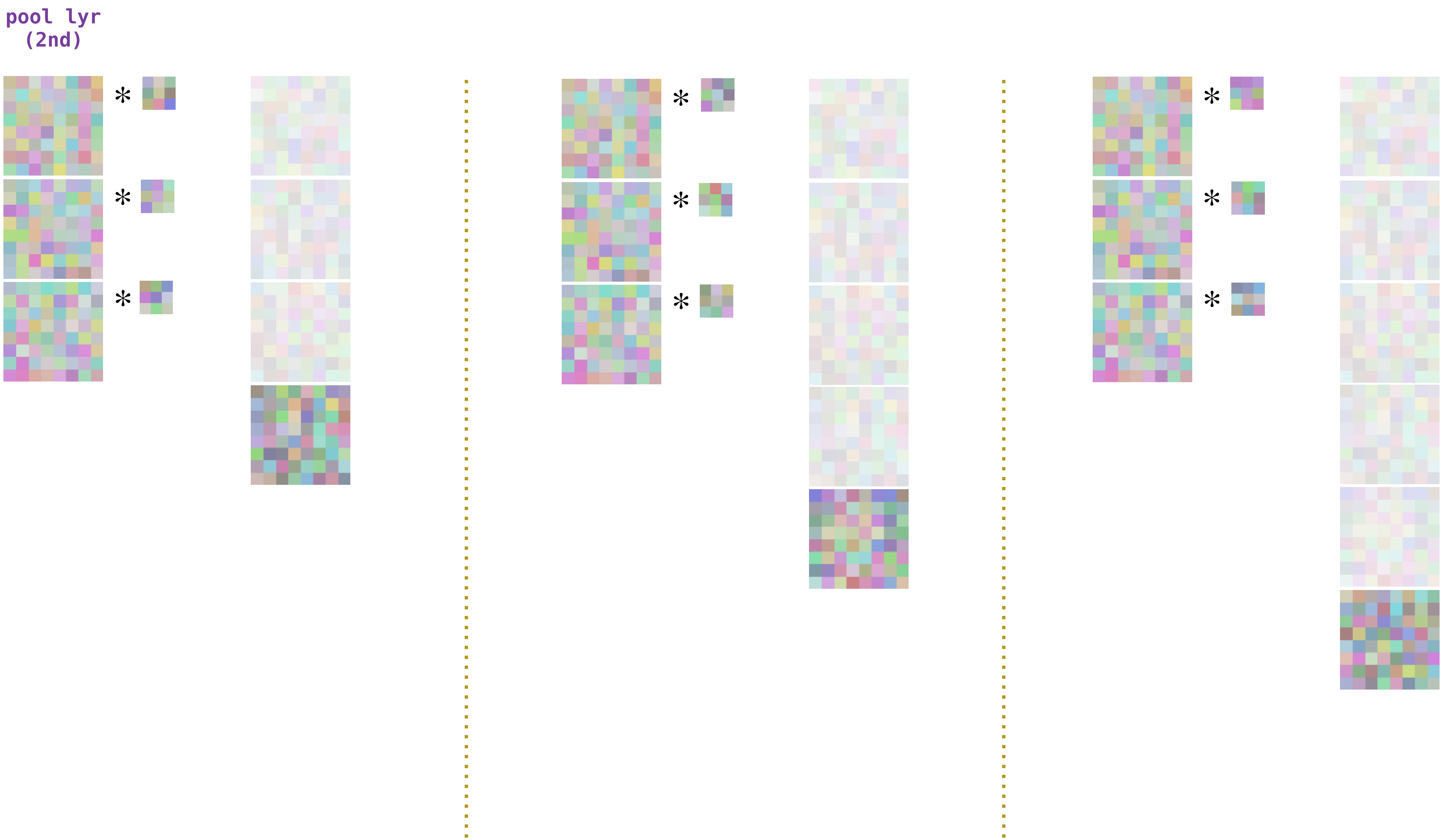
The second convolutional layer (part 1)

- Performs 6 separate multi-channel 2D convolutions (with padding) to generate 6 convolution outputs

The making of ...

The second convolutional layer (part 2)

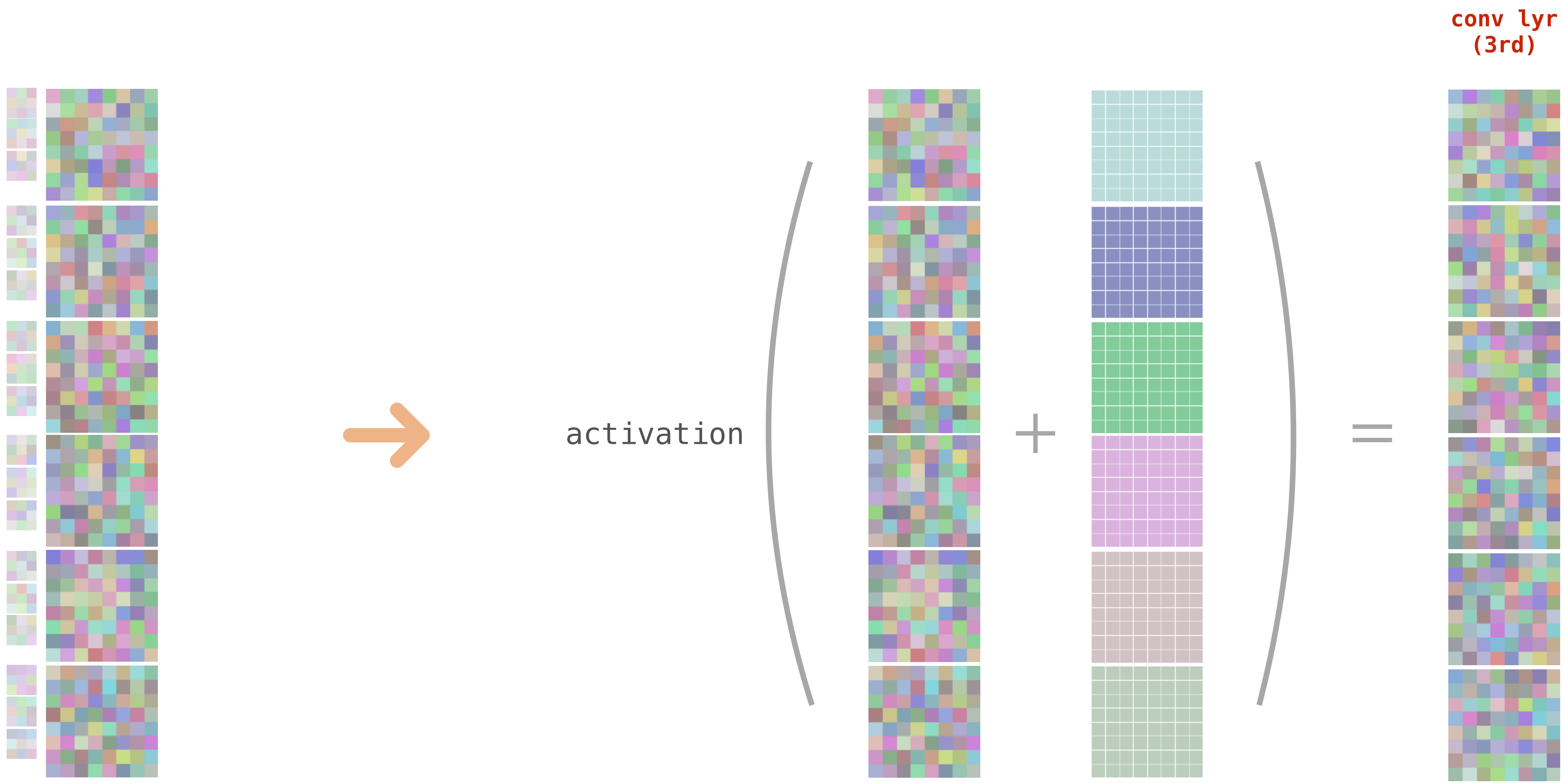
- Performs 6 separate multi-channel 2D convolutions (with padding) to generate 6 convolution outputs



The making of ...

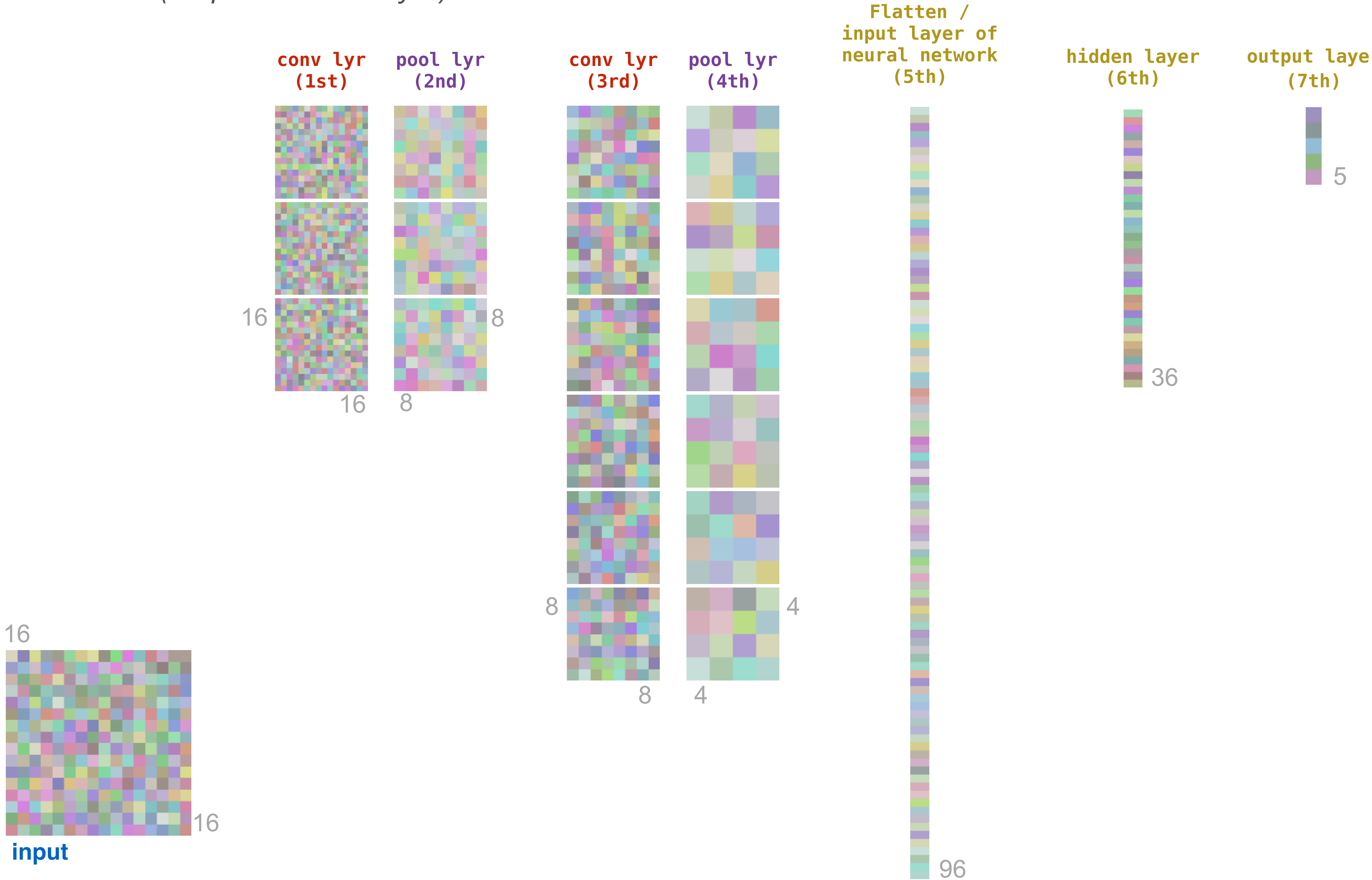
The first convolutional layer (part 3)

- Add bias to each intermediate output, and apply activation function to get the final output for the convolutional layer



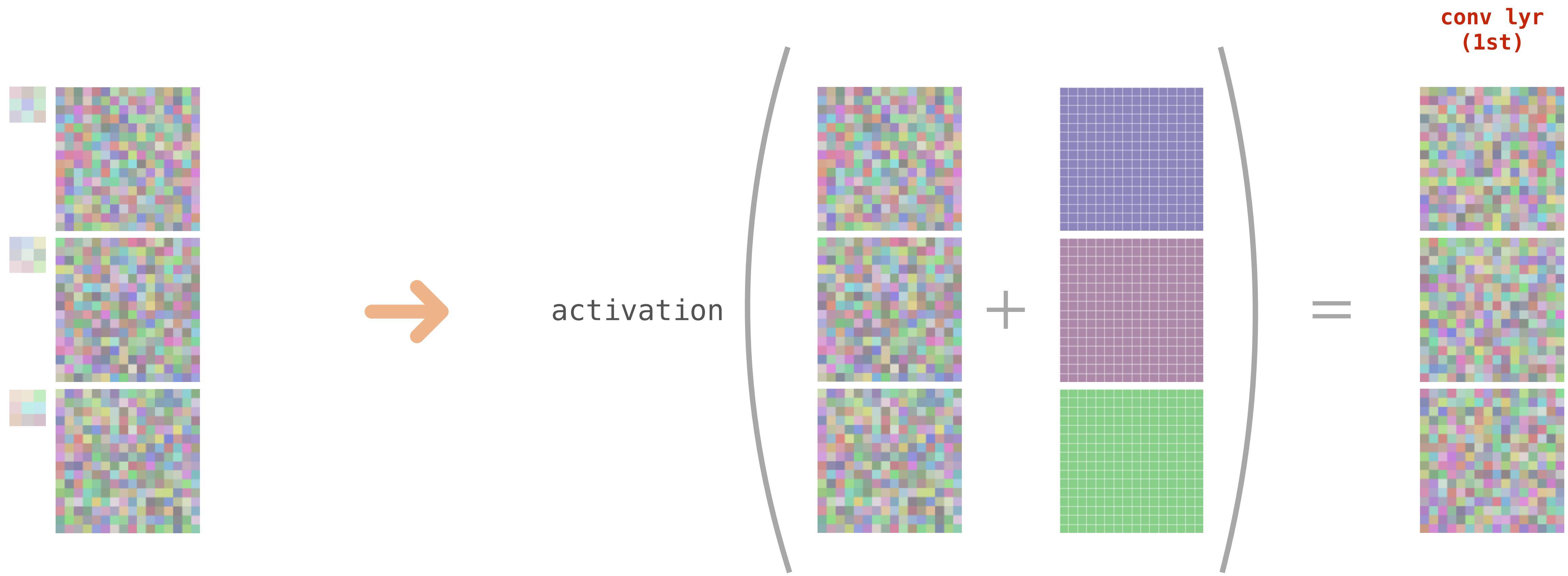
Convolutional neural network

Overview *(output of each layer)*



Calculating parameters

For the first convolutional layer

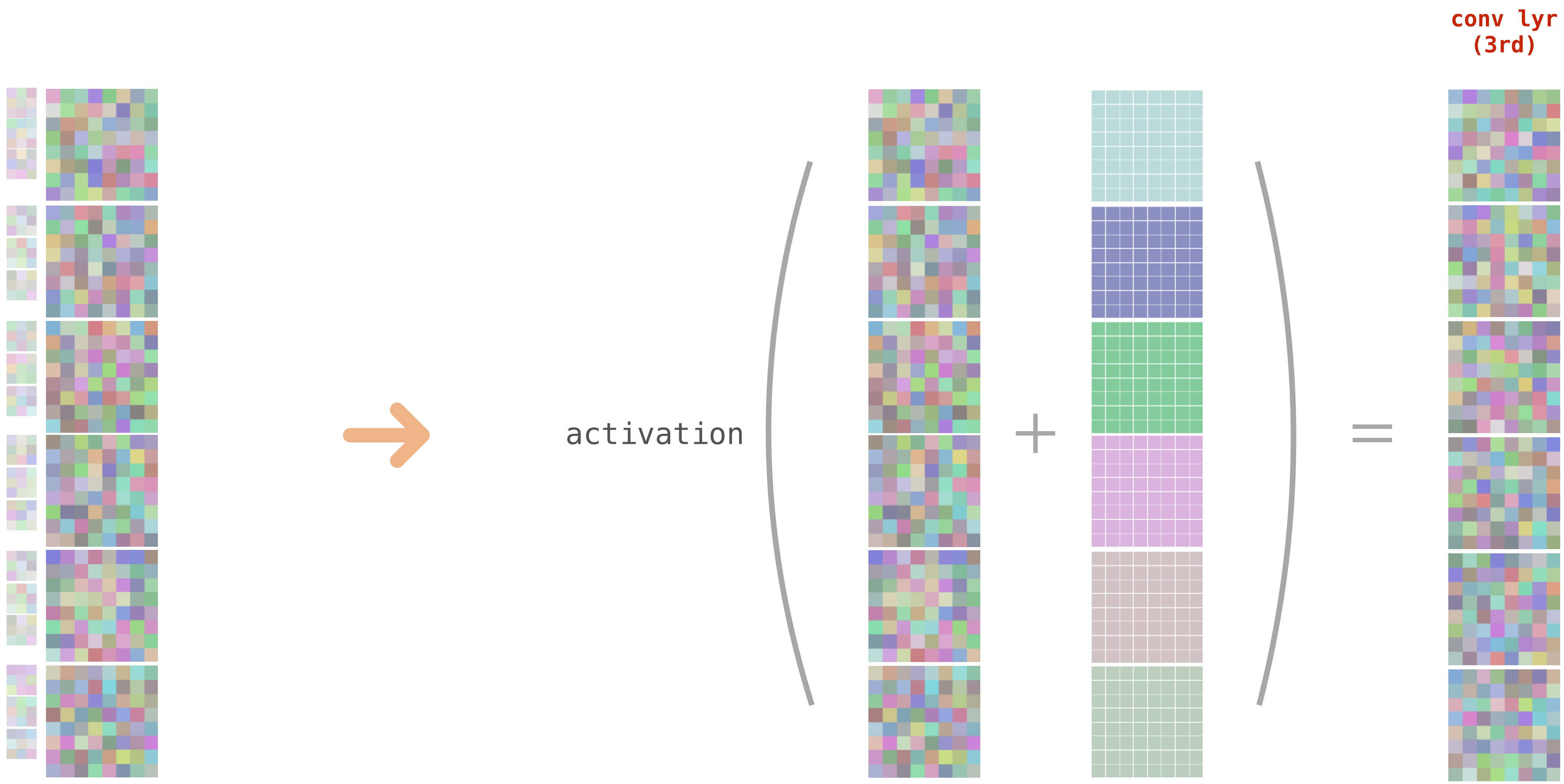


Number of parameters:

`(3 x 3) x 3 + 3 = 30`

Calculating parameters

For the second convolutional layer



Number of parameters:

`(3 x 3) x 3 x 6 + 6 = 6 x [(3 x 3) x 3 + 1] = 168`

Convolutional neural network

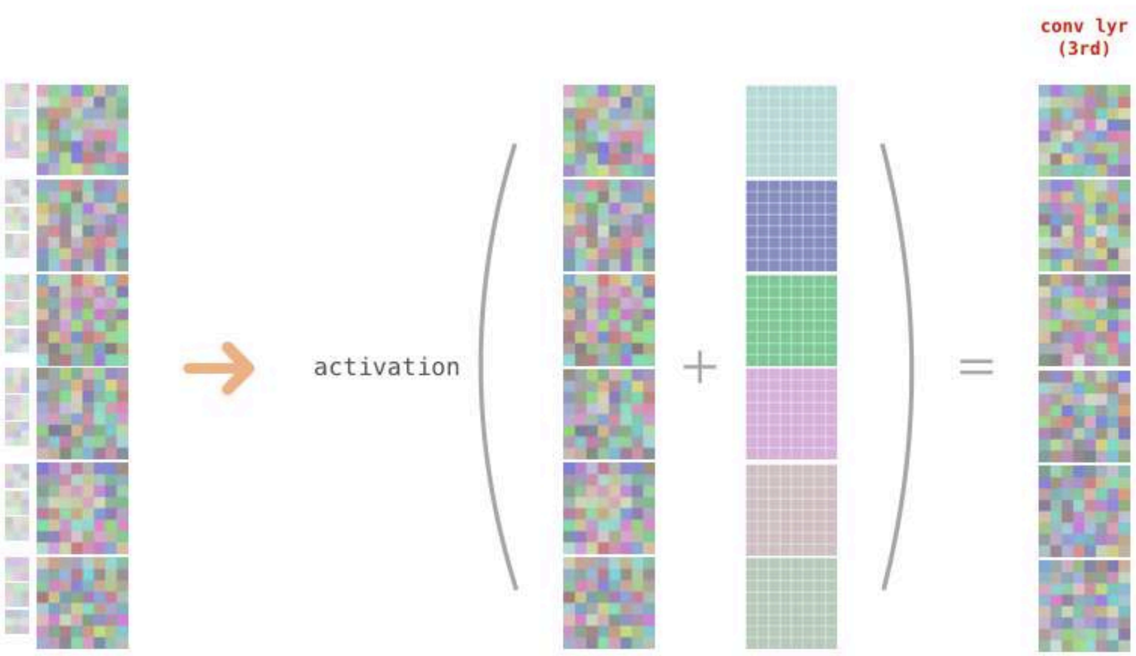
Calculate the parameters

- Assume the size of an input to a layer is (I_r, I_c, C_i) and a filter kernel size of (F_r, F_c)

- Thus to produce **1** feature map involves C_i number of (F_r, F_c) filters. The number of trainable parameters in this case is: $C_i \times (F_r \times F_c) + 1$

- To produce D number of feature maps, it involves C_i x D number of (F_r, F_c) filters, the number of trainable parameters is

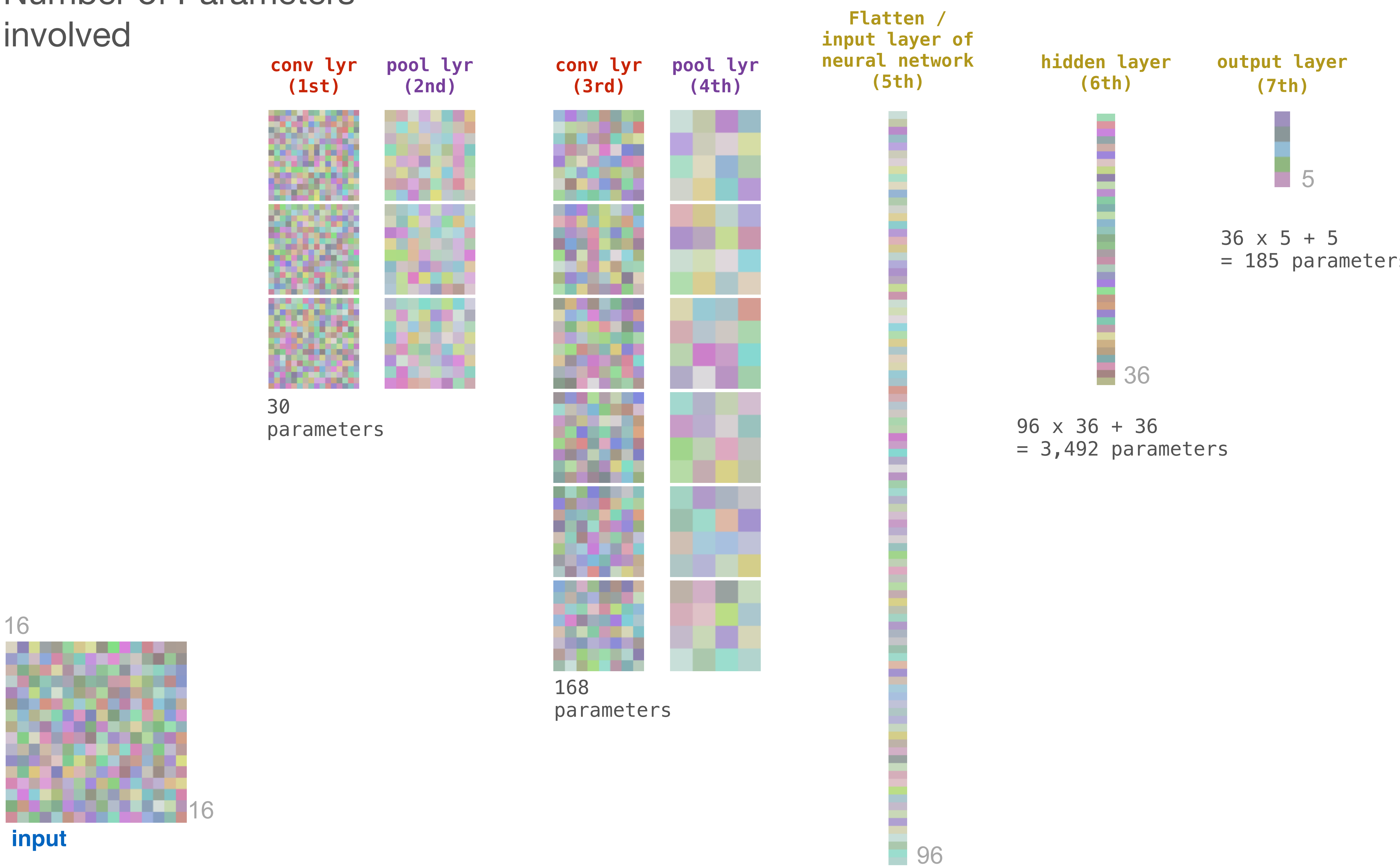
$$p_{tr} = \left[C_i \times \left(F_r \times F_c \right) + 1 \right] \times D$$



Number of parameters:
`(3 x 3) x 3 x 6 + 6 = 6 x [(3 x 3) x 3 + 1] = 168`

Convolutional neural network

Number of Parameters involved



Parameters

Determine the number of parameters

- Assume we have an input of size 128 x 128 x 3 (row x column x channel) going into a 2D pooling layer

- The kernel size for the layer is 7 x 7, the stride is 2 x 2, and the number of channels in the output of this layer is 18

$$p_{tr} = \left[3 \times (7 \times 7) + 1\right] \times 18$$

$$= \left[147 + 1\right] \times 18$$

$$= 2664$$

$$p_{tr} = \left[\underbrace{C_i}_{\text{the number of channels in input}} \times \left(\underbrace{F_r}_{\text{filter size for row}} \times \underbrace{F_c}_{\text{filter size for column}}\right) + 1\right] \times \underbrace{D}_{\text{the number of channels in output}}$$

Another exercise!

Convolutional neural network

Calculate the necessary

- Assume the size of an input to a layer is (32, 32, 3)
- No padding for all convolutions

Layer	Type	Kernel	Stride	No. of feature maps / neurons	Input size	Output size	No. of parameters
1	Conv	(3,3)	(1,1)	16	(32,32,3)		
2	Pool	(2,2)	(2,2)	16			
3	Conv	(5,5)	(1,1)	32			
4	Pool	(2,2)	(2,2)	32			
5	Conv	(3,3)	(1,1)	64			
6	Dense	–	–	128			
7	Dense	–	–	2		2	

Convolutional neural network

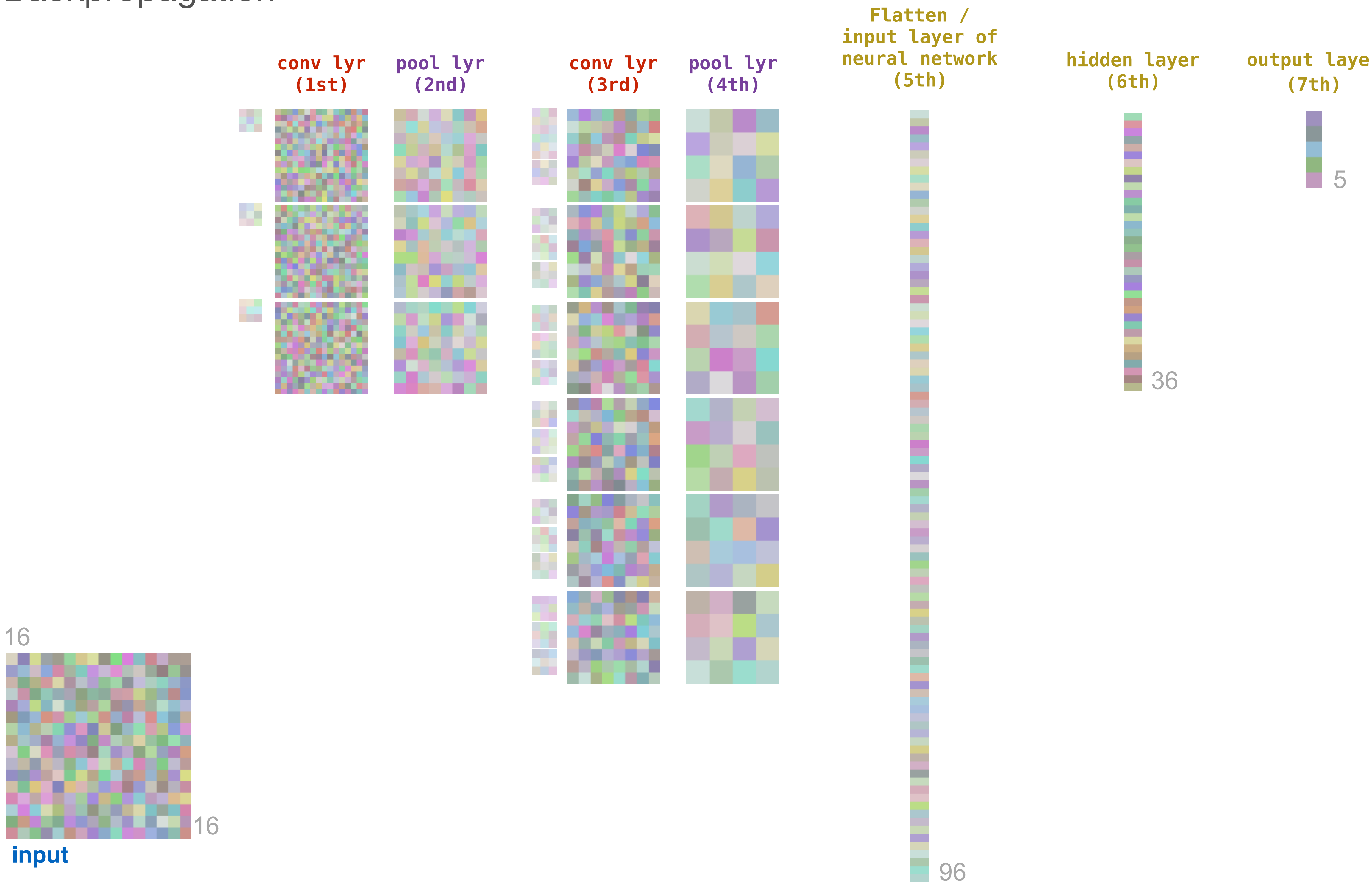
Determine the filter size

- You manage to see the details of a net in the below format
- The number of parameters and the layers' size are given, but not the filter size
- Assume the filter is a square, what is the filter size that produces the feature maps in second layer?

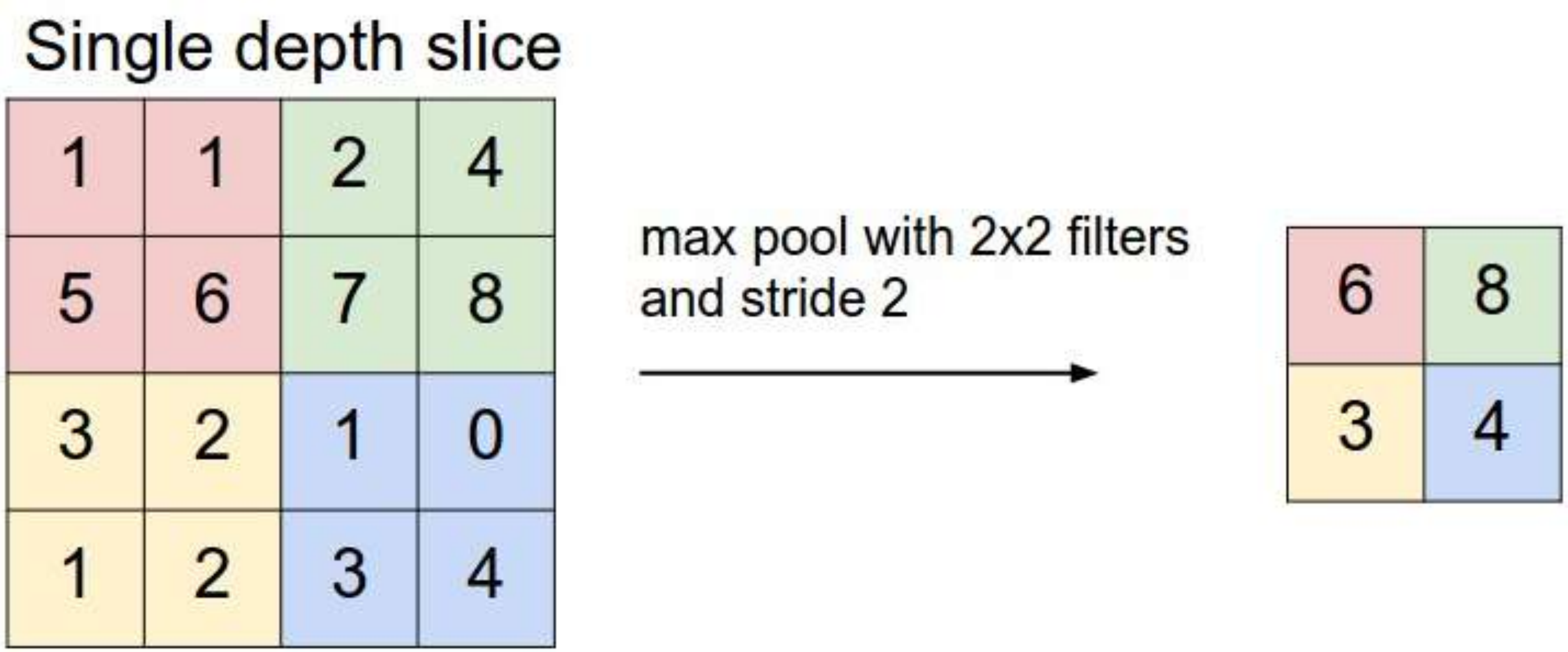
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 32, 32, 3)         0
_________________________________________________________________
conv2d (Conv2D)              (None, 32, 32, 32)        896
_________________________________________________________________
```

Convolutional neural network

Backpropagation



Backpropagation
For maxpooling



Source: http://cs231n.github.io/convolutional-networks/

Time for coding

Before we start ...

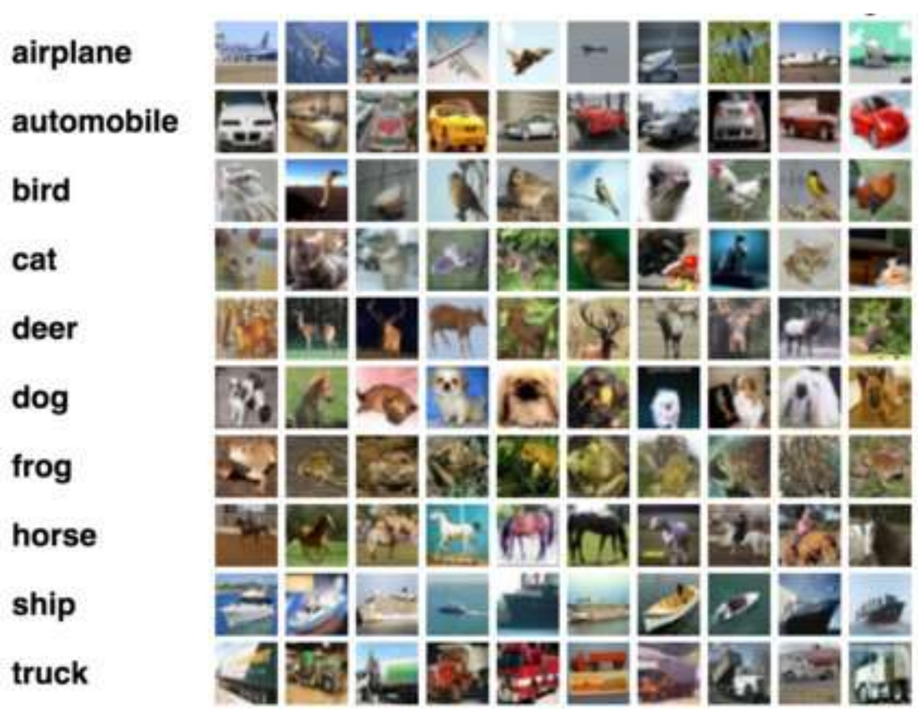
Dataset

- Cifar 10: Cifar stands for Canadian Institute For Advanced Research

- 60,000 32 x 32 colour images in 10 distinct classes

Airplane
Automobile
Bird
Cat
Deer
Dog
Frog
Horse
Ship
Trucks

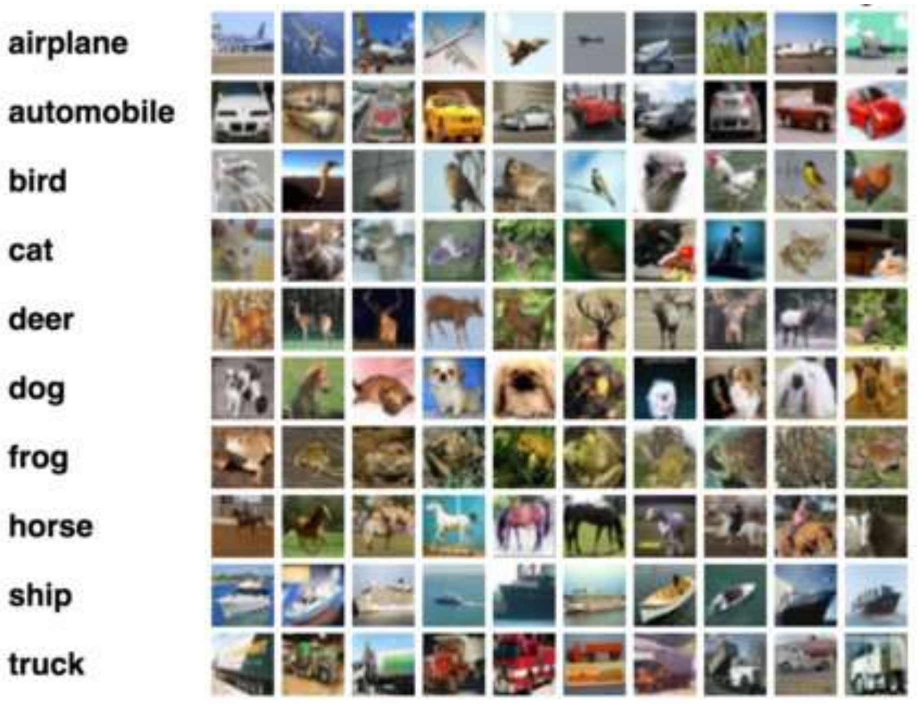
- Each class has 6,000 images



Source: https://appliedmachinelearning.blog/2018/03/24/achieving-90-accuracy-in-object-recognition-task-on-cifar-10-dataset-with-keras-convolutional-neural-networks/

Before we start ...
Dataset

- Dataset collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton
- Advantages: small image size yet large samples, good for quick idea testing
- One of the most widely used datasets for machine learning research
- Not easy to get good and comparable alternative (dataset)



Source: https://appliedmachinelearning.blog/2018/03/24/achieving-90-accuracy-in-object-recognition-task-on-cifar-10-dataset-with-keras-convolutional-neural-networks/

Keras

Or Tensorflow?

- Tensorflow is powerful, but a pain to learn
- Keras is simpler, but not as powerful/flexible as Tensorflow
- However, since Tensorflow r1.13, Keras has become officially the preferred higher level API to build deep learning model
- In Tensorflow 2.0, Keras-way is the default way to build deep learning model in Tensorflow
- Thus in this course, we use Tensorflow but build model in Keras way!

Cifar 10

The main layout for the code

1. Import libraries
2. Matplotlib setup
3. Data preparation
4. Define model
5. Train model
6. Test model

Cifar 10

1. Import libraries, part 1

- numpy for matrix manipulation
- sklearn for measuring performance
- matplotlib to show image and plot result;

```
> import numpy as np
> import sklearn.metrics as metrics
> import matplotlib.pyplot as plt
```

Cifar 10

1. Import libraries, part 2

- Import all the Keras functions that we are going to use in this problem

- Most of the key components to build a deep learning model fall under `tensorflow.keras.layers`

```
> from tensorflow.keras.callbacks import ModelCheckpoint,CSVLogger
> from tensorflow.keras.models import Sequential
> from tensorflow.keras.layers import Dense
> from tensorflow.keras.layers import Dropout
> from tensorflow.keras.layers import Flatten
> from tensorflow.keras.layers import Conv2D
> from tensorflow.keras.layers import MaxPooling2D
> from tensorflow.keras.utils import to_categorical
> from tensorflow.keras.datasets import cifar10
> from tensorflow.keras import optimizers
```

Cifar 10

2. Matplotlib setup

- Use 'ggplot' style to plot our training and testing result
- The setup uses 'ggplot' style for plot
- Also, for y axis, the labels and ticks put on right rather than left

```
> plt.style.use('ggplot')
> plt.rcParams['ytick.right']     = True
> plt.rcParams['ytick.labelright']= True
> plt.rcParams['ytick.left']      = False
> plt.rcParams['ytick.labelleft'] = False
> plt.rcParams['font.family']     = 'Arial'
```

Cifar 10

3. Data preparation, part 1

- Use Keras in-built cifar10 module to load data
- If `cifar10.load_data()` is never run before, it will download data from the internet

```
> data            = cifar10.load_data()
> (trDat, trLbl)  = data[0]
> (tsDat, tsLbl)  = data[1]
```

```
> trDat       = trDat.astype('float32')/255
> tsDat       = tsDat.astype('float32')/255
```

```
> imgrows     = trDat.shape[1]
> imgclms     = trDat.shape[2]
> channel     = trDat.shape[3]
```

Cifar 10

3. Data preparation, part 1

- The shape of trDat is `(50000, 32, 32, 3)`
- The shape of tsDat is `(10000, 32, 32, 3)`
- For deep learning training and testing, the data must be in the form of (sample, row, clm, channel)

Name ▲	Type	Size	Value
channel	int	1	3
data	tuple	2	((Numpy array, Numpy array), (Numpy array, Numpy array))
imgclms	int	1	32
imgrows	int	1	32
trDat	float32	(50000, 32, 32, 3)	[[[[0.23137255 0.24313726 0.24705882] [0.16862746 0.18039216 0.1764 ...
trLbl	uint8	(50000, 1)	[[6] [9]
tsDat	float32	(10000, 32, 32, 3)	[[[[0.61960787 0.4392157 0.19215687] [0.62352943 0.43529412 0.1843 ...
tsLbl	int64	(10000, 1)	[[3] [8]

Cifar 10

3. Data preparation, part 1

- (sample, row, clm, channel) is a 'channel last' channel ordering format
- Some frameworks prefer 'channel first' format, which is (sample, channel, row, clm)
- Why? Also, why put sample in the first dimension?

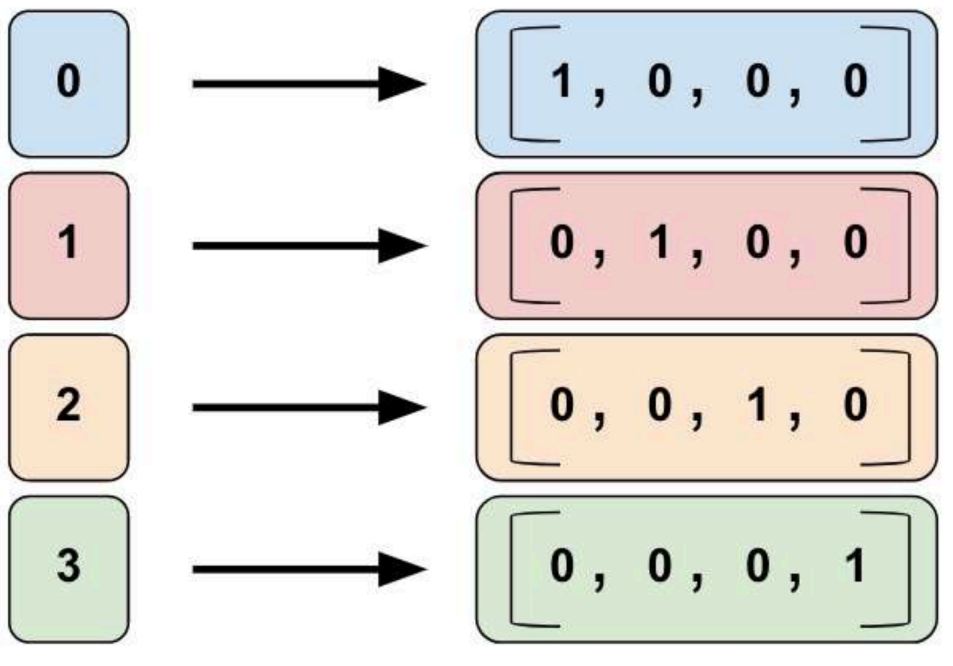
Cifar 10

3. Data preparation, part 2

- One-hot encode the train and test label information;

- `to_categorical` is imported from `tensorflow.keras.utils` in the beginning

```
> trLbl       = to_categorical(trLbl)
> tsLbl       = to_categorical(tsLbl)
> num_classes = tsLbl.shape[1]
```



Source: https://arxiv.org/pdf/1812.01718.pdf

Cifar 10

3. Data preparation, part 2

- One-hot encoding

Before

	0
0	6
1	9
2	9
3	4
4	1
5	1
6	2
7	7

After

	0	1	2	3	4	5	6	7	8	9
0	0	0	0	0	0	0	1	0	0	0
1	0	0	0	0	0	0	0	0	0	1
2	0	0	0	0	0	0	0	0	0	1
3	0	0	0	0	1	0	0	0	0	0
4	0	1	0	0	0	0	0	0	0	0
5	0	1	0	0	0	0	0	0	0	0
6	0	0	1	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1	0	0

Cifar 10

4. Define model, part 1

- Set up random seed
- Set up optimizer. Use RMSprop, lr stands for learning rate
- Give this model a name for later model saving and files saving usage

```
> seed      = 29
> np.random.seed(seed)

> optmz     = optimizers.RMSprop(lr=0.0001)
> modelname = 'wks2_3a'
```

$$E_{dw} = 0$$ Initialization

$$E_{dw} = \beta \cdot E_{dw} + (1-\beta) \cdot dw^2$$

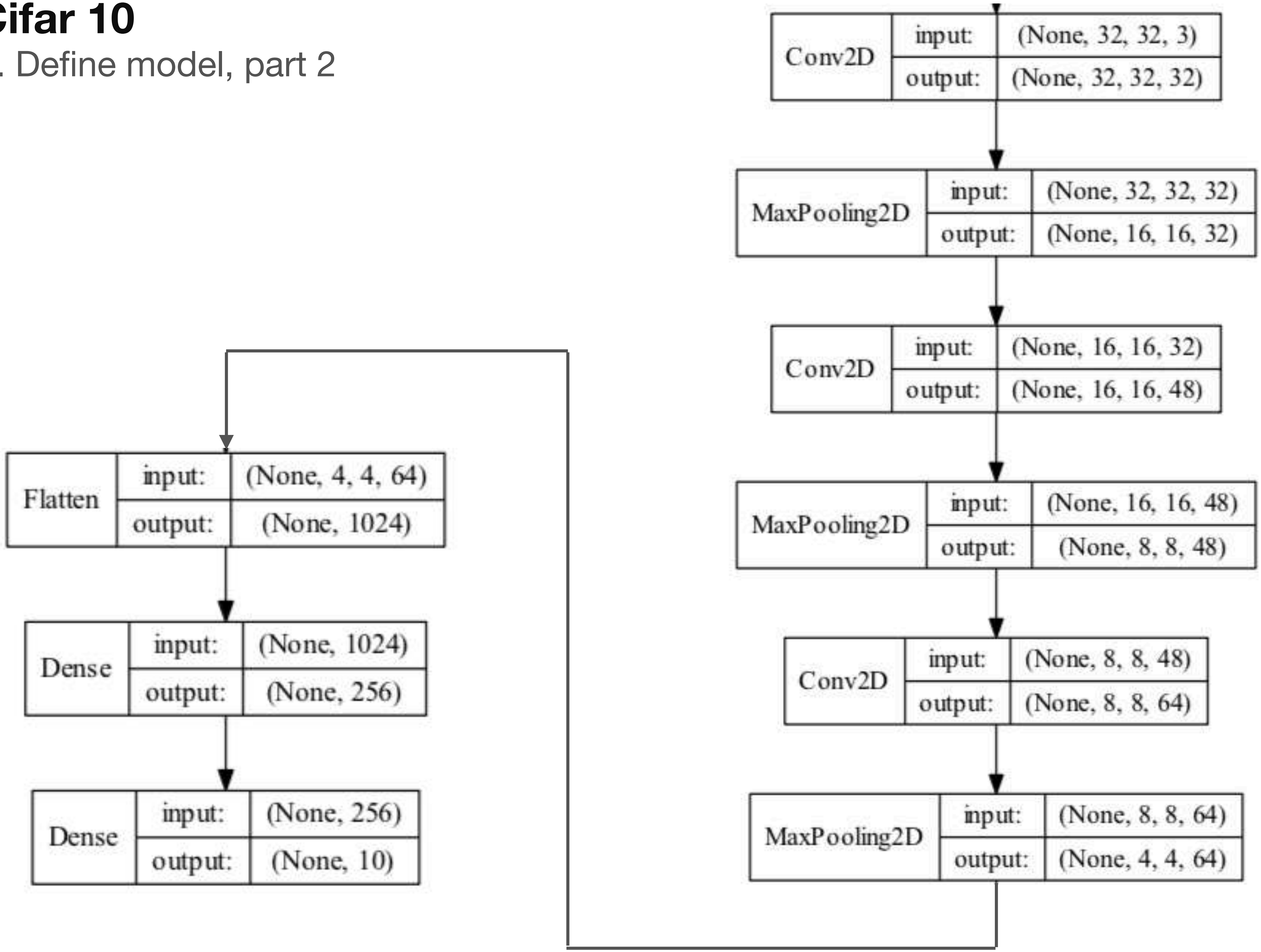
$$w = w - \alpha \cdot \frac{dw}{\sqrt{E_{dw}} + \epsilon}$$

$$b = b - \alpha \cdot \frac{db}{\sqrt{E_{db}} + \epsilon}$$

Source: https://towardsdatascience.com/understanding-rmsprop-faster-neural-network-learning-62e116fcf29a

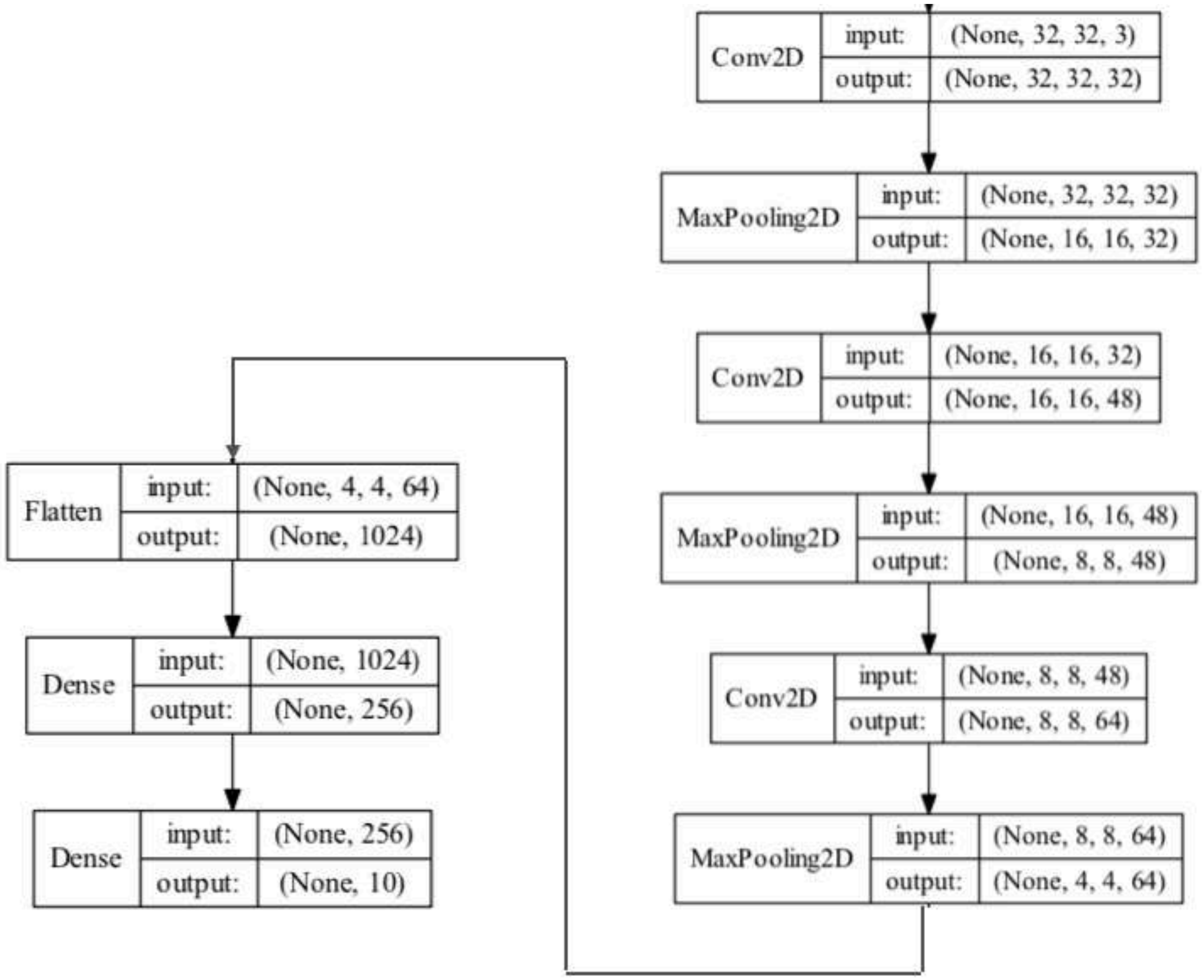
Cifar 10

4. Define model, part 2



Cifar 10

4. Define model, part 2




```
> def createModel():
    model   = Sequential()
    model.add(Conv2D(32,(3,3),
              input_shape=(imgrows,
                           imgclms,
                           channel),
              padding='same',
              activation='relu'))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(Conv2D(48,(3,3),padding='same',activation='relu'))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(Conv2D(64,(3,3),padding='same',activation='relu'))
    model.add(MaxPooling2D(pool_size=(2,2)))
    model.add(Flatten())
    model.add(Dense(256,activation='relu'))
    model.add(Dense(num_classes,activation='softmax'))
    model.compile(loss='categorical_crossentropy',
                  optimizer=optmz,
                  metrics=['accuracy'])
    return model
```

Cifar 10

4. Define model, part 2

- 'model' for training; 'modelGo' for final evaluation

```
> model       = createModel()
> modelGo     = createModel()

> model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 32, 32, 32)        896
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 16, 16, 48)        13872
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 8, 8, 48)          0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 8, 8, 64)          27712
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 4, 4, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 1024)              0
_________________________________________________________________
dense (Dense)                (None, 256)               262400
_________________________________________________________________
dense_1 (Dense)              (None, 10)                2570
=================================================================
Total params: 307,450
Trainable params: 307,450
Non-trainable params: 0
_________________________________________________________________
```

Cifar 10

4. Define model, part 3

- Create checkpoints to save model during training and save training data into csv
- ‘monitor’ can be ‘val_acc’ or ‘val_loss’
- When set to ‘val_acc’, ‘mode’ must be ‘max’; when set to ‘val_loss’, ‘mode’ must be ‘min’

```
> filepath        = modelname + ".hdf5"
> checkpoint      = ModelCheckpoint(filepath,
                                    monitor='val_acc',
                                    verbose=0,
                                    save_best_only=True,
                                    mode='max')
```

```
> csv_logger      = CSVLogger(modelname + '.csv')
> callbacks_list  = [checkpoint,csv_logger]
```

Cifar 10

5. Train model

- Training is only a single line

```
> model.fit(trDat,
            trLbl,
            validation_data=(tsDat, tsLbl),
            epochs=100,
            batch_size=128,
            shuffle=True,
            callbacks=callbacks_list)
```

```
Train on 50000 samples, validate on 10000 samples
Epoch 1/100
50000/50000 [==============================] - 4s 87us/sample - loss: 1.9316 - acc: 0.3231 - val_loss: 1.7215 - val_acc: 0.3937
Epoch 2/100
50000/50000 [==============================] - 3s 61us/sample - loss: 1.6368 - acc: 0.4176 - val_loss: 1.5545 - val_acc: 0.4454
Epoch 3/100
50000/50000 [==============================] - 3s 61us/sample - loss: 1.5251 - acc: 0.4542 - val_loss: 1.4865 - val_acc: 0.4624
Epoch 4/100
50000/50000 [==============================] - 3s 61us/sample - loss: 1.4538 - acc: 0.4819 - val_loss: 1.4130 - val_acc: 0.4941
Epoch 5/100
50000/50000 [==============================] - 3s 61us/sample - loss: 1.3988 - acc: 0.5034 - val_loss: 1.3744 - val_acc: 0.5135
......
```

Cifar 10

6. Test model, part 1

- Use a new object to load the weights and re-compile again

```
> modelGo.load_weights(filepath)
> modelGo.compile(loss='categorical_crossentropy',
                  optimizer=optmz,
                  metrics=['accuracy'])
```

Cifar 10

6. Test model, part 2

- Test the model, calculate the accuracy and confusion matrix

```
> predicts     = modelGo.predict(tsDat)

> predout      = np.argmax(predicts,axis=1)
> testout      = np.argmax(tsLbl,axis=1)
> labelname    = ['airplane',
                  'automobile',
                  'bird',
                  'cat',
                  'deer',
                  'dog',
                  'frog',
                  'horse',
                  'ship',
                  'truck']

> testScores   = metrics.accuracy_score(testout,predout)
> confusion    = metrics.confusion_matrix(testout,predout)
```

cifar 10

6. Test model, part 3

- Test the model, calculate the accuracy and confusion matrix

```
> print("Best accuracy (on testing dataset): %.2f%%" % (testScores*100))
> print(metrics.classification_report(testout,predout,target_names=labelname,digits=4))
> print(confusion)
```

```
Best accuracy (on testing dataset): 73.16%
             precision    recall  f1-score   support

   airplane     0.8013    0.7380    0.7683      1000
 automobile     0.8653    0.7710    0.8154      1000
       bird     0.6959    0.5950    0.6415      1000
        cat     0.5365    0.6100    0.5709      1000
       deer     0.6491    0.7640    0.7019      1000
        dog     0.7007    0.5620    0.6238      1000
       frog     0.7888    0.7880    0.7884      1000
      horse     0.7946    0.7930    0.7938      1000
       ship     0.8713    0.7990    0.8336      1000
      truck     0.6876    0.8960    0.7781      1000

avg / total     0.7391    0.7316    0.7316     10000
```

```
[[738  18  36  18  40   4  10  11  52  73]
 [  7 771   7  10   1   2  11   2  18 171]
 [ 60   6 595  75 108  44  51  35   9  17]
 [ 17  11  49 610  81 103  53  33  11  32]
 [ 11   2  49  43 764  23  37  56   7   8]
 [ 13   2  46 224  63 562  26  48   4  12]
 [  7   4  32  79  46  24 788   5   3  12]
 [  7   7  22  43  61  31  10 793   2  24]
 [ 44  34  13  24  11   6   8   3 799  58]
 [ 17  36   6  11   2   3   5  12  12 896]]
```

Cifar 10

6. Test model, part 4

- Plot the result

```
> import pandas as pd

> records       = pd.read_csv(modelname +'.csv')
> plt.figure()
> plt.subplot(211)
> plt.plot(records['val_loss'])
> plt.yticks([0.00,0.60,0.70,0.80])
> plt.title('Loss value',fontsize=12)

> ax            = plt.gca()
> ax.set_xticklabels([])

> plt.subplot(212)
> plt.plot(records['val_acc'])
> plt.yticks([0.5,0.6,0.7,0.8])
> plt.title('Accuracy',fontsize=12)
> plt.show()
```