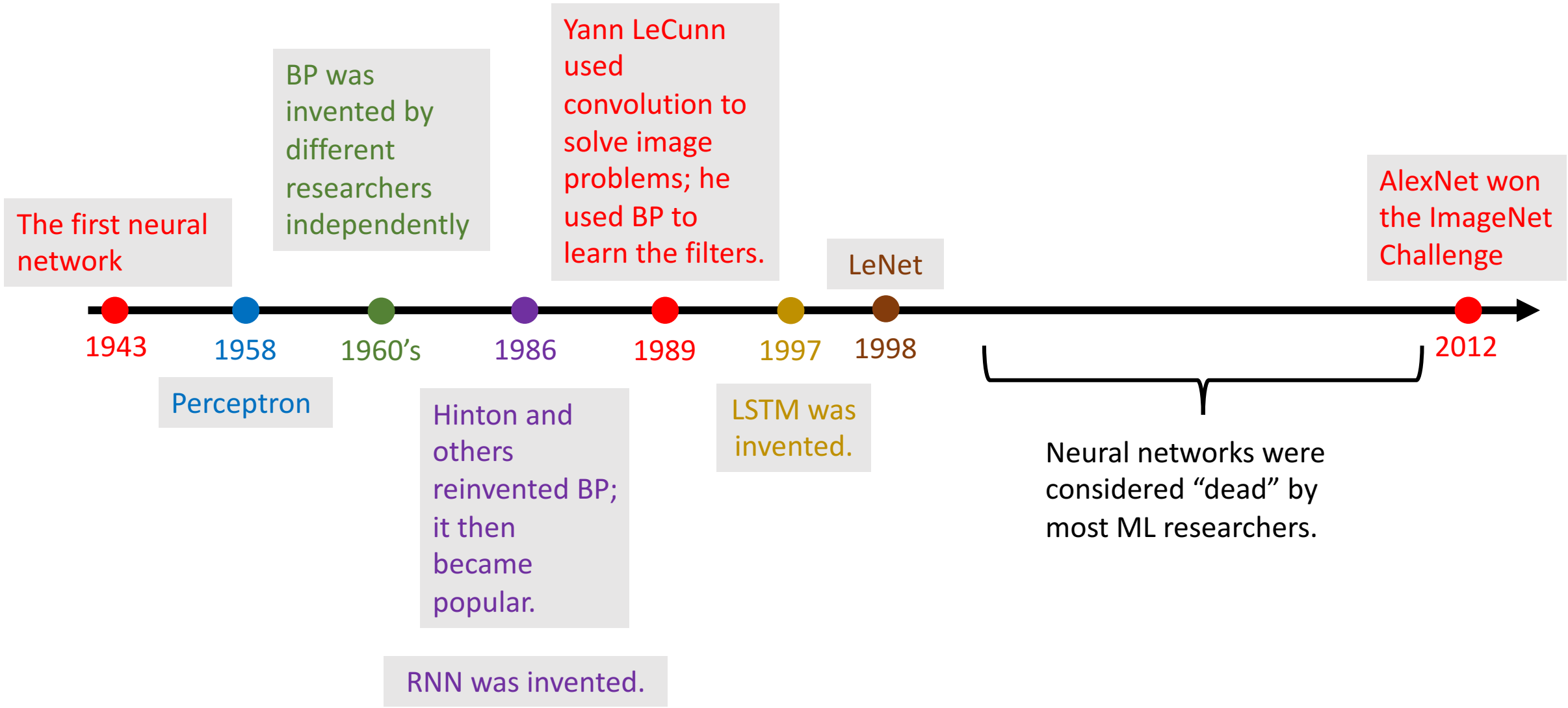
Common CNN Architectures

Shusen Wang

Background

History of Neural Networks



Traditional Approaches

SIFT Feature

HOG Feature

LBP Feature

Traditional Approaches

SIFT Feature

HOG Feature

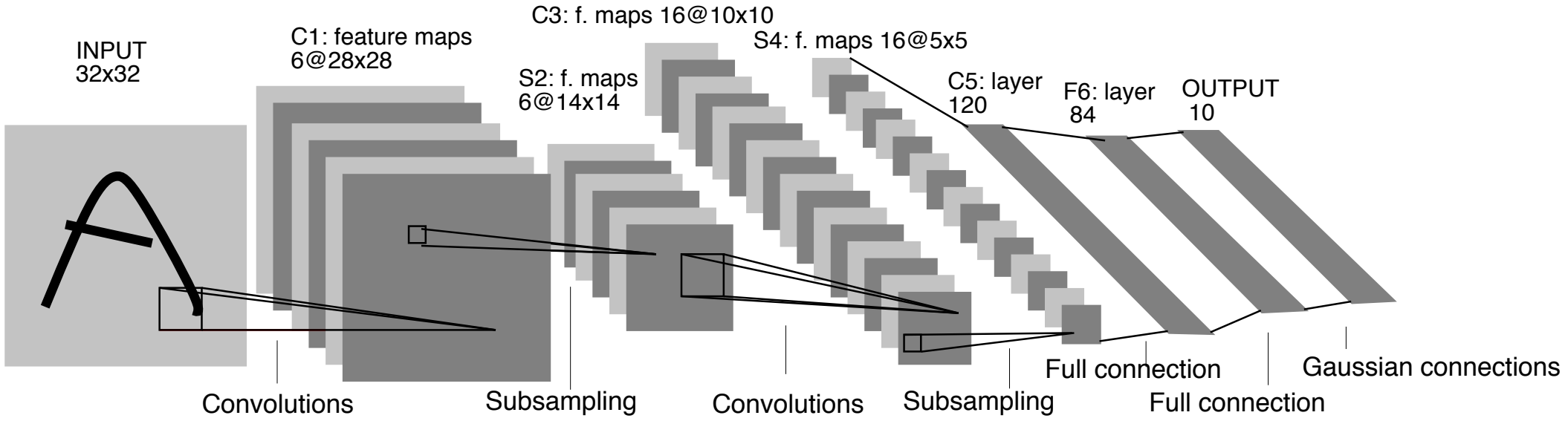
LBP Feature

Linear Model

“dog”

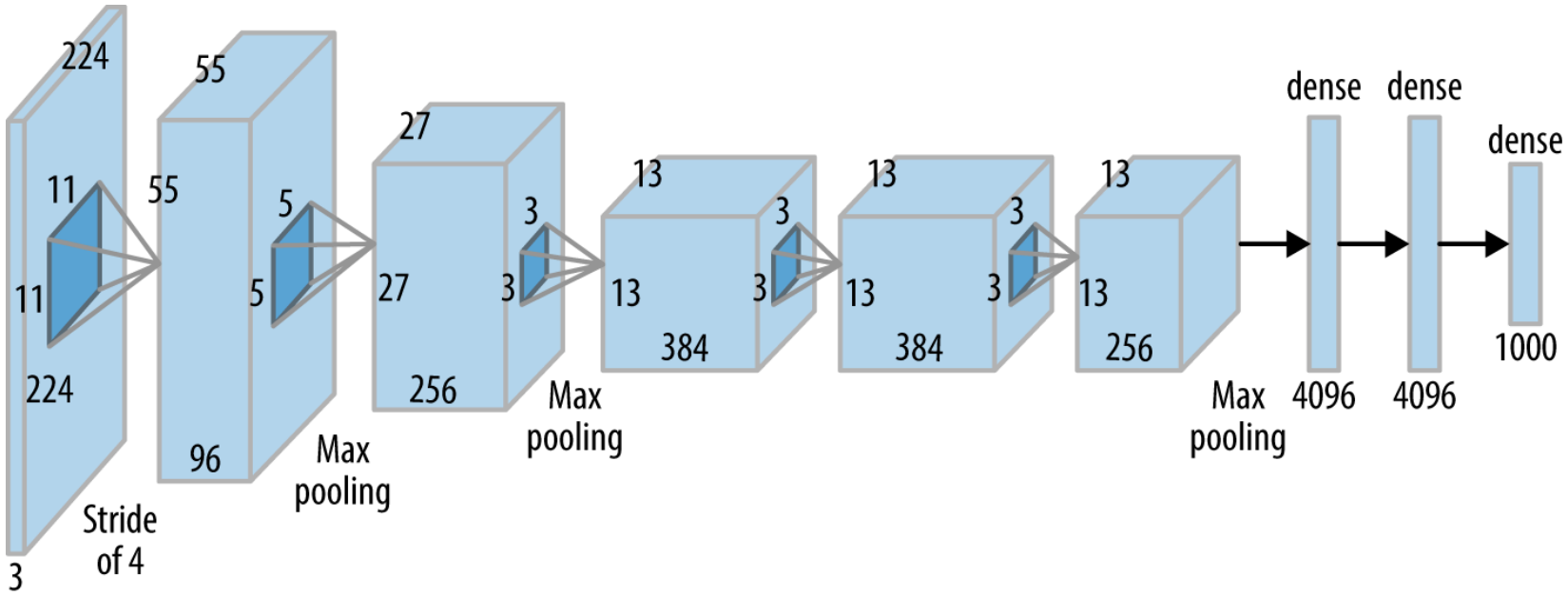
Classic CNN Architectures

LeNet-5 [Yan LeCun *et al.* 1998]



- Layers: 2 Conv + 2 FC layers.
- Paper: Gradient-based learning applied to document recognition

AlexNet [Alex Krizhevsky *et al.* 2012]



- Layers: 5 Conv + 3 FC layers.
- Number of trainable parameters: $60M$.
- Paper: ImageNet Classification with Deep Convolutional Neural Networks
- Keras implementation: http://dandxy89.github.io/ImageModels/

```python
DROPOUT = 0.5
model_input = Input(shape = (227, 227, 3))

# First convolutional Layer (96x11x11)
z = Conv2D(filters = 96, kernel_size = (11,11), strides = (4,4), activation = "relu")(model_input)
z = MaxPooling2D(pool_size = (3,3), strides=(2,2))(z)
z = BatchNormalization()(z)

# Second convolutional Layer (256x5x5)
z = ZeroPadding2D(padding = (2,2))(z)
z = Convolution2D(filters = 256, kernel_size = (5,5), strides = (1,1), activation = "relu")(z)
z = MaxPooling2D(pool_size = (3,3), strides=(2,2))(z)
z = BatchNormalization()(z)

# Rest 3 convolutional layers
z = ZeroPadding2D(padding = (1,1))(z)
z = Convolution2D(filters = 384, kernel_size = (3,3), strides = (1,1), activation = "relu")(z)

z = ZeroPadding2D(padding = (1,1))(z)
z = Convolution2D(filters = 384, kernel_size = (3,3), strides = (1,1), activation = "relu")(z)

z = ZeroPadding2D(padding = (1,1))(z)
z = Convolution2D(filters = 256, kernel_size = (3,3), strides = (1,1), activation = "relu")(z)

z = MaxPooling2D(pool_size = (3,3), strides=(2,2))(z)
z = Flatten()(z)

z = Dense(4096, activation="relu")(z)
z = Dropout(DROPOUT)(z)

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z = Dropout(DROPOUT)(z)

final_dim = 1 if N_CATEGORY == 2 else N_CATEGORY
final_act = "sigmoid" if N_CATEGORY == 2 else "softmax"
model_output = Dense(final_dim, activation=final_act)(z)

model = Model(model_input, model_output)
model.summary()
```
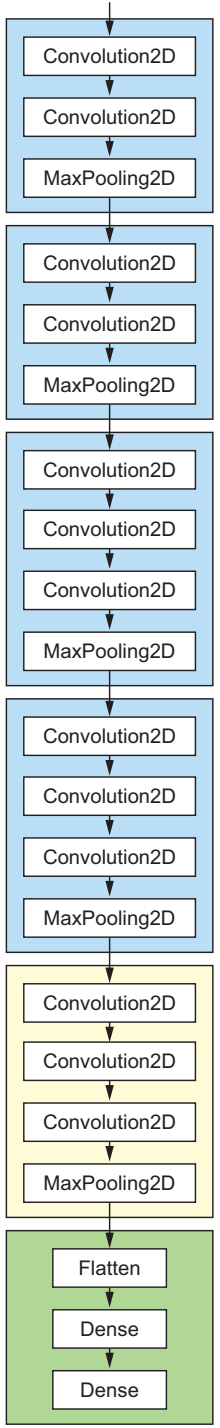
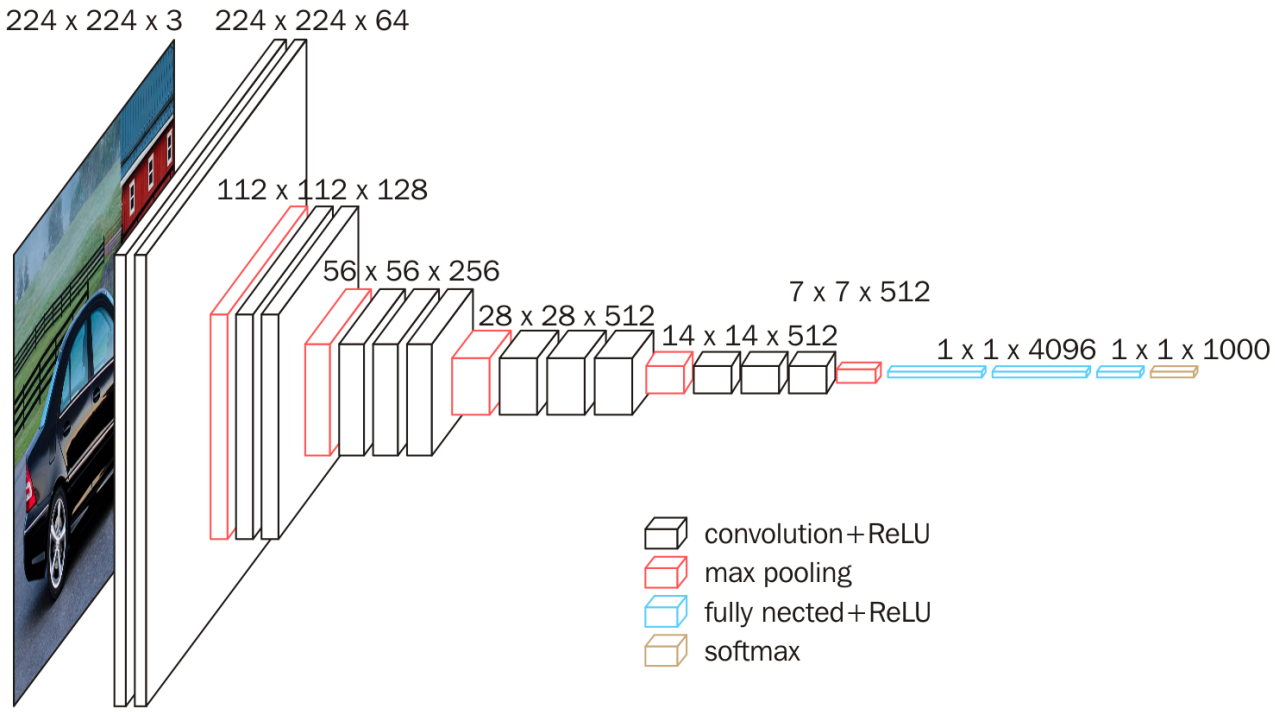

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input_2 (InputLayer)         (None, 227, 227, 3)       0
_________________________________________________________________
conv2d_6 (Conv2D)            (None, 55, 55, 96)        34944
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 27, 27, 96)        0
_________________________________________________________________
batch_normalization_3 (Batch (None, 27, 27, 96)        384
_________________________________________________________________
zero_padding2d_5 (ZeroPaddin (None, 31, 31, 96)        0
_________________________________________________________________
conv2d_7 (Conv2D)            (None, 27, 27, 256)       614656
_________________________________________________________________
max_pooling2d_5 (MaxPooling2 (None, 13, 13, 256)       0
_________________________________________________________________
batch_normalization_4 (Batch (None, 13, 13, 256)       1024
_________________________________________________________________
zero_padding2d_6 (ZeroPaddin (None, 15, 15, 256)       0
_________________________________________________________________
conv2d_8 (Conv2D)            (None, 13, 13, 384)       885120
_________________________________________________________________
zero_padding2d_7 (ZeroPaddin (None, 15, 15, 384)       0
_________________________________________________________________
conv2d_9 (Conv2D)            (None, 13, 13, 384)       1327488
_________________________________________________________________
zero_padding2d_8 (ZeroPaddin (None, 15, 15, 384)       0
_________________________________________________________________
conv2d_10 (Conv2D)           (None, 13, 13, 256)       884992
_________________________________________________________________
max_pooling2d_6 (MaxPooling2 (None, 6, 6, 256)         0
_________________________________________________________________
flatten_2 (Flatten)          (None, 9216)              0
_________________________________________________________________
dense_3 (Dense)              (None, 4096)              37752832
_________________________________________________________________
dropout_3 (Dropout)          (None, 4096)              0
_________________________________________________________________
dense_4 (Dense)              (None, 4096)              16781312
_________________________________________________________________
dropout_4 (Dropout)          (None, 4096)              0
_________________________________________________________________
dense_5 (Dense)              (None, 100)               409700
=================================================================
Total params: 58,692,452.0
Trainable params: 58,691,748.0
Non-trainable params: 704.0
_________________________________________________________________
```



VGG16 [Simonyan & Zisserman 2014]

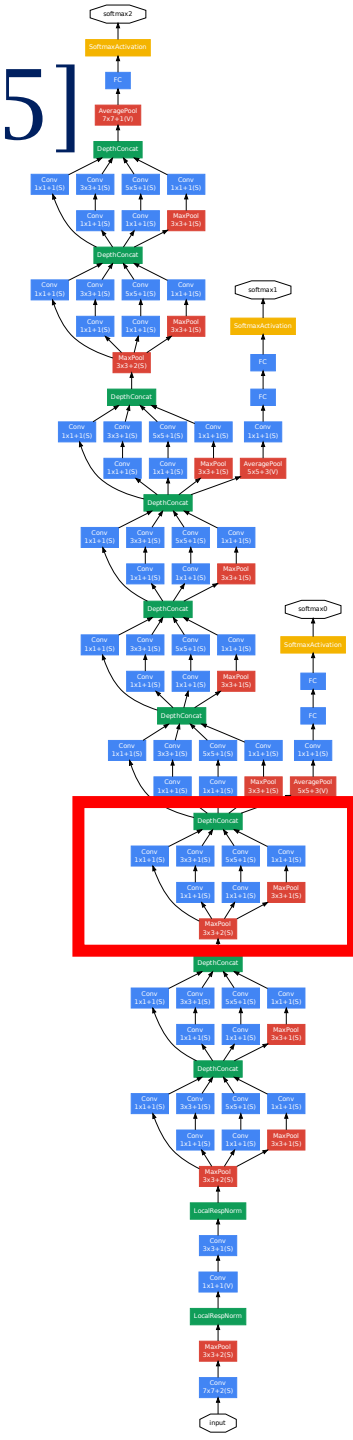


- Layers: 13 Conv + 2 FC layers.
- Number of trainable parameters: $138M$.
- Paper: [Very Deep Convolutional Networks for Large-Scale Image Recognition]

“Modern” CNN Architectures

GoogLeNet/Inception [Szegedy *et al.* 2015]

- Stack of the "Inception" modules.
- Only $5M$ parameters. (VGG16 has $138M$ parameters!)



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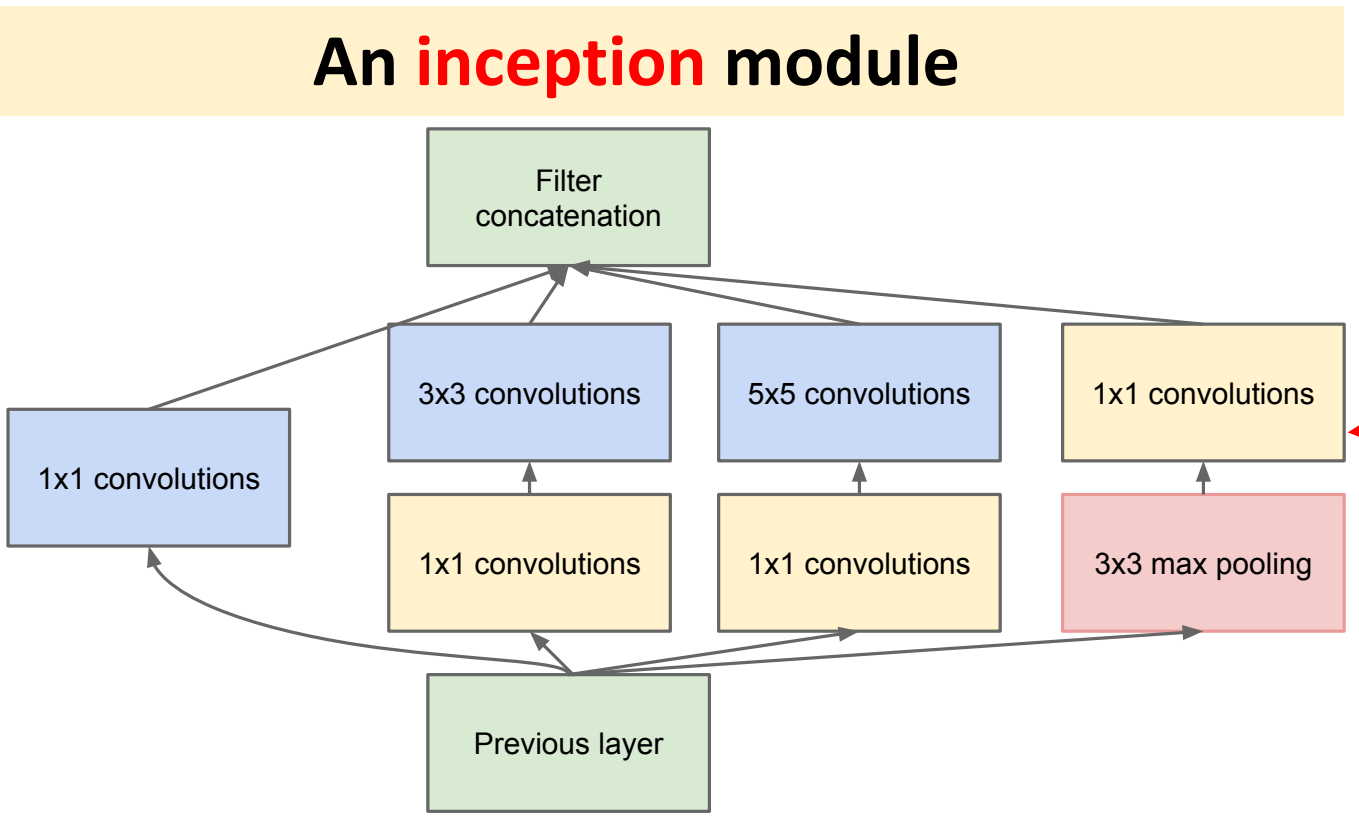
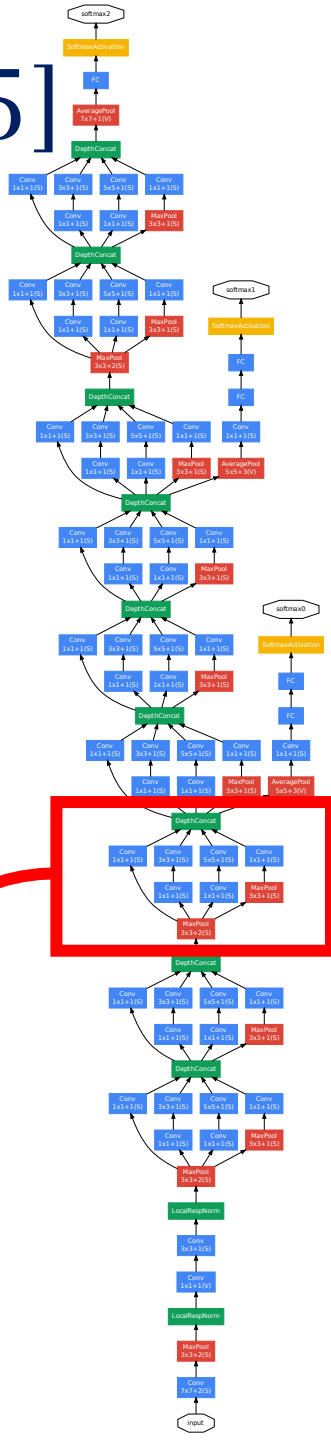
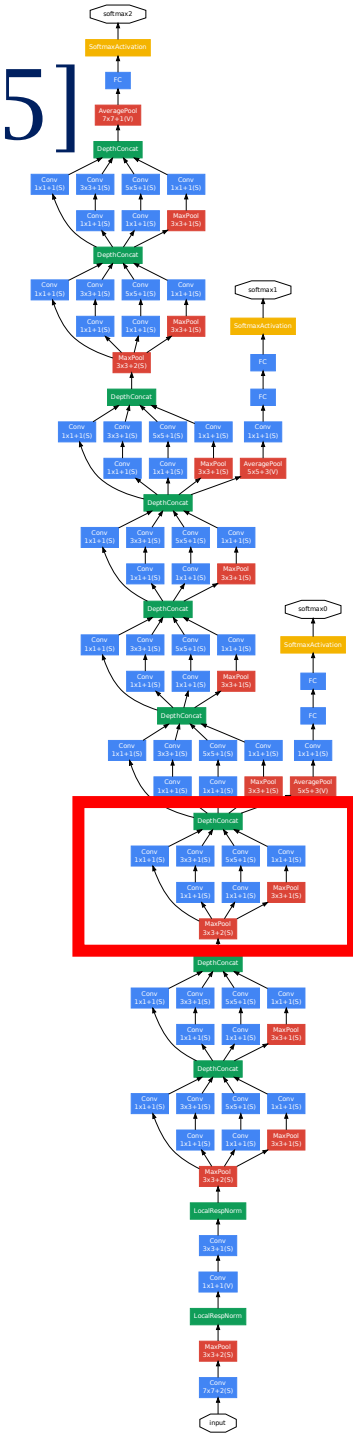




GoogLeNet/Inception [Szegedy *et al.* 2015]

```
from keras.layers import Input, Conv2D, MaxPooling2D, concatenate

x_input = Input(shape=(d1, d2, 64*4))

tower1 = Conv2D(64, (1,1), padding='same', activation='relu')(x_input)

tower2 = Conv2D(64, (1,1), padding='same', activation='relu')(x_input)
tower2 = Conv2D(64, (3,3), padding='same', activation='relu')(tower2)

tower3 = Conv2D(64, (1,1), padding='same', activation='relu')(x_input)
tower3 = Conv2D(64, (5,5), padding='same', activation='relu')(tower3)

tower4 = MaxPooling2D((3,3), strides=(1,1), padding='same')(x_input)
tower4 = Conv2D(64, (1,1), padding='same', activation='relu')(tower4)

x_output = concatenate([tower1, tower2, tower3, tower4], axis = 3)
```

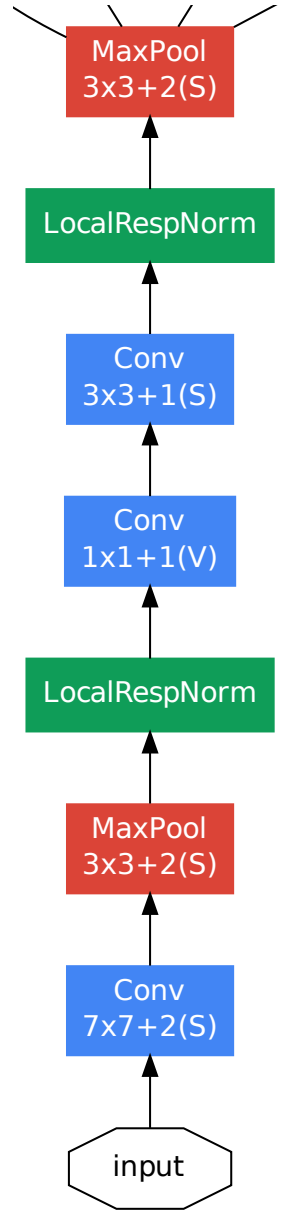
Output: $d_1 \times d_2 \times 256$ (the same as input)

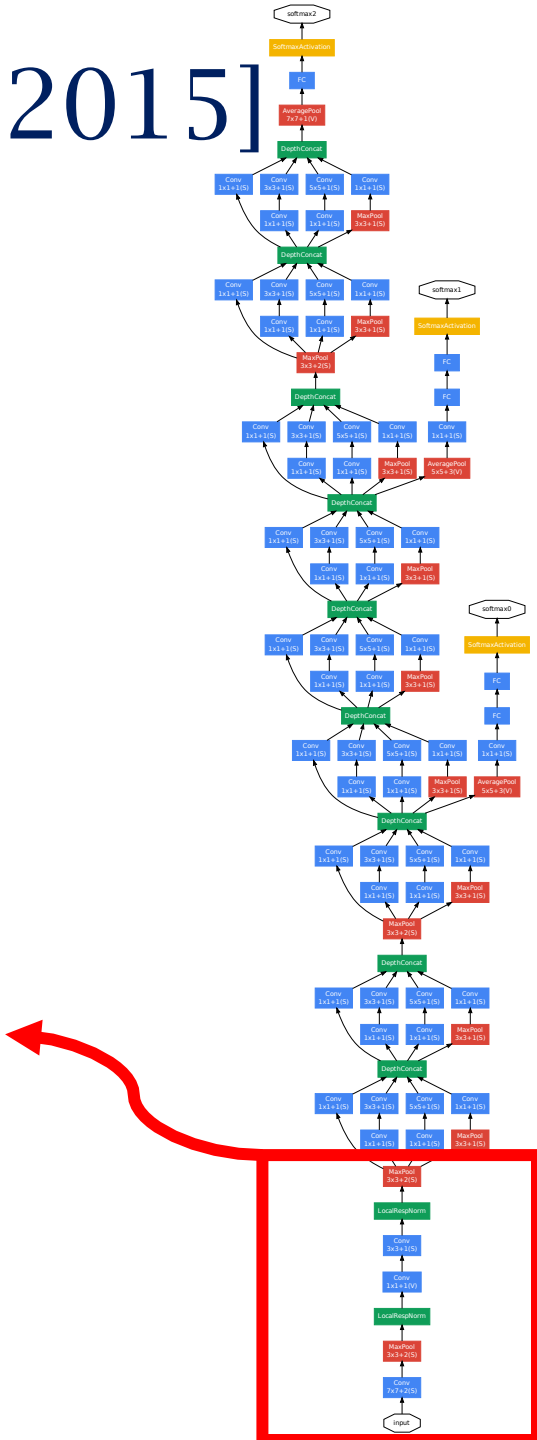


GoogLeNet/Inception [Szegedy *et al.* 2015]

Bottom layers

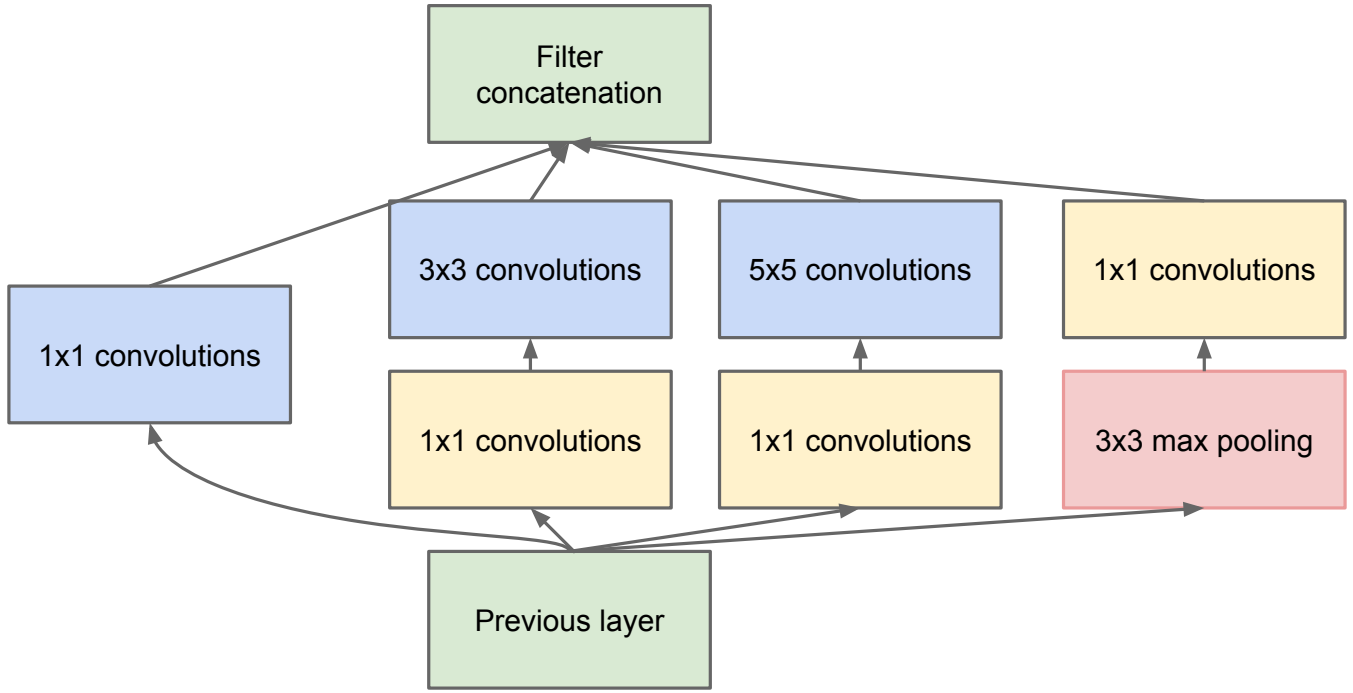
- A simple ConvNet.
- 3 Conv + 2 Pooling + 2 Normalization Layers.

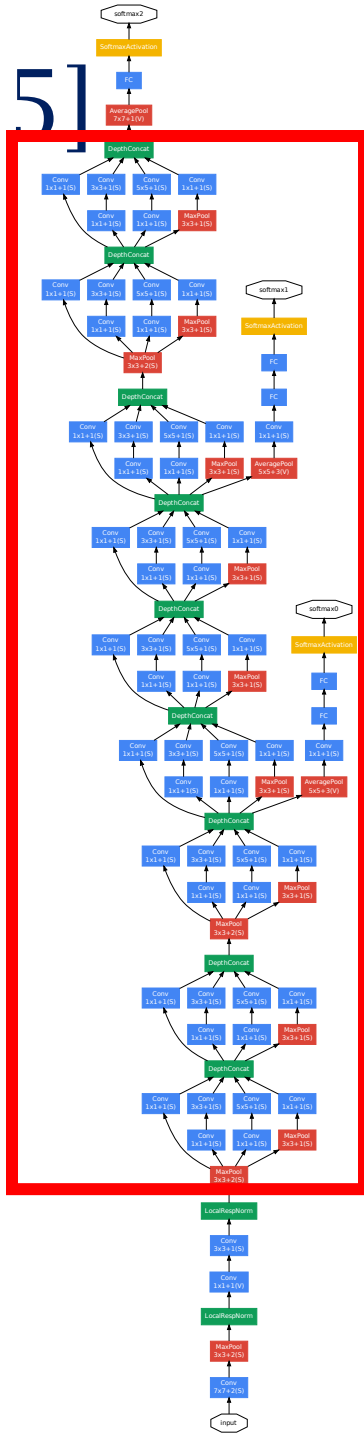




GoogLeNet/Inception [Szegedy *et al.* 2015]

Stack of 9 Inception modules



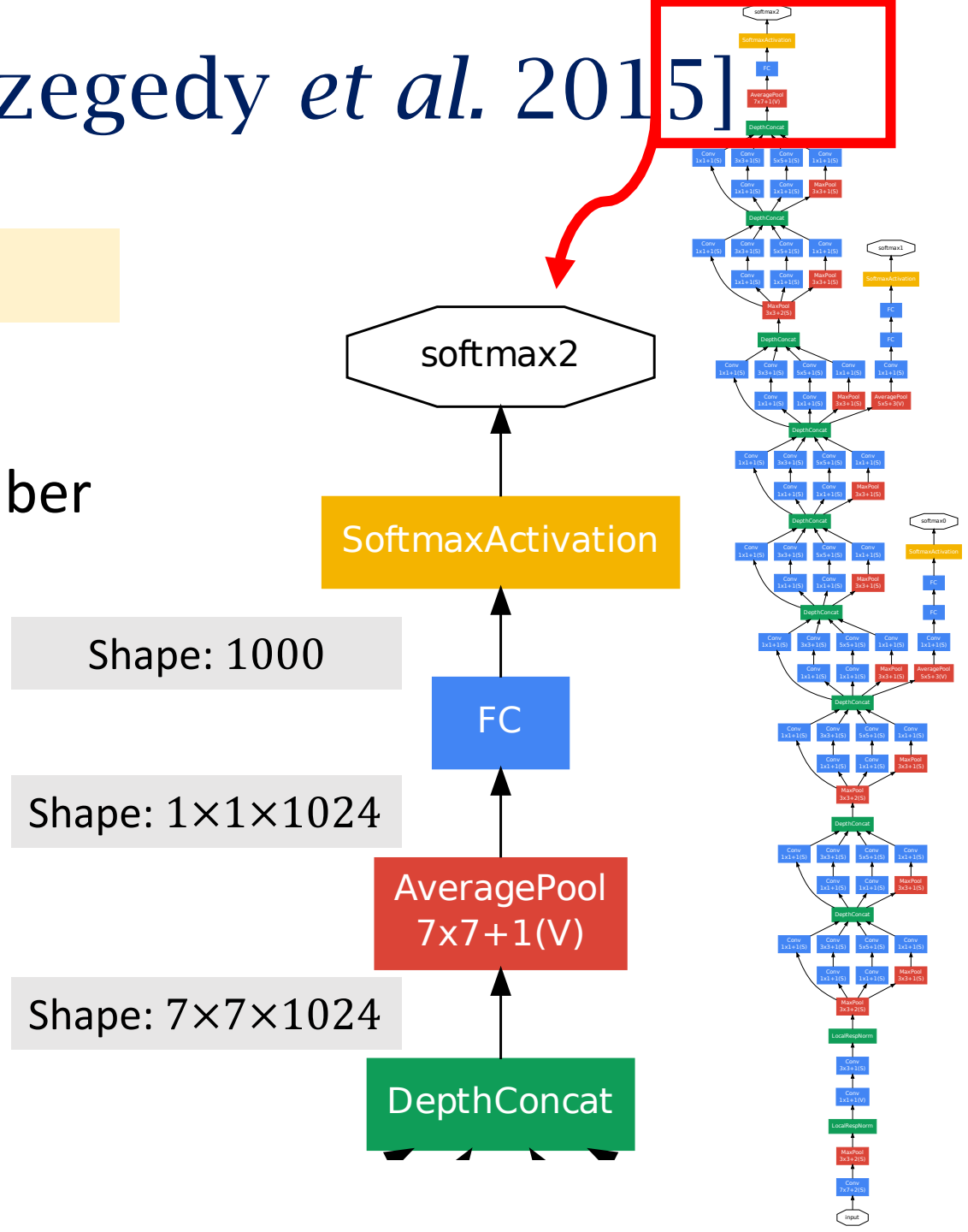


GoogLeNet/Inception [Szegedy *et al.* 2015]

Output layers

- Using AveragePool instead of Flatten.
- AveragePool Layer for reducing the number of parameters.

Question: If AveragePool is replaced by Flatten, then what will be #params in the FC layer?



GoogLeNet/Inception [Szegedy *et al.* 2015]

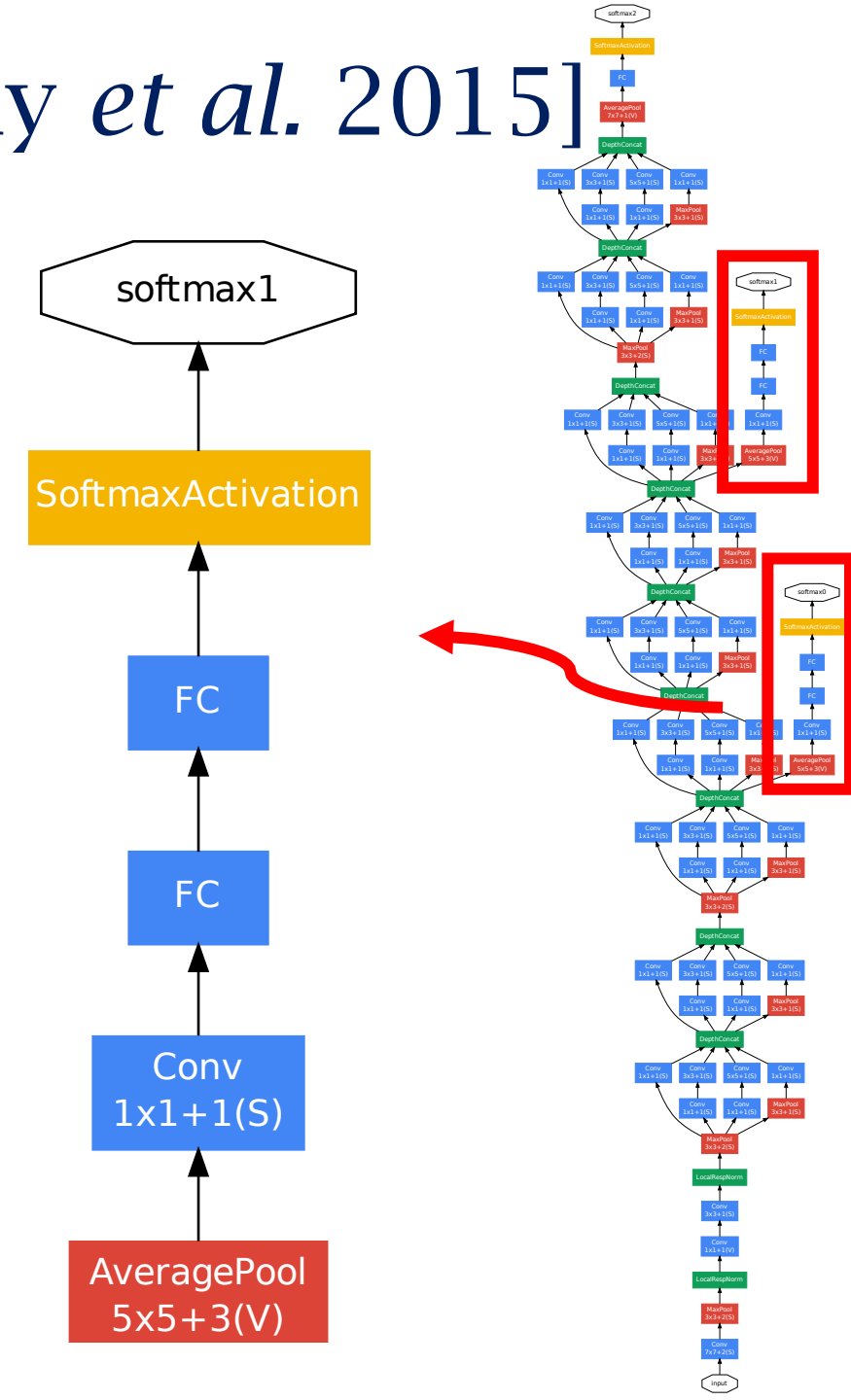
Auxiliary outputs

During Training:

- Inject additional gradient at lower layers.
- Make the optimization easier.

During Test:

- Disable the auxiliary outputs.



How Deep Can We Go?

- LeNet-5: 2 Conv + 2 FC layers.
- AlexNet: 5 Conv + 3 FC layers.
- VGG16: 13 Conv + 2 FC layers.

} classic architectures (sequential)

Question: Why VGG16 and VGG19? Why not deeper classic architectures?

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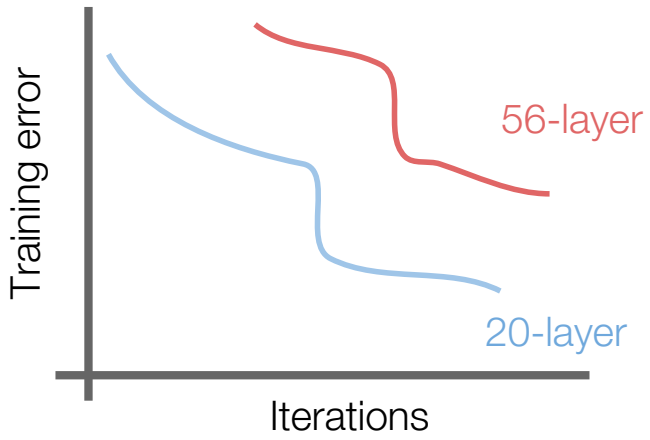
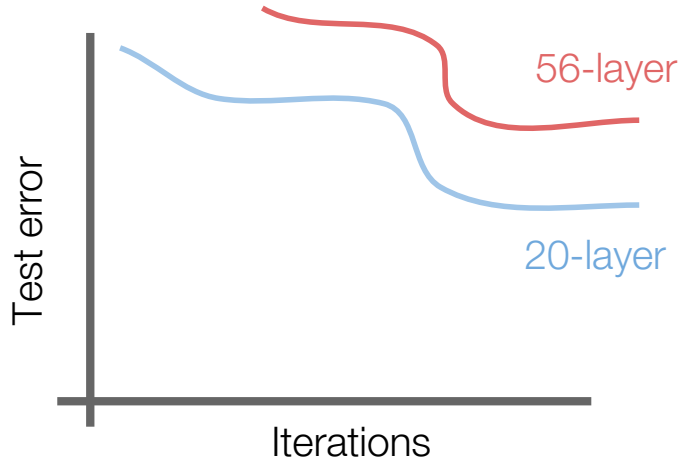
Question: Why VGG16 and VGG19? Why not deeper classic architectures?

Answer: Deeper nets have worse training and test errors.





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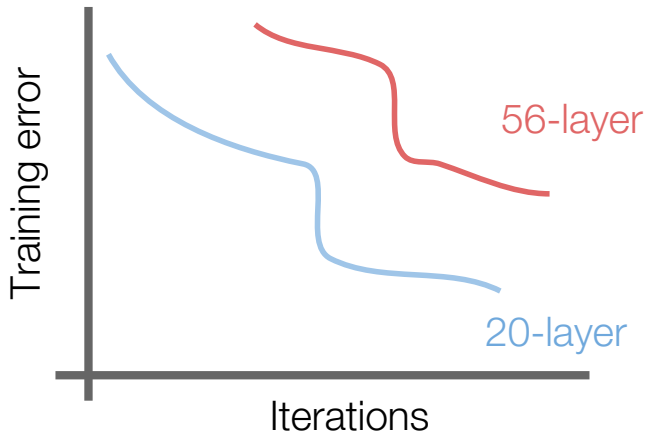
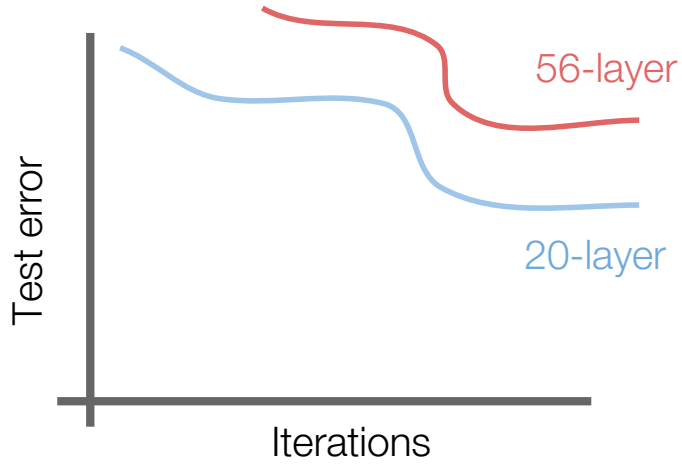
Question: What makes deeper VGG nets worse?

Answer: It is bad optimization, not overfitting.





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} classic architectures (sequential)

Question: What makes deeper VGG nets worse?

- The vanishing gradient problem.
  - Derivative of the loss function w.r.t. a bottom layer can be vanishingly small.
  - It makes deep nets difficult to optimize. The bottom layers are not well trained.
  - The model is good; but you cannot find a good local minimum.

How Deep Can We Go?

- LeNet-5: 2 Conv + 2 FC layers.
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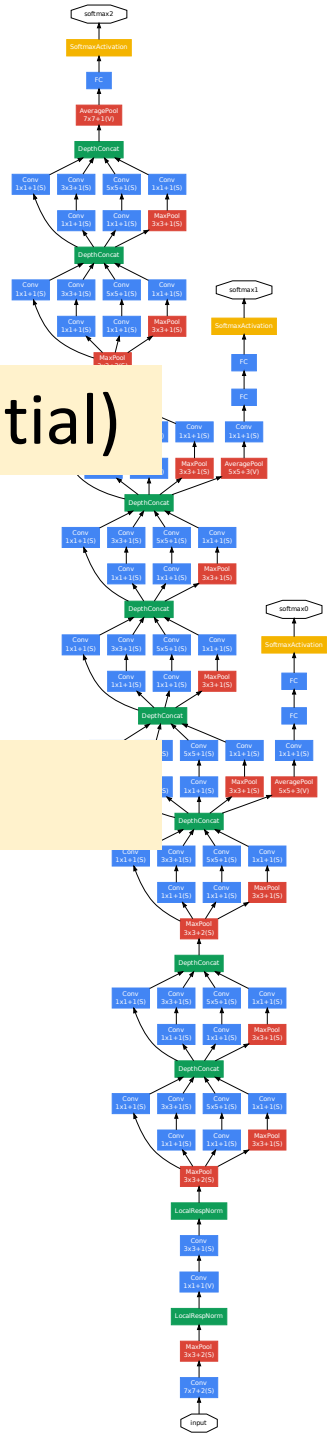
classic architectures (sequential)

- Inception: 21 Conv + 1 FC layers.

Question: Why can Inception go deeper than VGG16?



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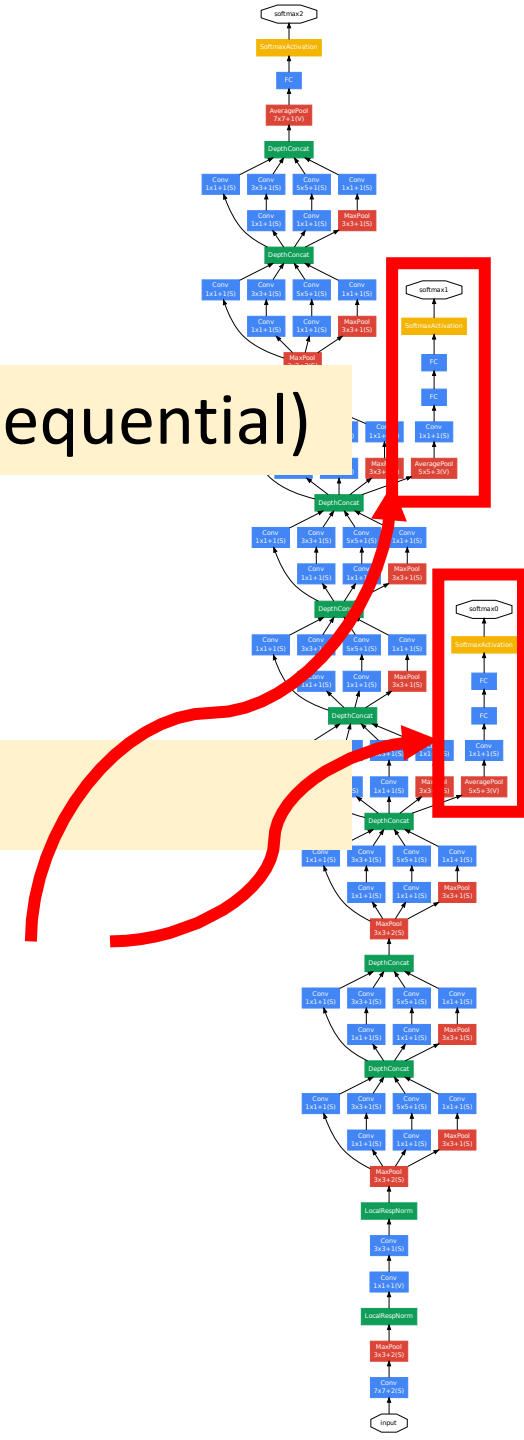
classic architectures (sequential)

Question: Why can Inception go deeper than VGG16?

- Auxiliary outputs inject additional gradient at lower layers.



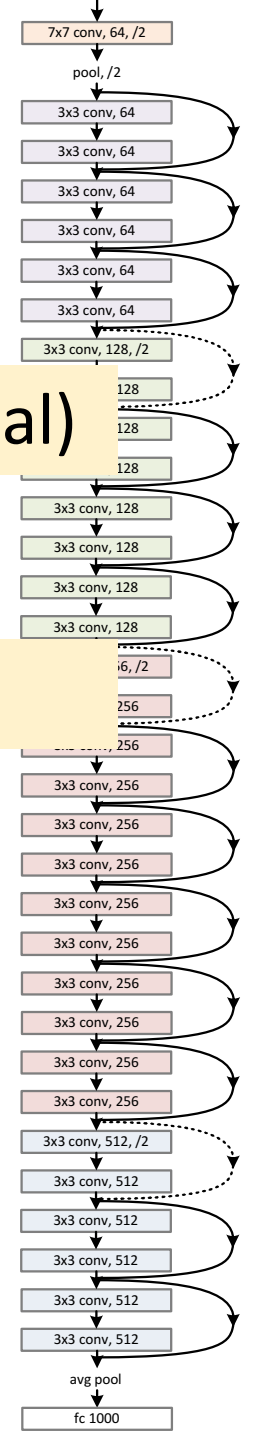
How Deep Can We Go?

- LeNet-5: 2 Conv + 2 FC layers.
- AlexNet: 5 Conv + 3 FC layers.
- VGG16: 13 Conv + 2 FC layers.
- Inception: 21 Conv + 1 FC layers.
- ResNet: Up to 151 Conv + 1 FC layers.

classic architectures (sequential)

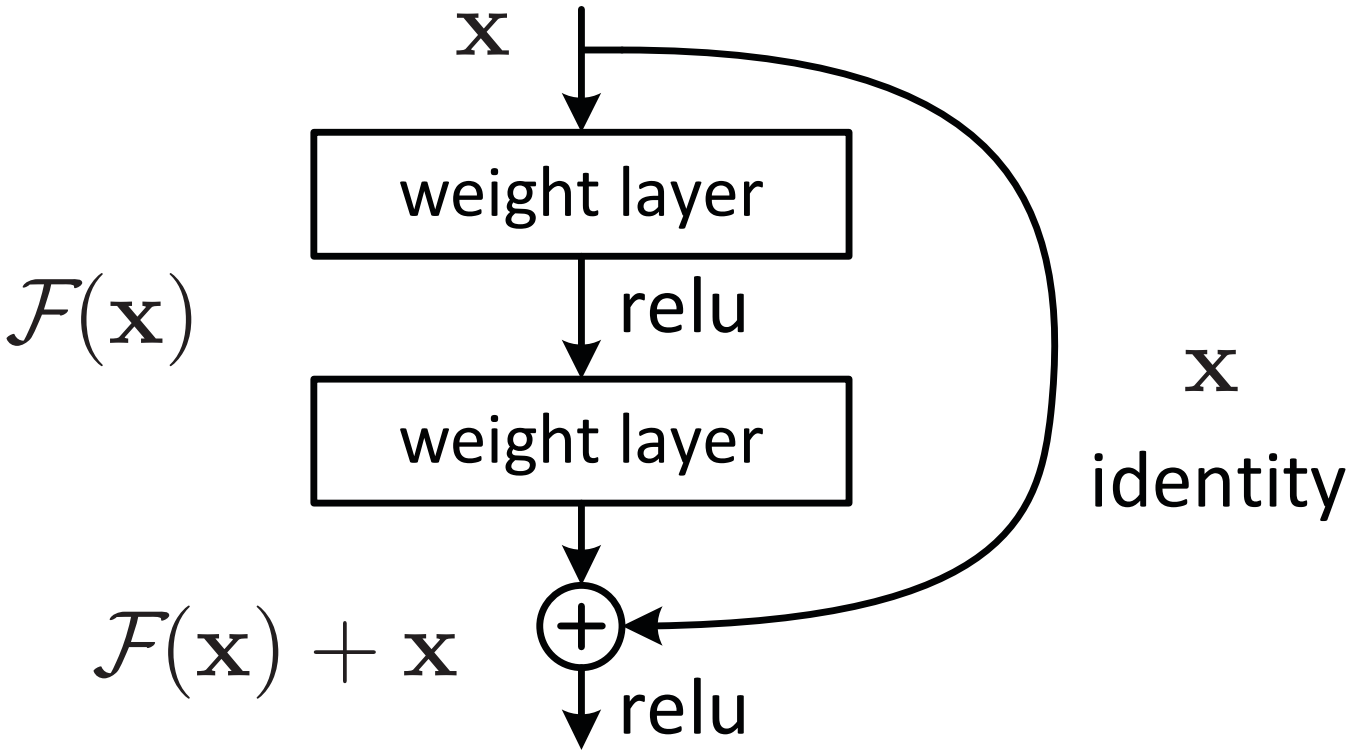
modern architectures

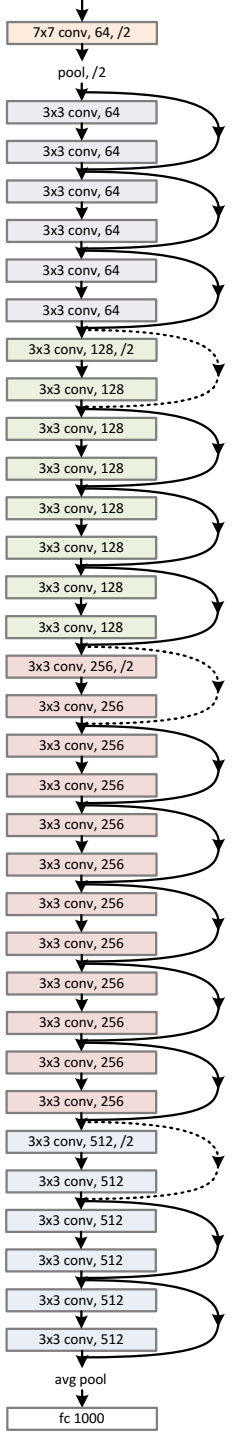
ResNet's key idea: skip connections for curing vanishing gradient.



ResNet [He *et al.* 2015]

A block of ResNet

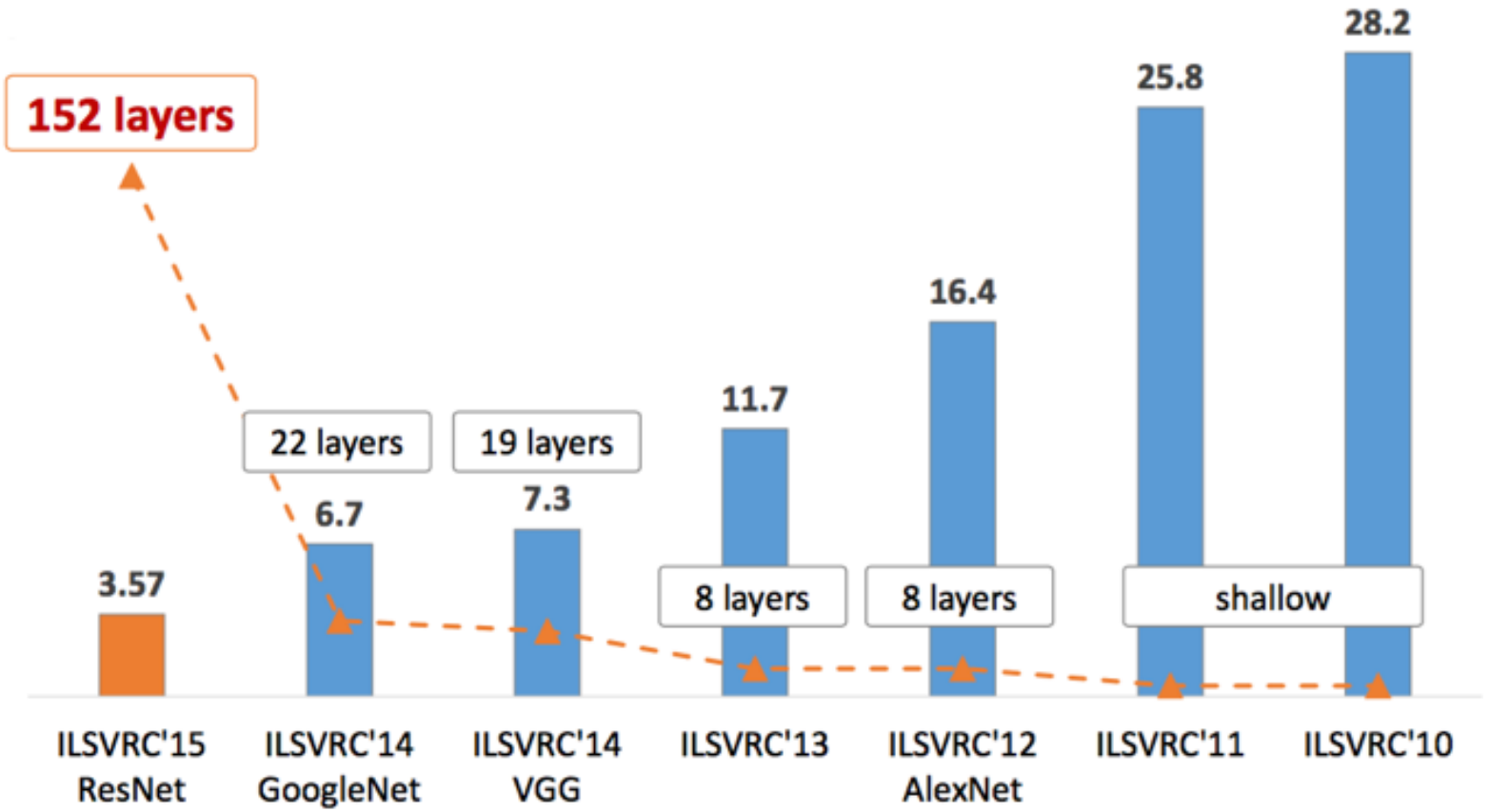




Winners of the ImageNet Challenge

number of layers

top-5 error rate



Classification Error: Top-1 vs. Top-5

Label: “wolf”

ConvNet

class	pred. probability
husky	0.50
wolf	0.20
dog	0.18
fox	0.08
snow	0.01
fur	0.01
forest	0.01
⋮	

Classification Error: Top-1 vs. Top-5

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Evaluated by the Top-1 error,
this prediction is **wrong**!

Classification Error: Top-1 vs. Top-5

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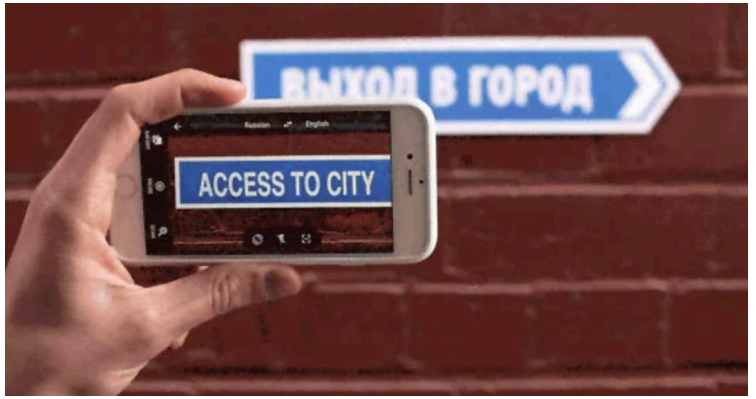
Evaluated by the Top-5 error,
the prediction is **correct**!

Beyond the Accuracy

Deep Learning on the Edge

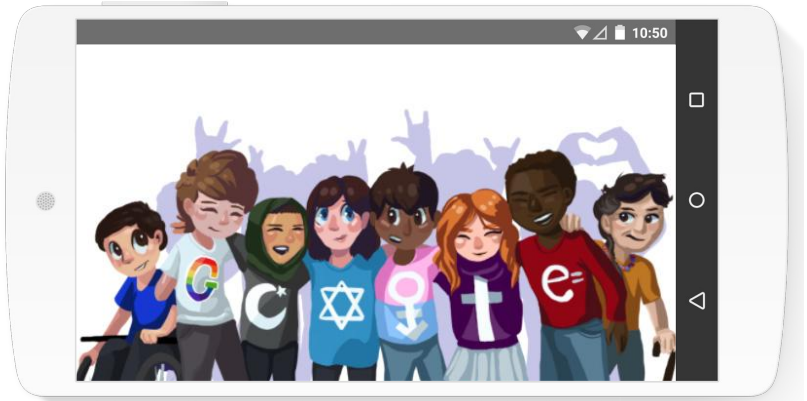
Object Detection

Photo by Juanedc (CC BY 2.0)

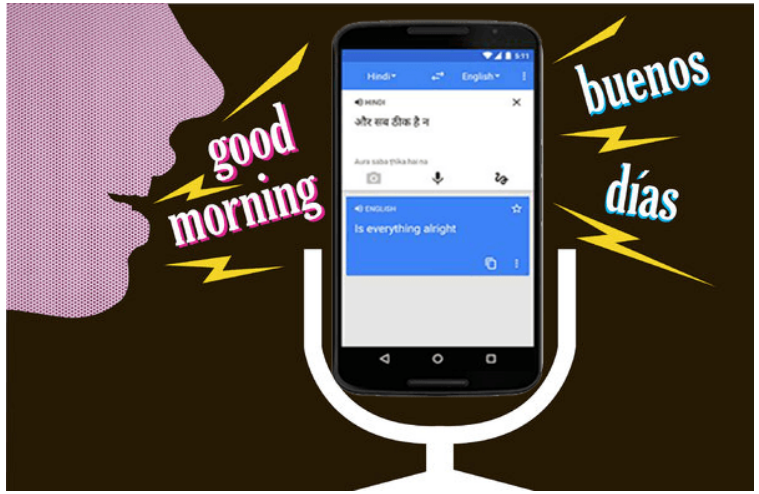


OCR & Translation

Face Attributes

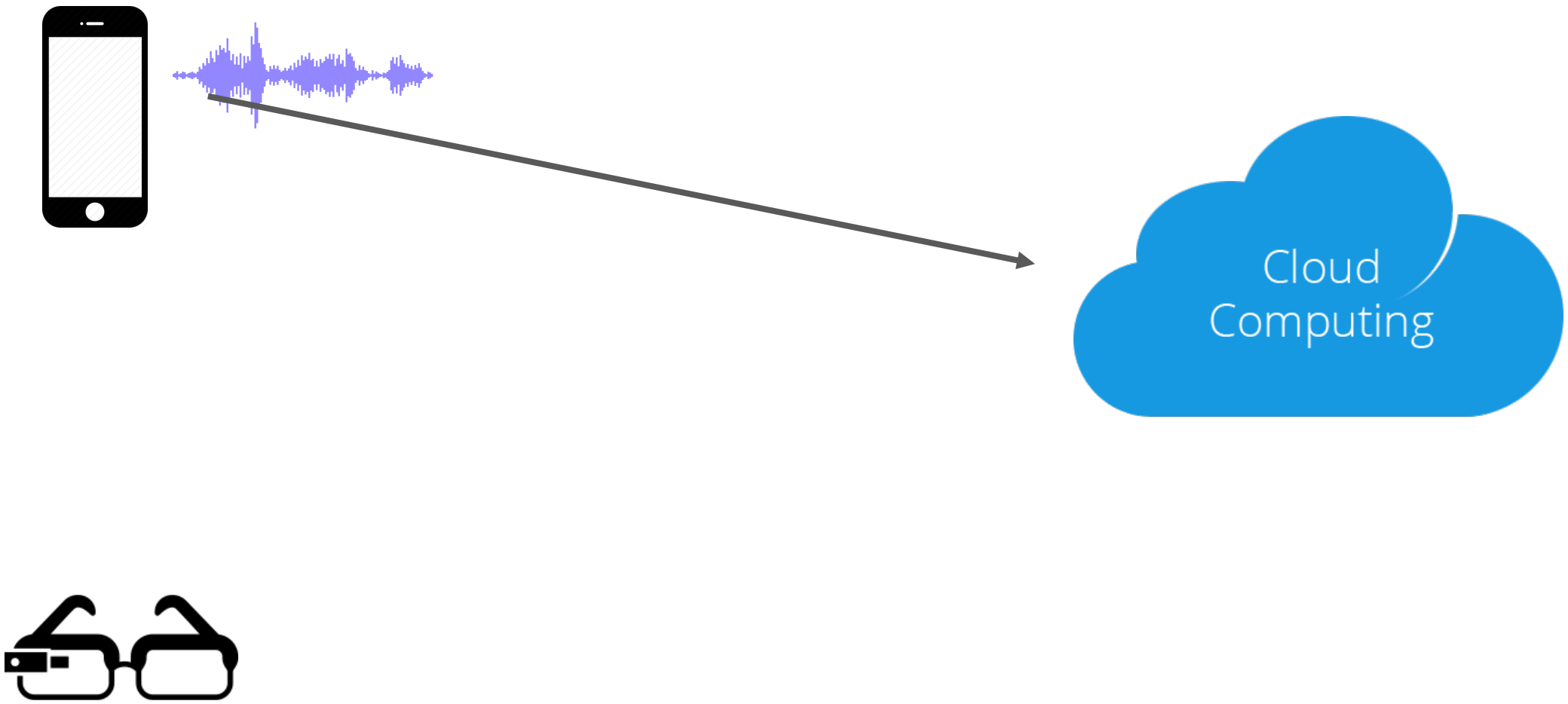


Google Doodle by Sarah Harrison

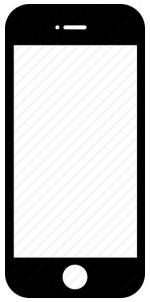


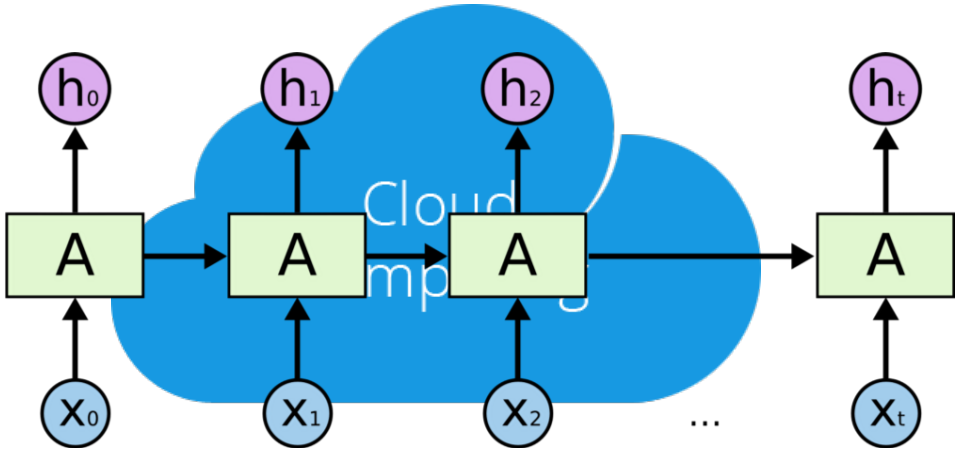
Speech Recognition & Translation

Solution 1: Could Computing

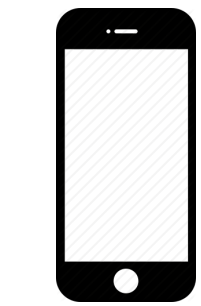


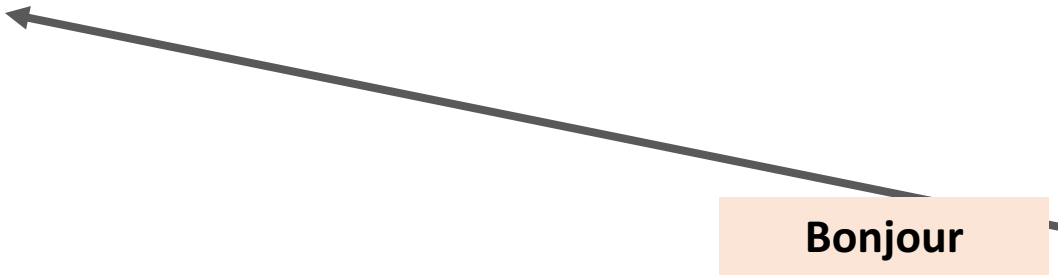
Solution 1: Could Computing



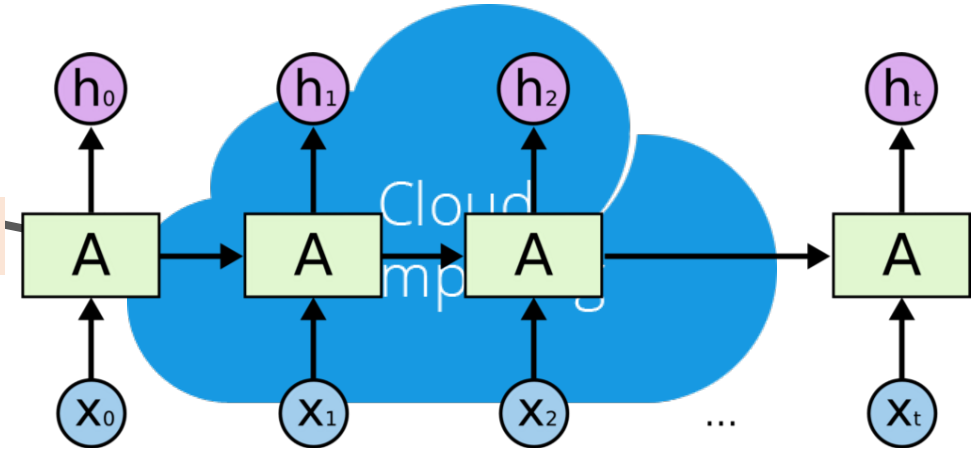


Solution 1: Could Computing





Bonjour



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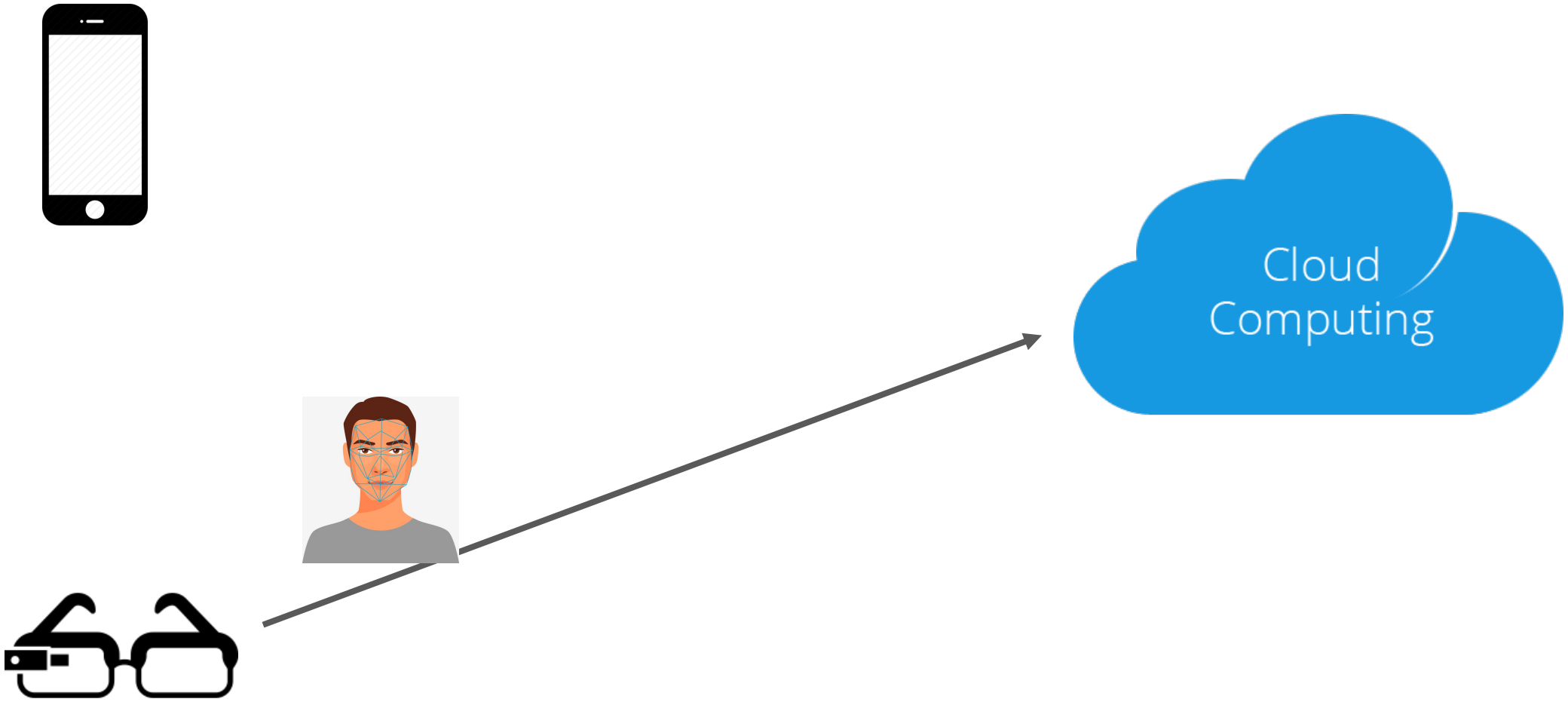

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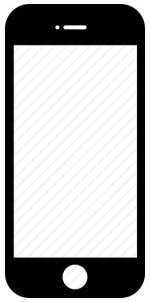

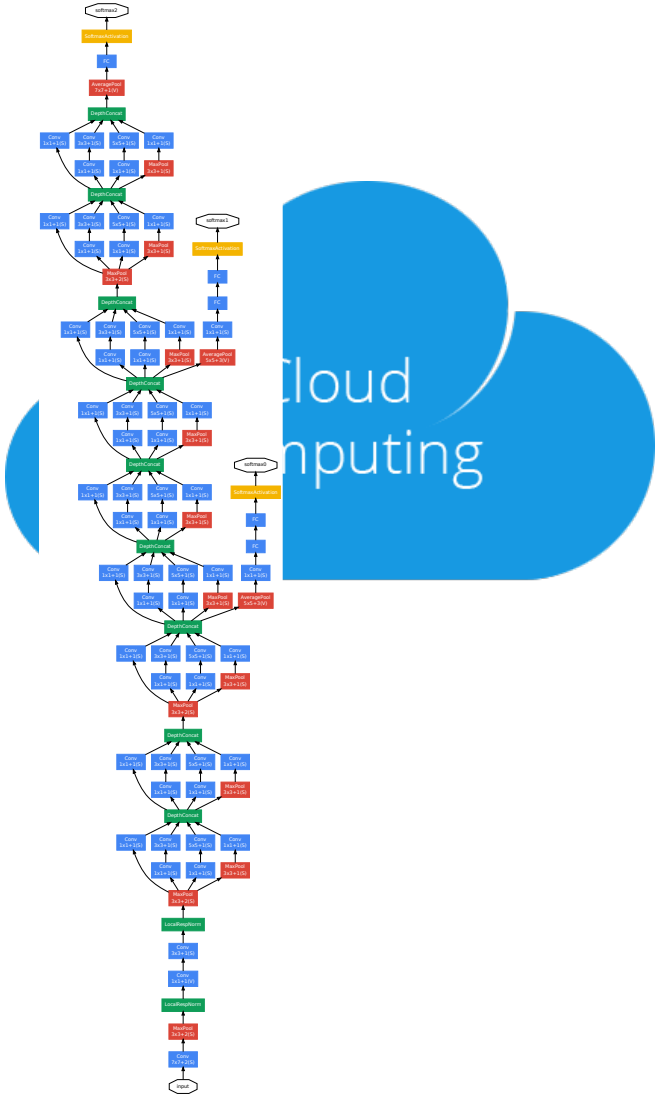

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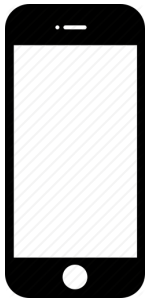
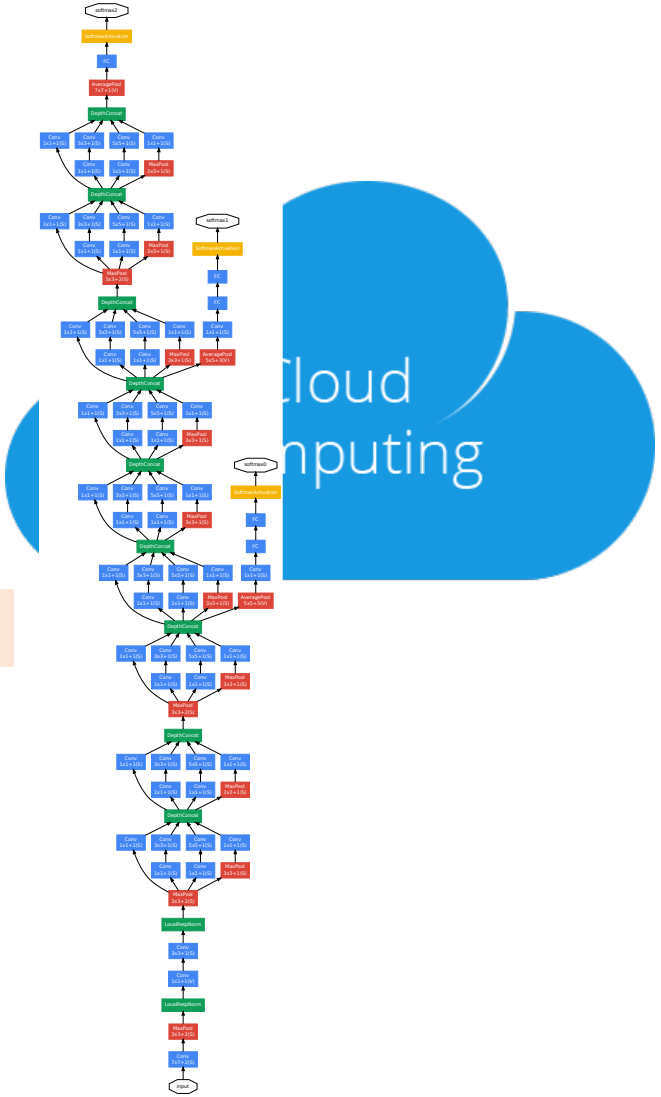


Name and ID

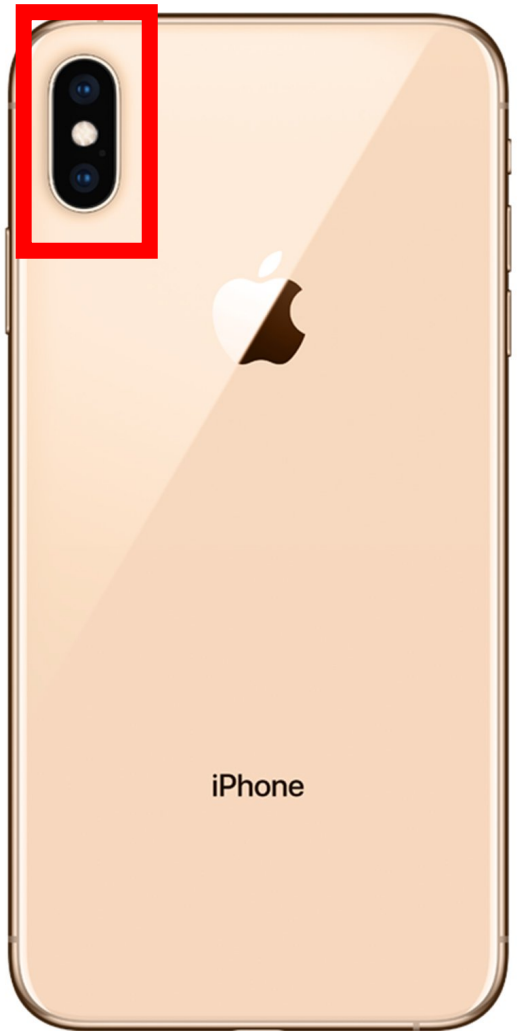


Solution 1: Could Computing

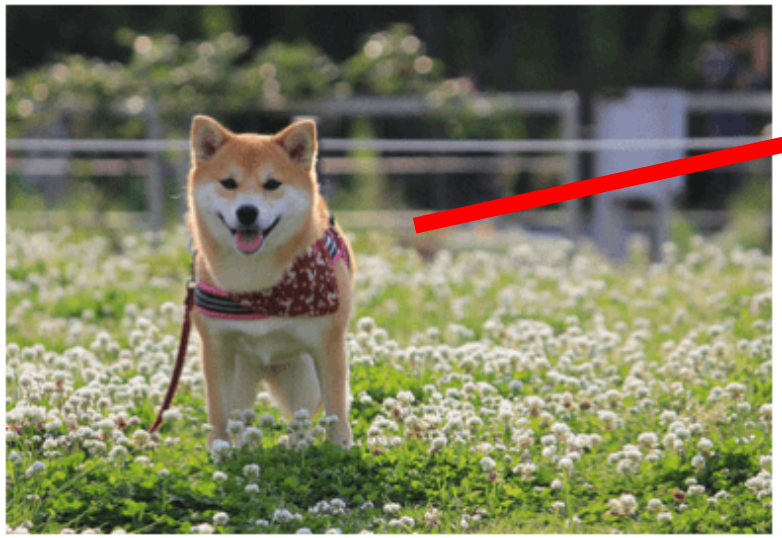
Downsides:

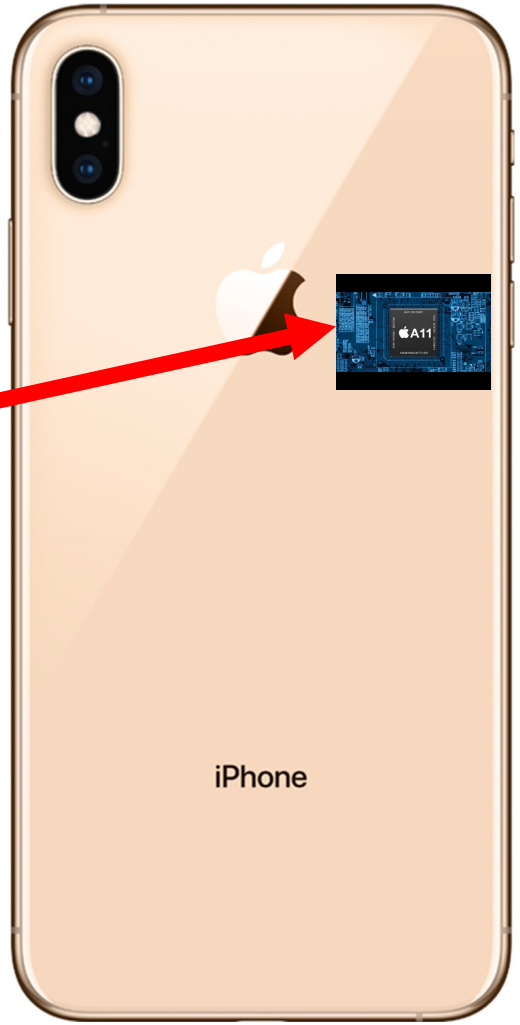
1. Sending data between client and server is relatively slow (in comparing with local computation on the device.)
2. Sending data through 3G/4G/5G network may be charged.
3. User's privacy.

Solution 2: Edge Computing



Solution 2: Edge Computing





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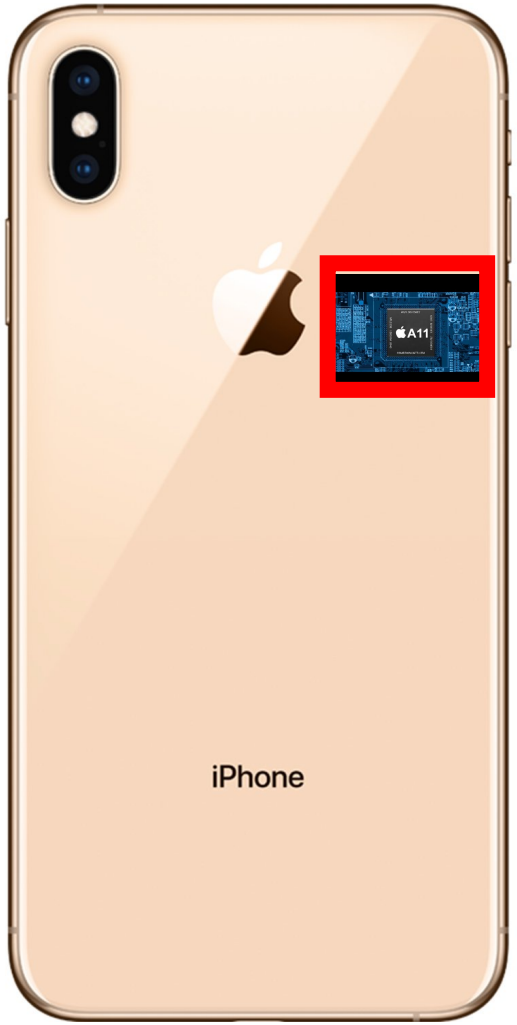

Run a ConvNet on the chip to make prediction.
(The ConvNet has been trained on the server.)

Solution 2: Edge Computing

Advantages:

1. Faster. (Computation is typically faster than communication.)
2. Avoid sending and receiving data.
   - Save money.
   - Works without internet.
3. Protect user's privacy.

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Advantages:

1. Faster. (Computation is typically faster than communication.)
2. Avoid sending and receiving data.
   - Save money.
   - Works without internet.
3. Protect user's privacy.

Disadvantages:

1. Energy consumption. (Heavy matrix and tensor computation.)
2. Cost local memory and storage. (Deep ConvNets has at least millions of parameters.)

Run a ConvNet on the chip to make prediction.
(The ConvNet has been trained on the server.)

Cloud Computing V.S. Edge Computing

- Edge computing is more popular for the deep learning tasks (at present).
- Research: deep learning on the edge
  1. Less float point operations (FLOPs). (Thus less energy consumption.)
  2. Less network parameters. (Thus less memory and storage.)

MobileNet [Howard *et al.* 2017]

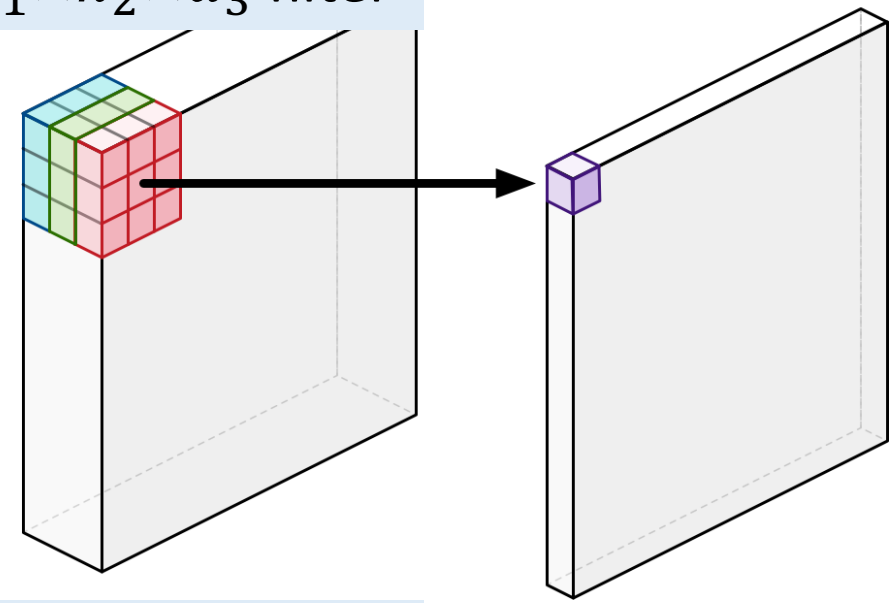
- Motivations
  - Small enough to fit in an iPhone (just $4M$ parameters).
  - Less computation than the standard ConvNets.
- Key idea: Depthwise separable convolution.
- Paper: https://arxiv.org/pdf/1704.04861.pdf
- Further reading:
  - http://machinethink.net/blog/googles-mobile-net-architecture-on-iphone/
  - https://medium.com/@yu4u/why-mobilenet-and-its-variants-e-g-shufflenet-are-fast-1c7048b9618d

Convolution

convolution

`keras.layers.Conv2D`

One $k_1 \times k_2 \times d_3$ filter



$d_1 \times d_2 \times d_3$ input

In this example, $d_3 = 3$.

Convolution

convolution

`keras.layers.Conv2D`

One $k_1 \times k_2 \times d_3$ filter

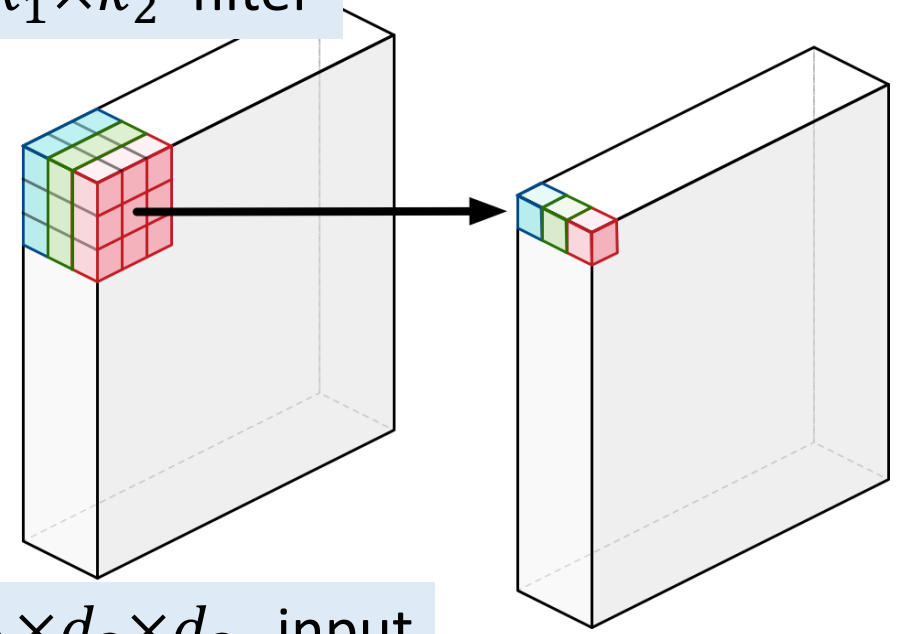
$d_1 \times d_2 \times d_3$ input

$d_1 \times d_2 \times 1$ output

depthwise convolution

`keras.layers.DepthwiseConv2D`

One $k_1 \times k_2$ filter



$d_1 \times d_2 \times d_3$ input

Convolution

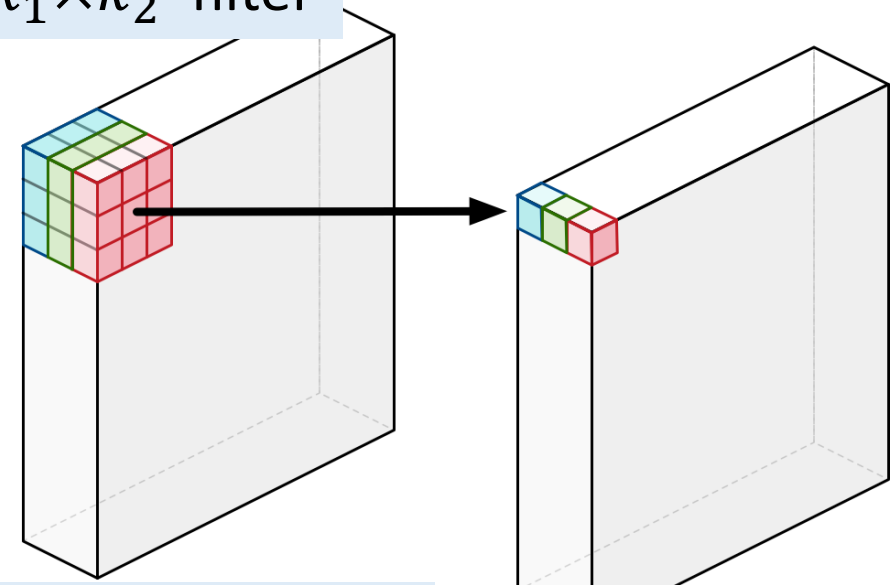
depthwise convolution

`keras.layers.DepthwiseConv2D`

For $i = 1$ to d_3 (each of the slices):

- Compute the convolution of the i-th slice (shape $d_1 \times d_2$) and the filter (shape $k_1 \times k_2$).
- Output: a matrix (shape $d_1 \times d_2$).

One $k_1 \times k_2$ filter



$d_1 \times d_2 \times d_3$ input

Convolution

depthwise convolution

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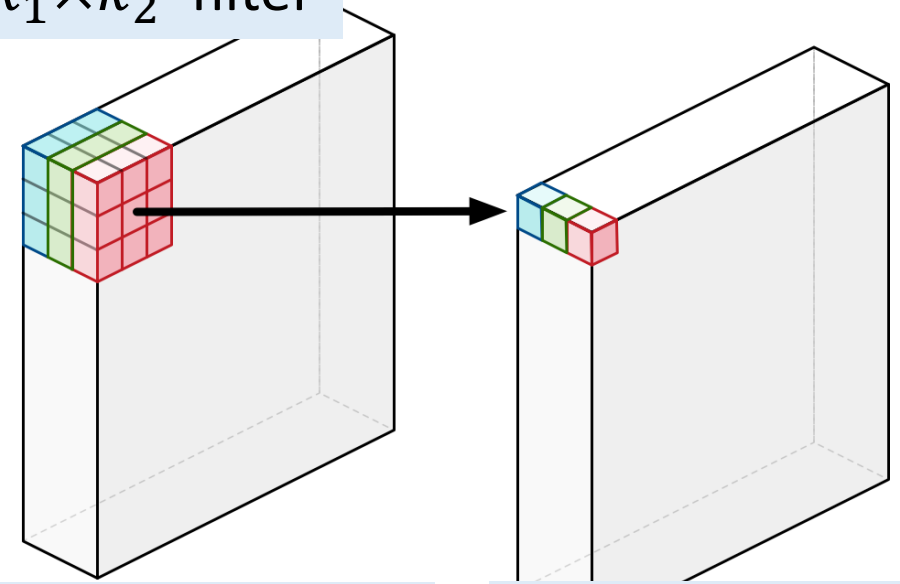
For $i = 1$ to d_3 (each of the slices):

- Compute the convolution of the i-th slice (shape $d_1 \times d_2$) and the filter (shape $k_1 \times k_2$).
- Output: a matrix (shape $d_1 \times d_2$).

Thus the final output is $d_1 \times d_2 \times d_3$.

One $k_1 \times k_2$ filter

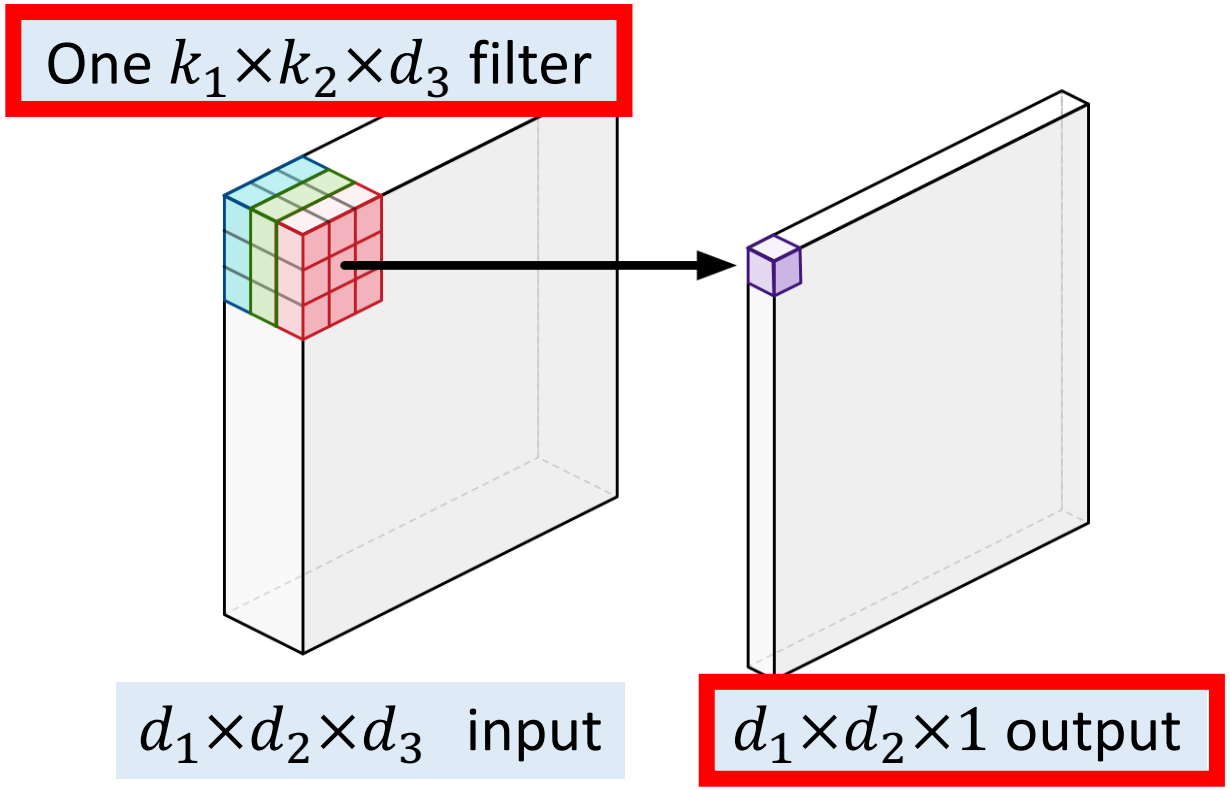


$d_1 \times d_2 \times d_3$ input

$d_1 \times d_2 \times d_3$ output

Convolution

convolution
`keras.layers.Conv2D`



depthwise convolution
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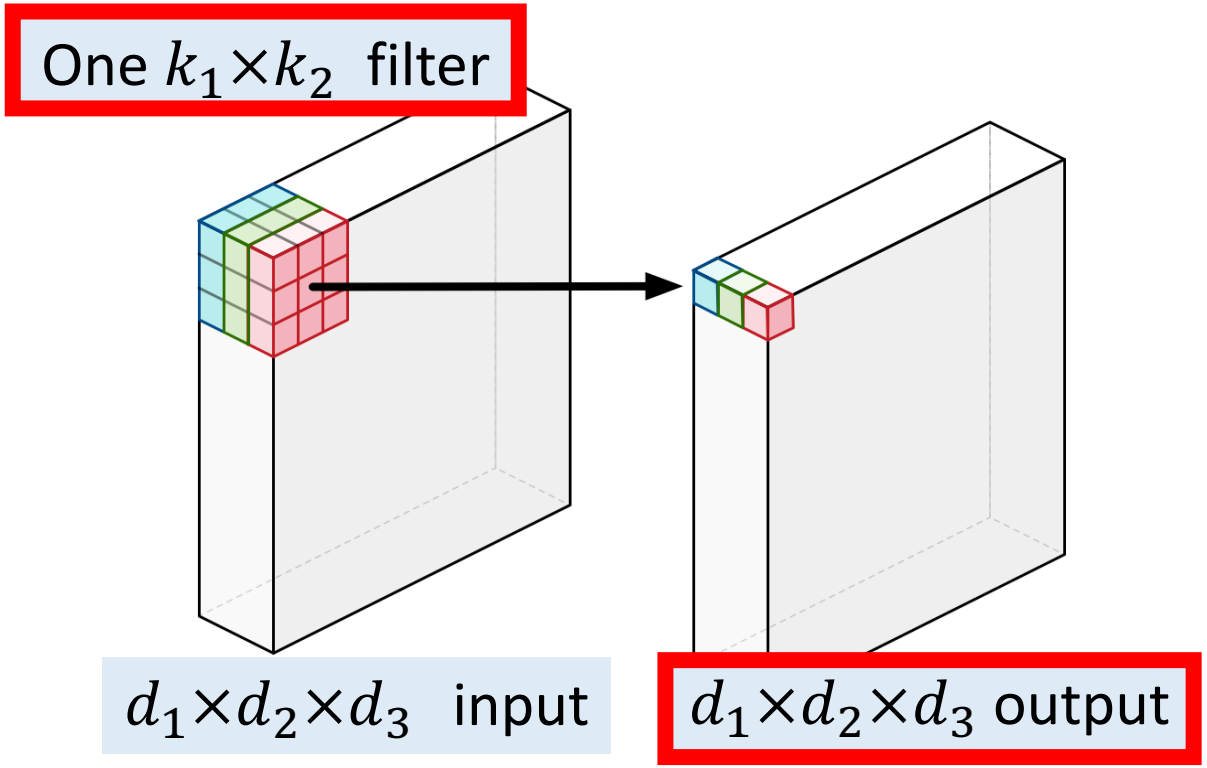
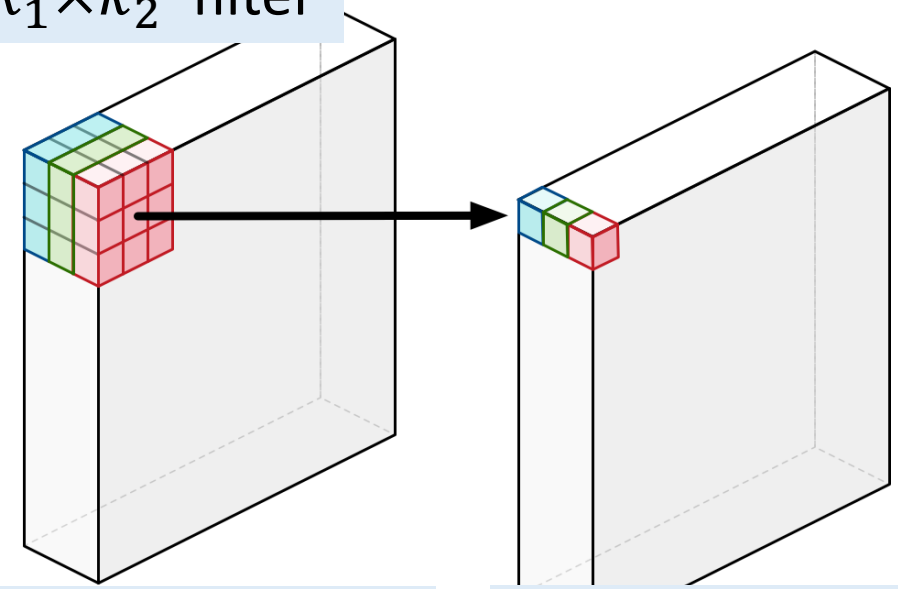


MobileNet: Depthwise Conv + 1×1 Conv

depthwise convolution
`keras.layers.DepthwiseConv2D`

One $k_1 \times k_2$ filter

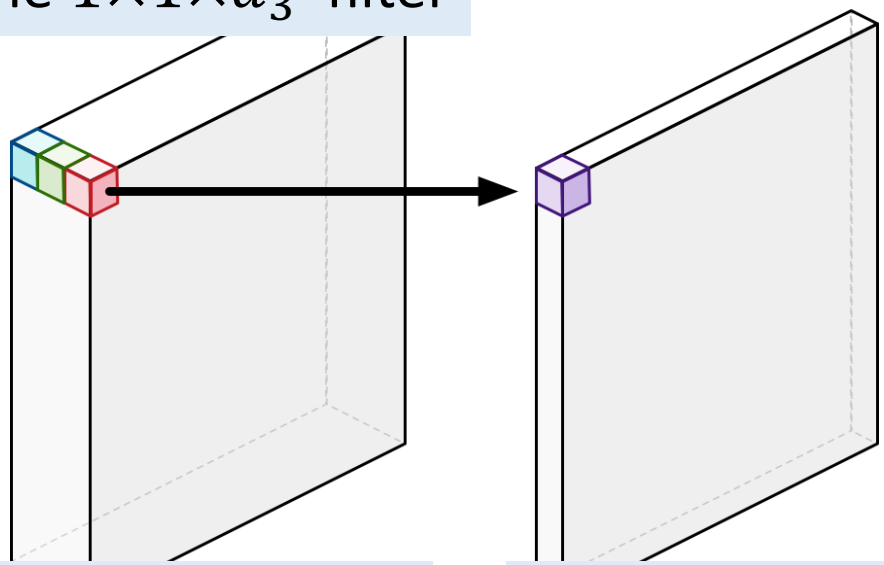


$d_1 \times d_2 \times d_3$ input

$d_1 \times d_2 \times d_3$ output

1×1 convolution
`keras.layers.Conv2D`

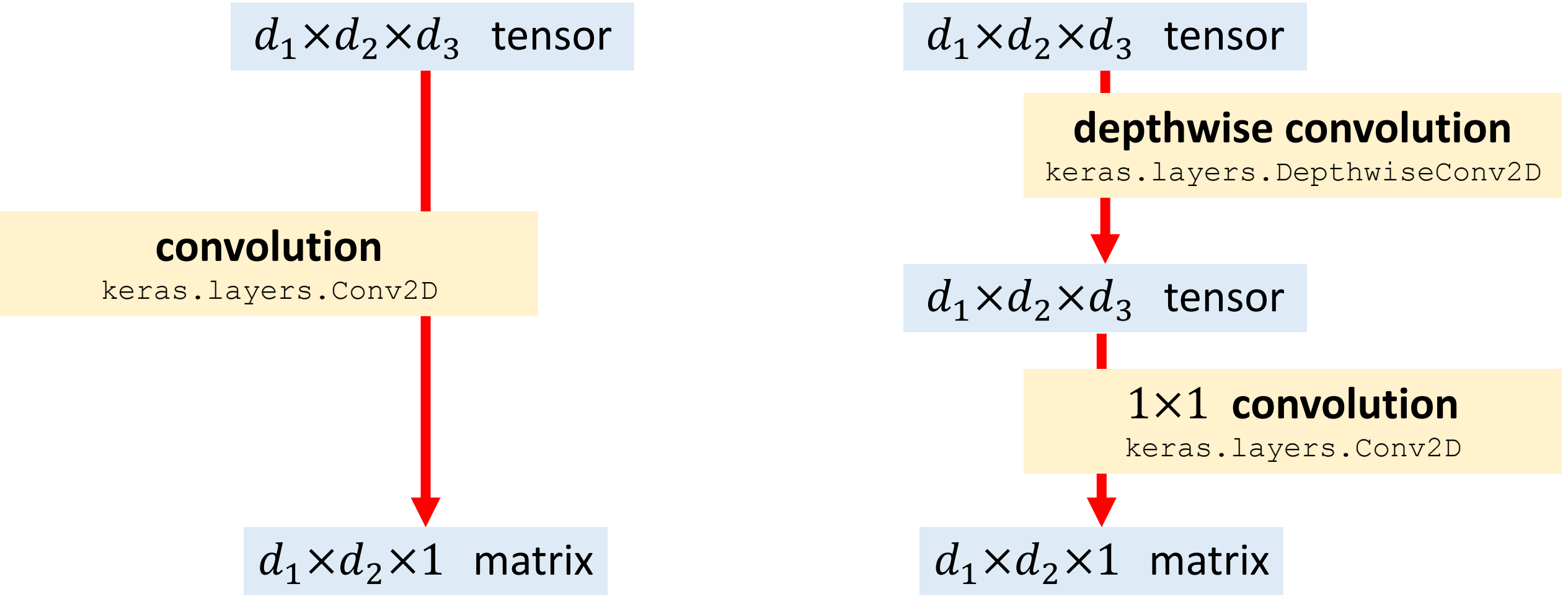
One $1 \times 1 \times d_3$ filter



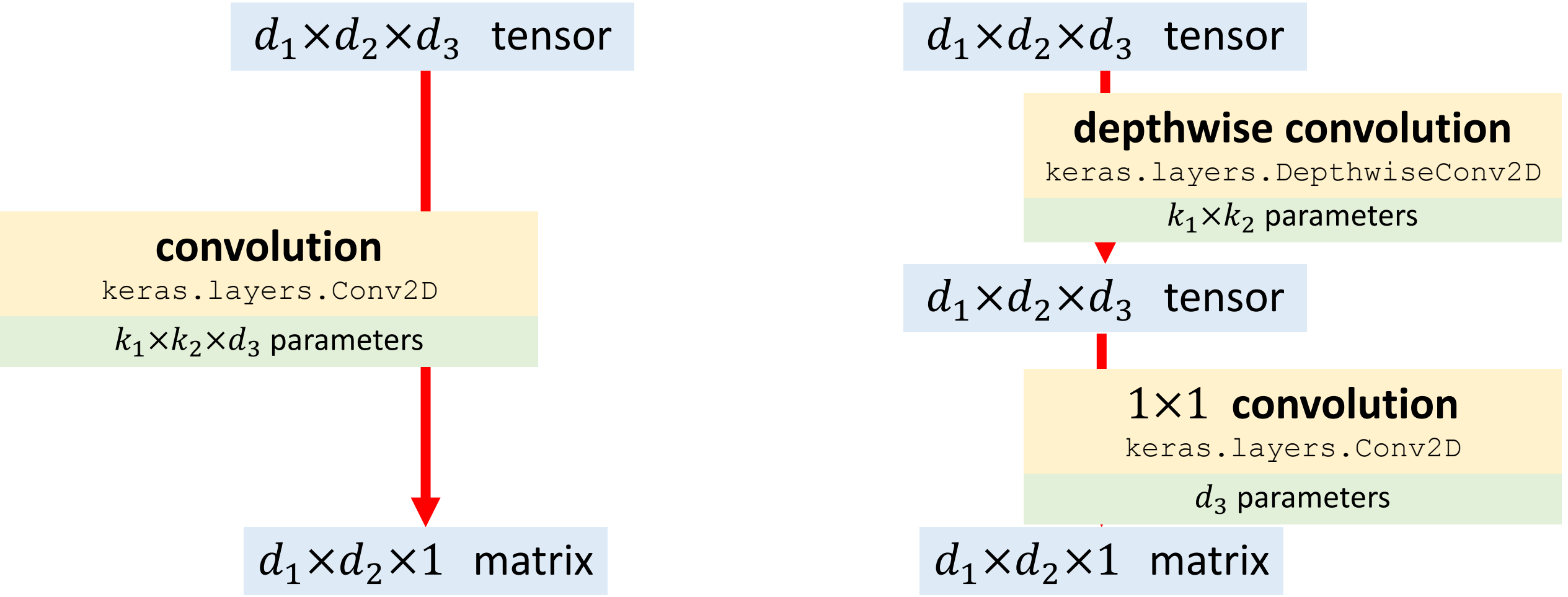
$d_1 \times d_2 \times d_3$ input

$d_1 \times d_2 \times 1$ output

MobileNet: Depthwise Separable Conv + 1×1 Conv



MobileNet: Depthwise Separable Conv + 1×1 Conv



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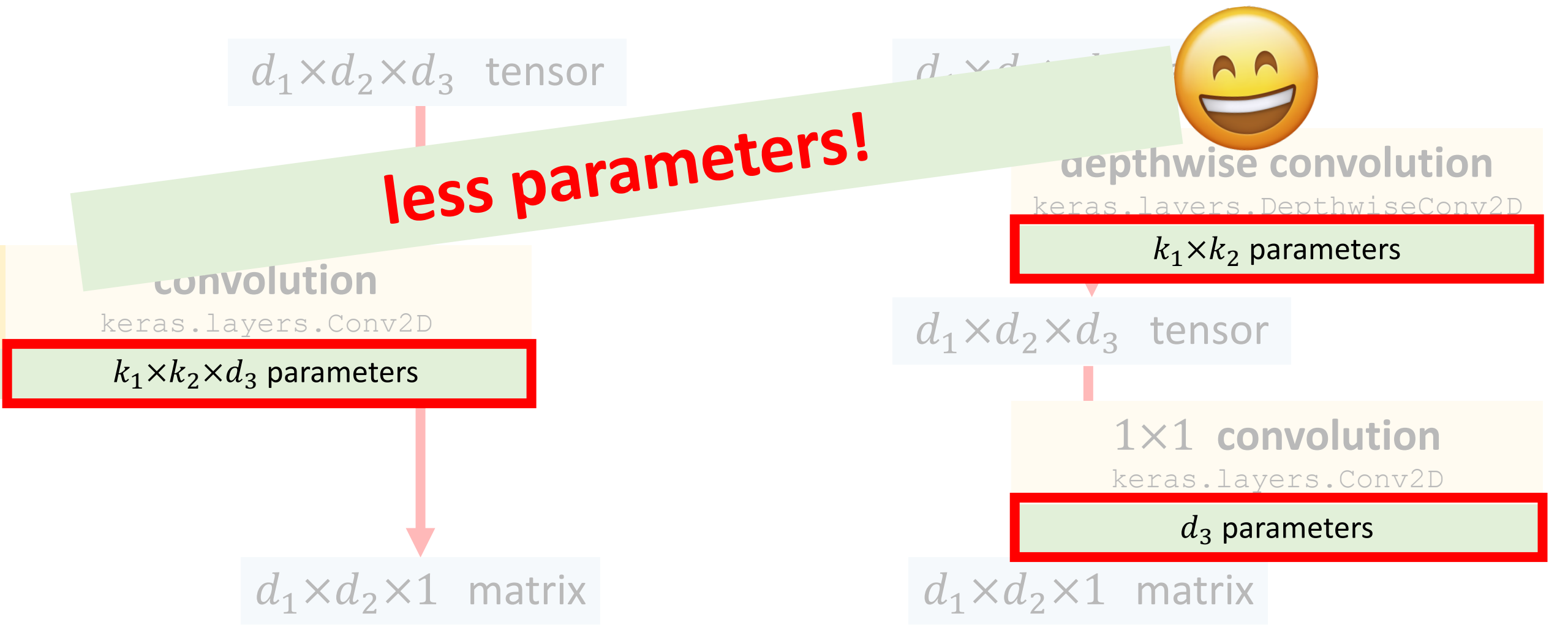

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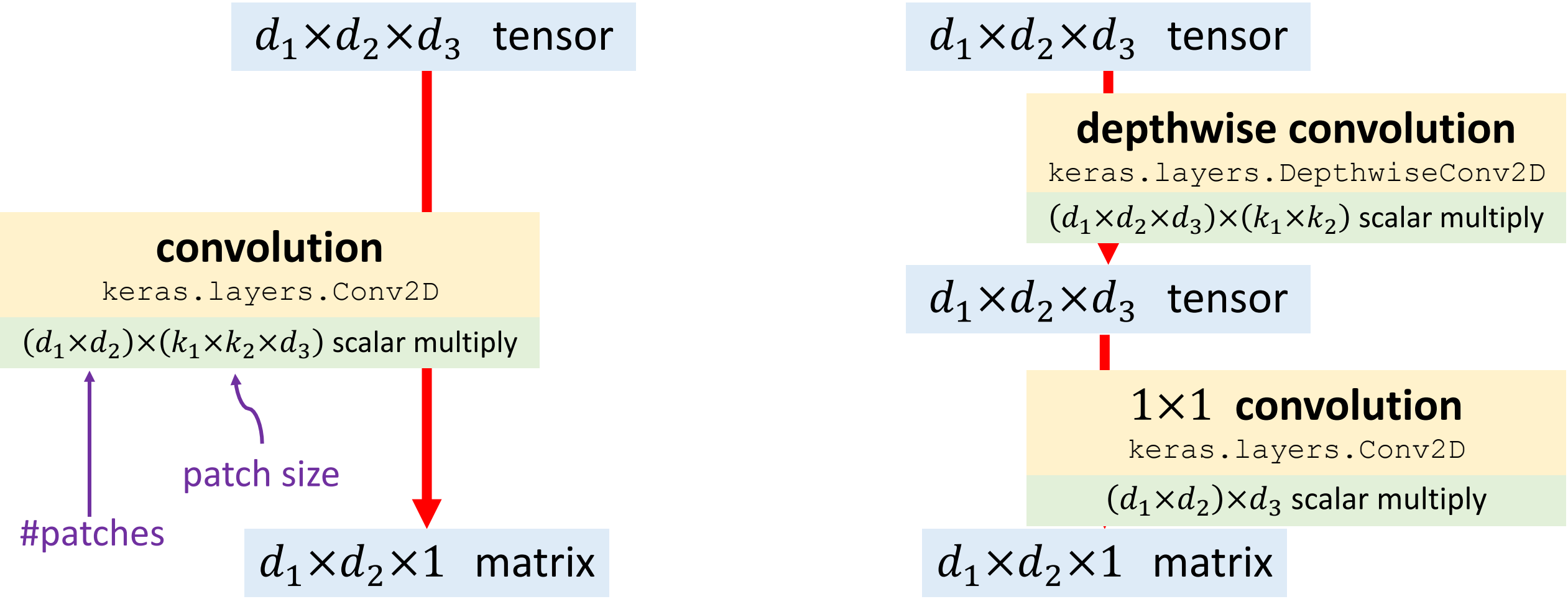

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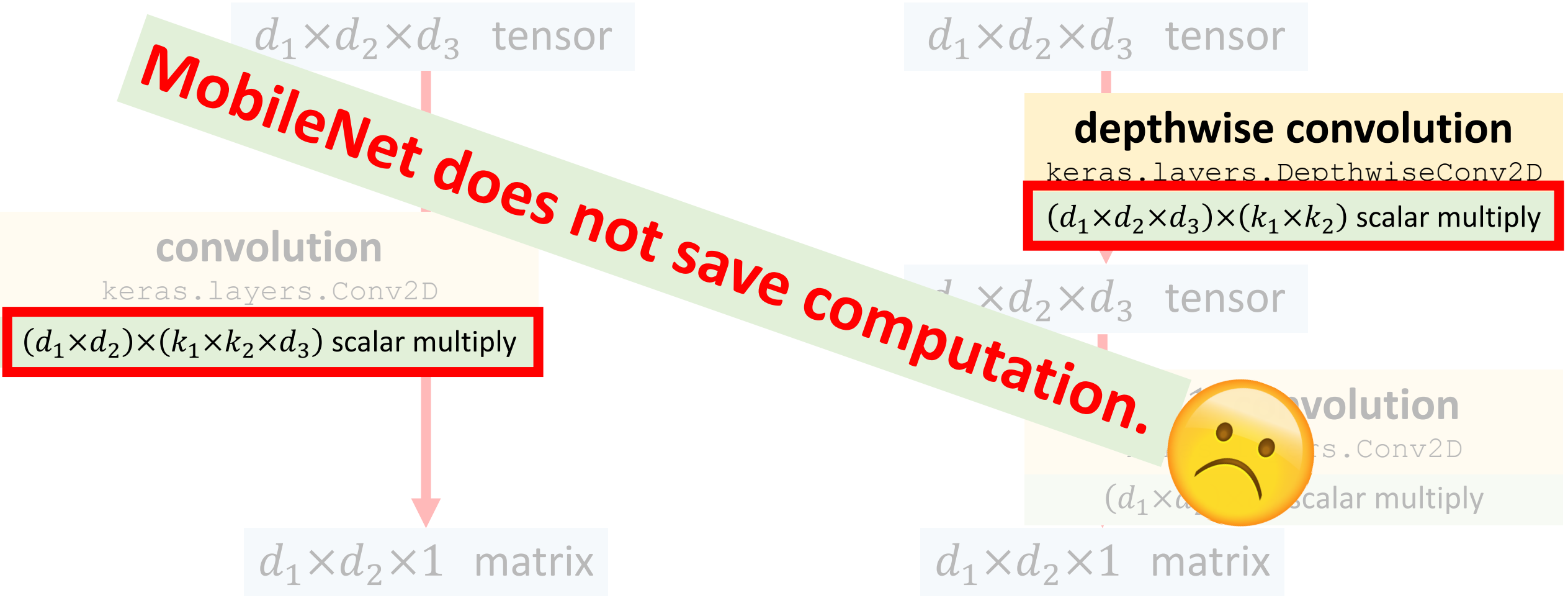
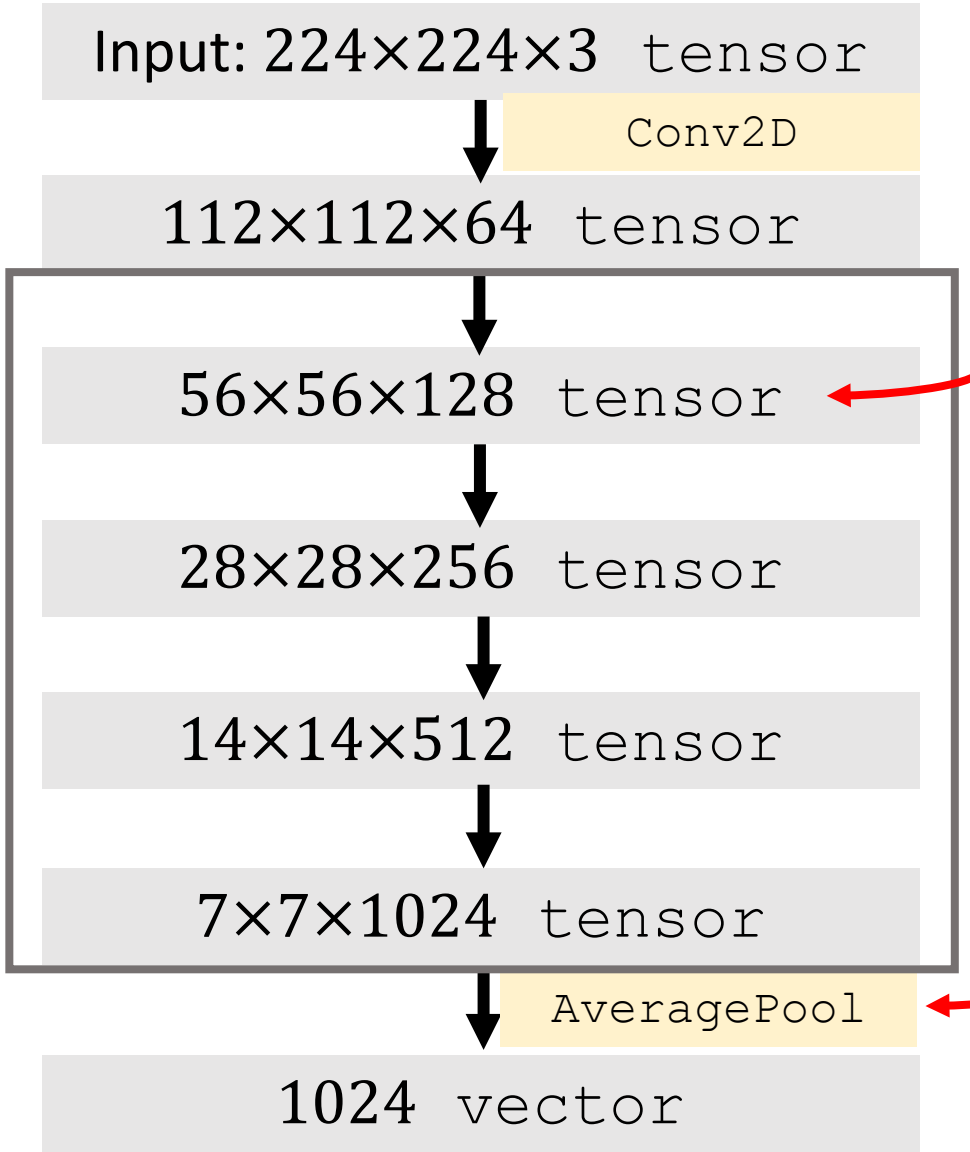


MobileNet



Half the width and height, double the depth.

Why not using “Flatten”?

Implementation in Keras

separable convolution
`keras.layers.SeparableConv2D`

- In Keras, you can directly use `SeparableConv2D` to build MobileNet.
- `SeparableConv2D = DepthwiseConv2D + Conv2D(1×1)`

depthwise convolution
`keras.layers.DepthwiseConv2D`

+

1×1 convolution
`keras.layers.Conv2D`

Implementation in Keras

```
import keras
model = keras.applications.mobilenet.MobileNet(input_shape=None,
            alpha=1.0, depth_multiplier=1, dropout=1e-3,
            include_top=True, weights='imagenet',
            input_tensor=None, pooling=None, classes=1000)
model.summary()
```

Summary

CNN Architectures

- LeNet-5: 2 Conv + 2 FC layers.
- AlexNet: 5 Conv + 3 FC layers.
- VGG16: 13 Conv + 2 FC layers.

} classic architectures (sequential)

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} classic architectures (sequential)

Question: Can the classic architectures go deeper?

Answer: No.

- Deeper nets have worse training and test errors.
- Vanishing gradient.

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- AlexNet: 5 Conv + 3 FC layers.
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classic architectures (sequential)

- Inception: 21 Conv + 1 FC layers.
- ResNet: Up to 151 Conv + 1 FC layers.

modern architectures

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classic architectures (sequential)

- Inception: 21 Conv + 1 FC layers.
- ResNet: Up to 151 Conv + 1 FC layers.

modern architectures

Tricks:

- Inception: auxiliary output (gradient injection).
- ResNet: skip connection.

Reduce Memory and Computation

- Deploy a deep neural network to a smart device.
- Challenges:
  - Computation → Power consumption.
  - Parameters → Storage and memory.

Reduce Memory and Computation

- Deploy a deep neural network to a smart device.
- Challenges:
  - Computation ➔ Power consumption.
  - Parameters ➔ Storage and memory.
- MobileNet's solutions:
  - Separable Convolution instead of Tensor Convolution.
  - AveragePool Layer instead of Flatten Layer. (Proposed by Inception Net.)