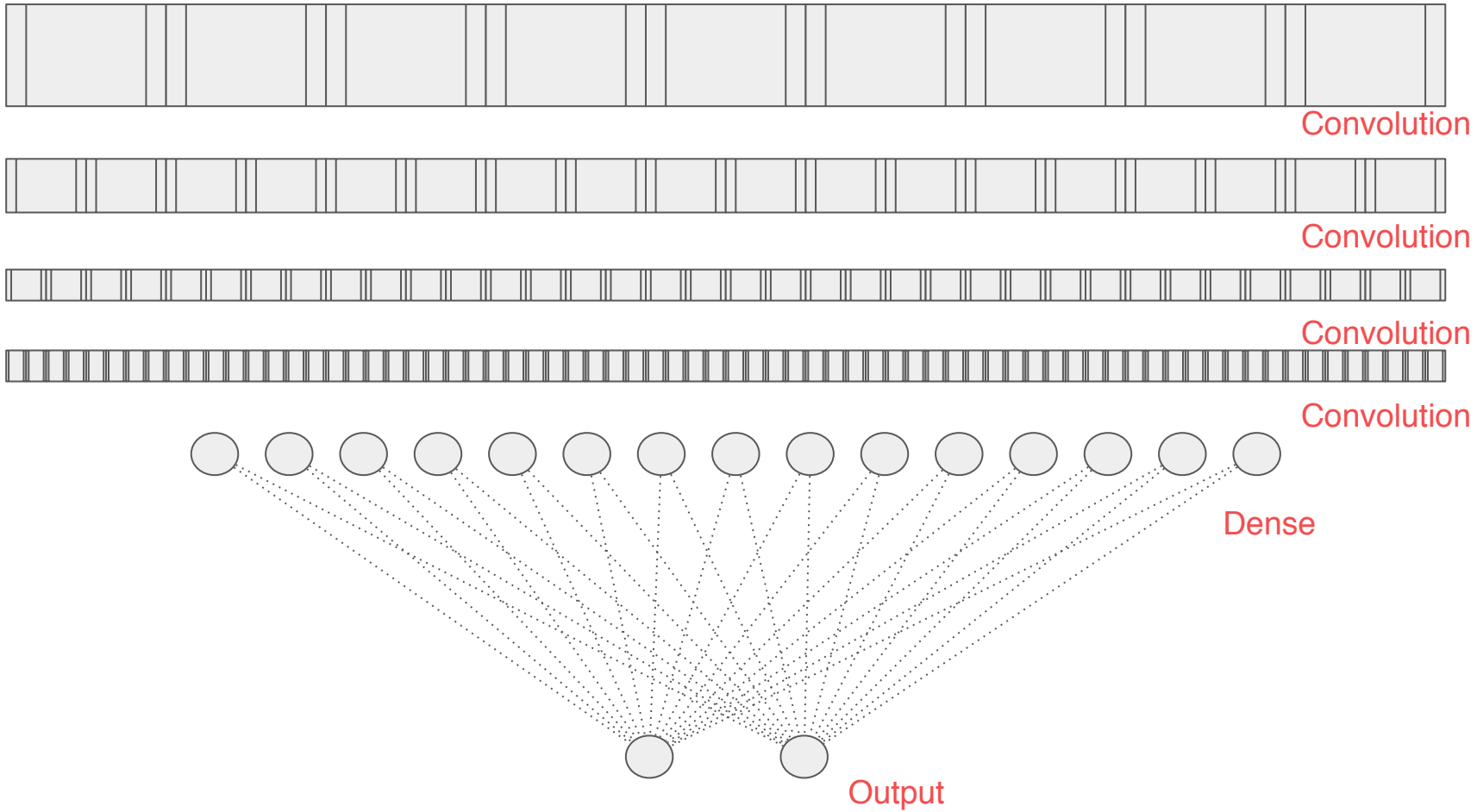
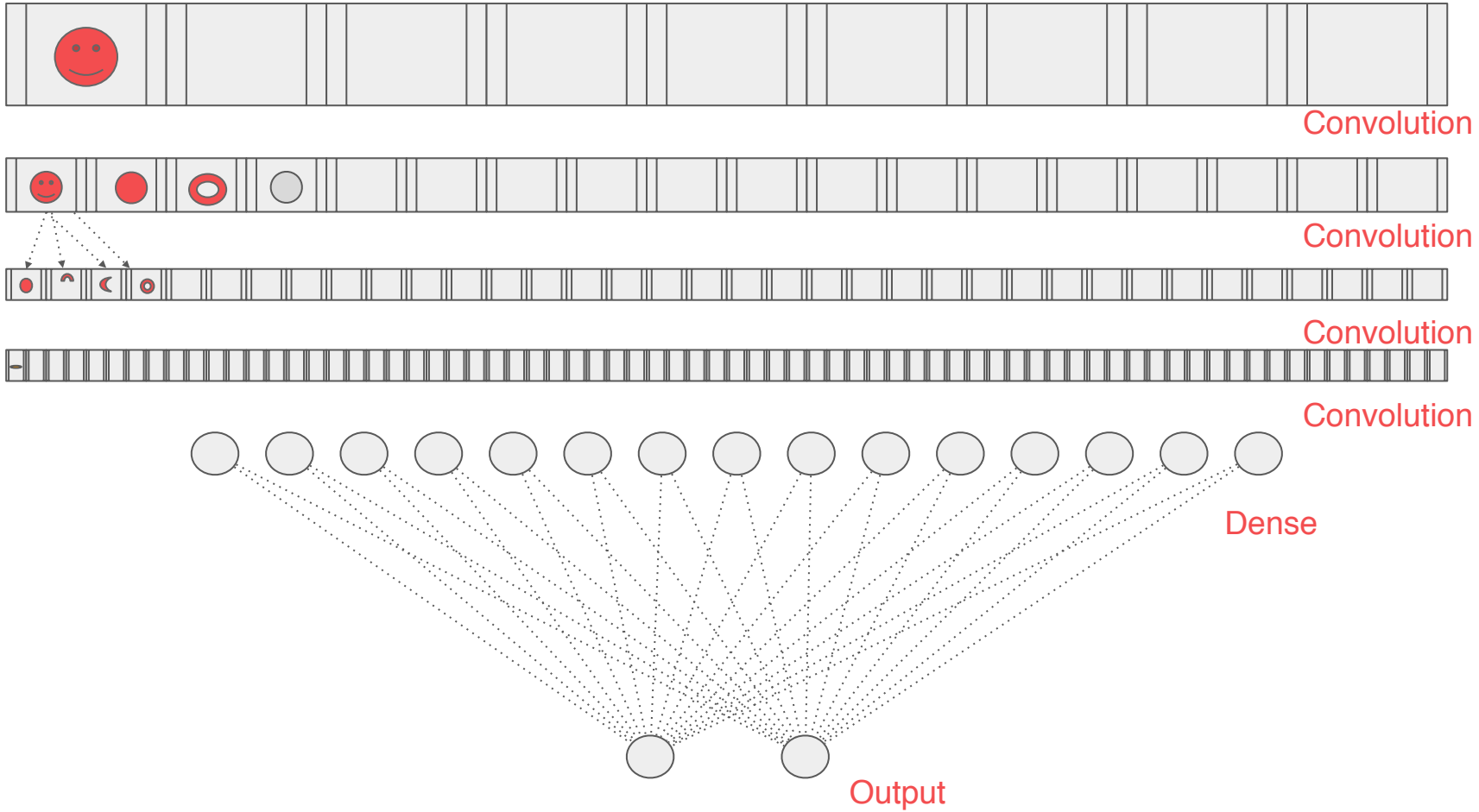
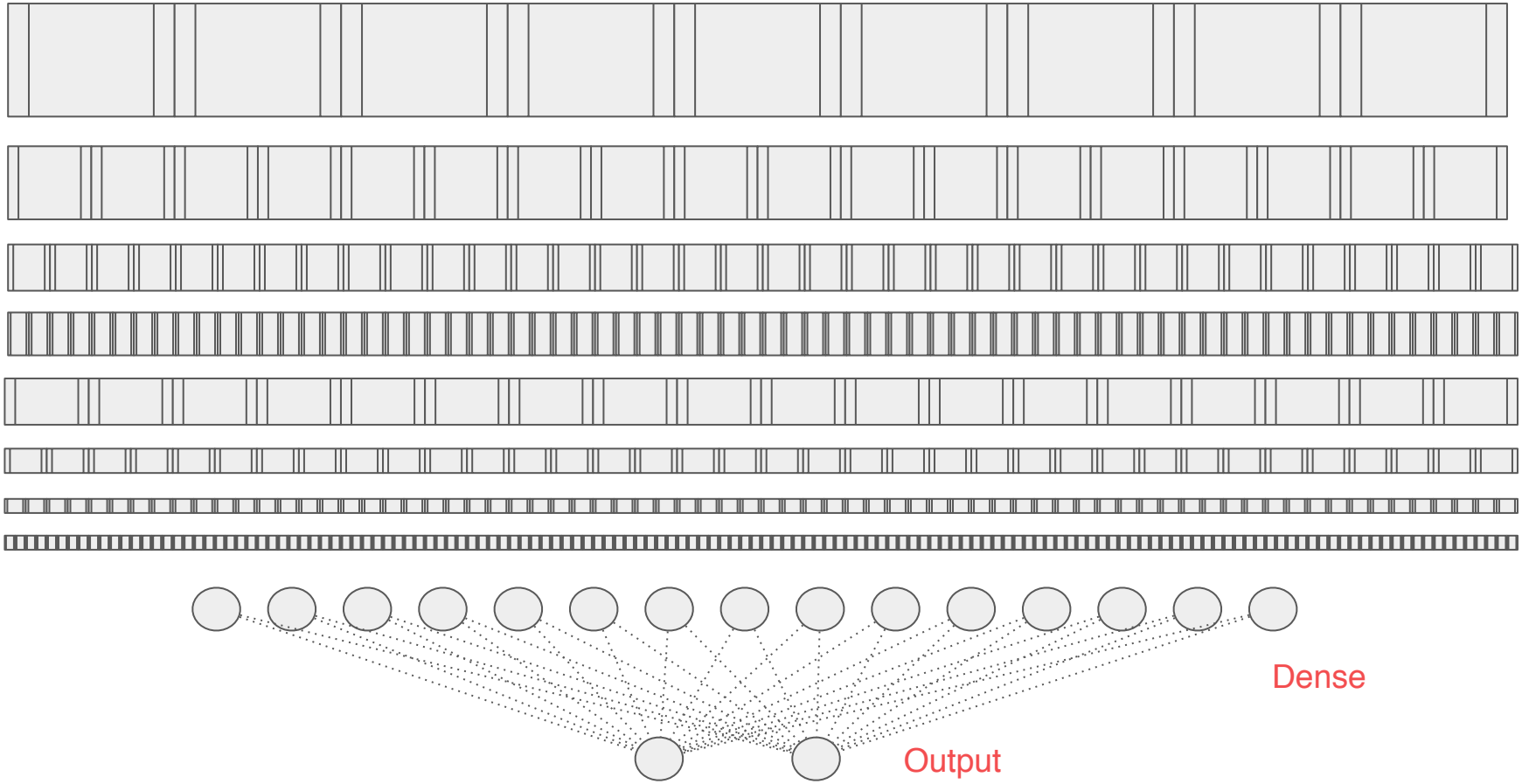
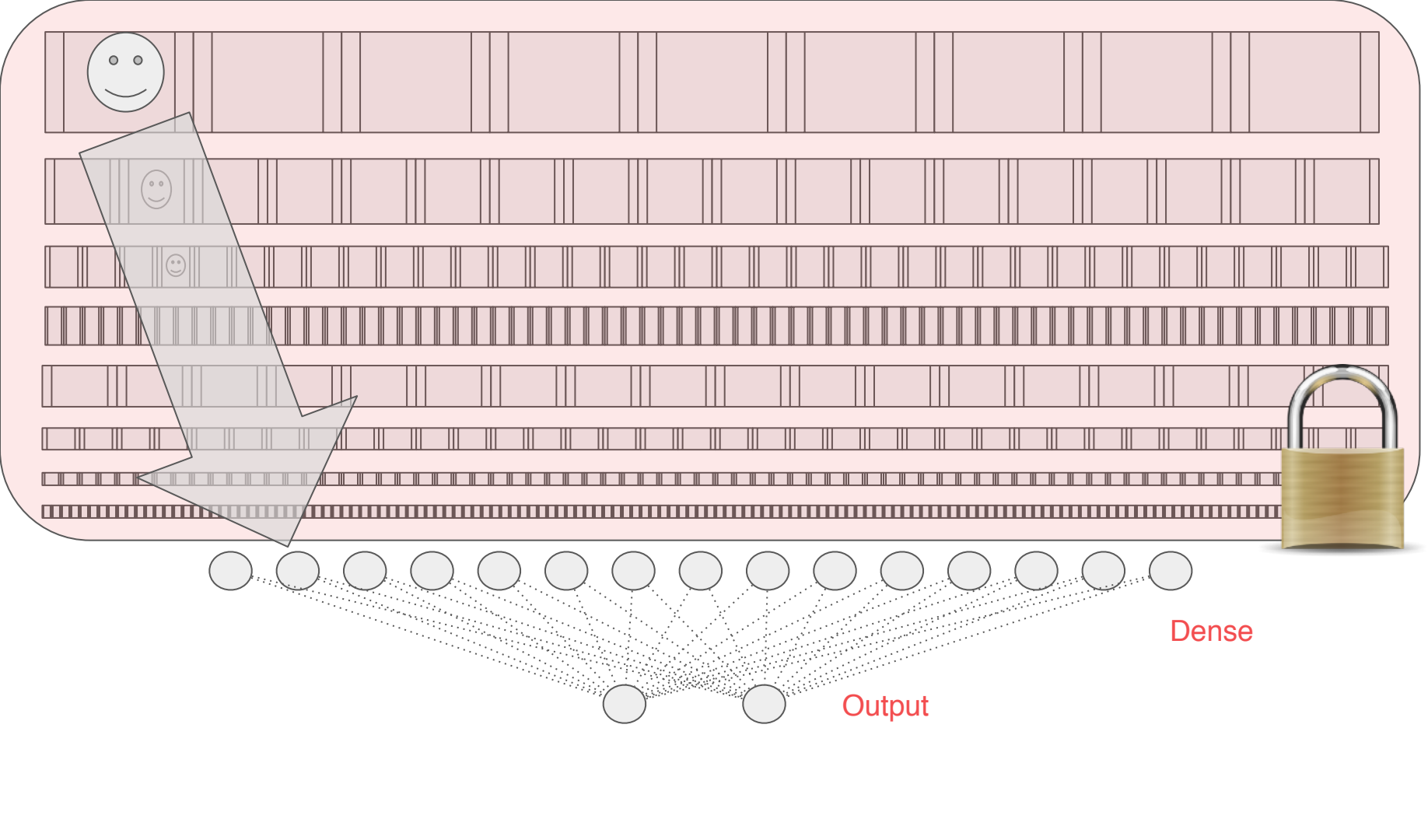
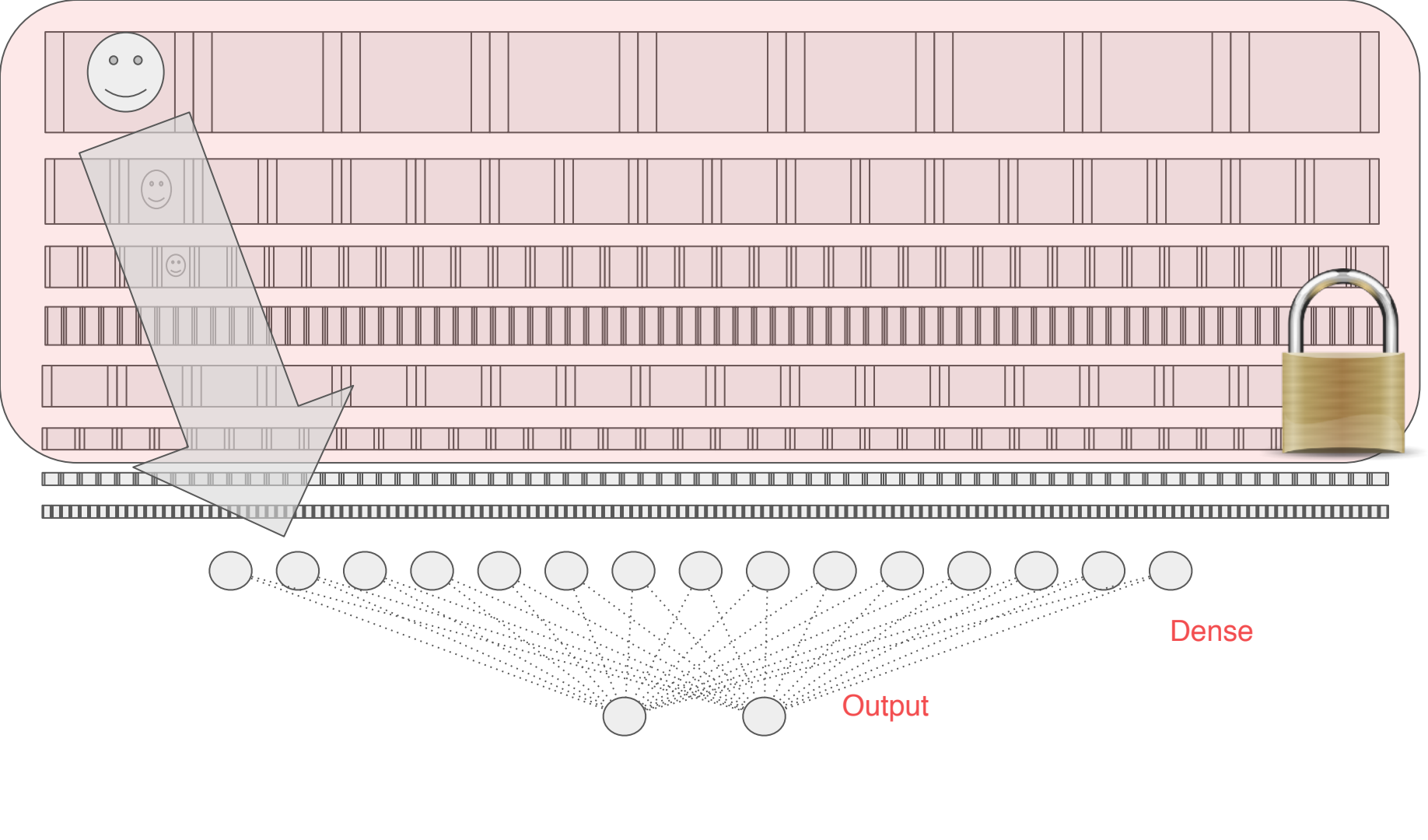
Copyright Notice


Convolution
Convolution
Convolution
Convolution
Dense
Output


Convolution
Convolution
Convolution
Convolution
Dense
Output


Dense
Output


Dense
Output


Dense
Output

https://arxiv.org/abs/1512.00567

Computer Science > Computer Vision and Pattern Recognition

Rethinking the Inception Architecture for Computer Vision

Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, Zbigniew Wojna

(Submitted on 2 Dec 2015 (v1), last revised 11 Dec 2015 (this version, v3))

Convolutional networks are at the core of most state-of-the-art computer vision solutions for a wide variety of tasks. Since 2014 very deep convolutional networks started to become mainstream, yielding substantial gains in various benchmarks. Although increased model size and computational cost tend to translate to immediate quality gains for most tasks (as long as enough labeled data is provided for training), computational efficiency and low parameter count are still enabling factors for various use cases such as mobile vision and big-data scenarios. Here we explore ways to scale up networks in ways that aim at utilizing the added computation as efficiently as possible by suitably factorized convolutions and aggressive regularization. We benchmark our methods on the ILSVRC 2012 classification challenge validation set demonstrate substantial gains over the state of the art: 21.2% top-1 and 5.6% top-5 error for single frame evaluation using a network with a computational cost of 5 billion multiply-adds per inference and with using less than 25 million parameters. With an ensemble of 4 models and multi-crop evaluation, we report 3.5% top-5 error on the validation set (3.6% error on the test set) and 17.3% top-1 error on the validation set.

http://image-net.org/

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Click here to learn more about ImageNet, Click here to join the ImageNet mailing list.

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Check out the ImageNet Challenge on Kaggle!

```
import os

from tensorflow.keras import layers
from tensorflow.keras import Model
```

https://storage.googleapis.com/mledu-datasets/

inception_v3_weights_tf_dim_ordering_tf_kernels

```
from tensorflow.keras.applications.inception_v3 import InceptionV3

local_weights_file = '/tmp/inception_v3_weights_tf_dim_ordering_tf_kernels_notop.h5'

pre_trained_model = InceptionV3(input_shape = (150, 150, 3),
                                include_top = False, => set False to go straight to Convolution
                                weights = None)

pre_trained_model.load_weights(local_weights_file)
```

```
for layer in pre_trained_model.layers:
  layer.trainable = False
```
=> Lock all the convolutions and features that already learned into your model in all layers
In order to use pre-trained model layers

```
pre_trained_model.summary()
```

```
last_layer = pre_trained_model.get_layer('mixed7') => Choose Layer to set the output

last_output = last_layer.output => Obtain the layer's output
```

```
from tensorflow.keras.optimizers import RMSprop

x = layers.Flatten()(last_output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dense  (1, activation='sigmoid')(x)

model = Model( pre_trained_model.input, x)
model.compile(optimizer = RMSprop(learning_rate=0.0001),
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

=> Create Flatten Layer by taking the set output

```
from tensorflow.keras.optimizers import RMSprop

x = layers.Flatten()(last_output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dense  (1, activation='sigmoid')(x)

model = Model( pre_trained_model.input, x)
model.compile(optimizer = RMSprop(learning_rate=0.0001),
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

=> Hidden Layers

```
from tensorflow.keras.optimizers import RMSprop

x = layers.Flatten()(last_output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dense  (1, activation='sigmoid')(x)

model = Model( pre_trained_model.input, x)
model.compile(optimizer = RMSprop(learning_rate=0.0001),
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

=> Set up Output Layer for your own model

```
from tensorflow.keras.optimizers import RMSprop

x = layers.Flatten()(last_output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dense  (1, activation='sigmoid')(x)

model = Model( pre_trained_model.input, x)
model.compile(optimizer = RMSprop(learning_rate=0.0001),
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

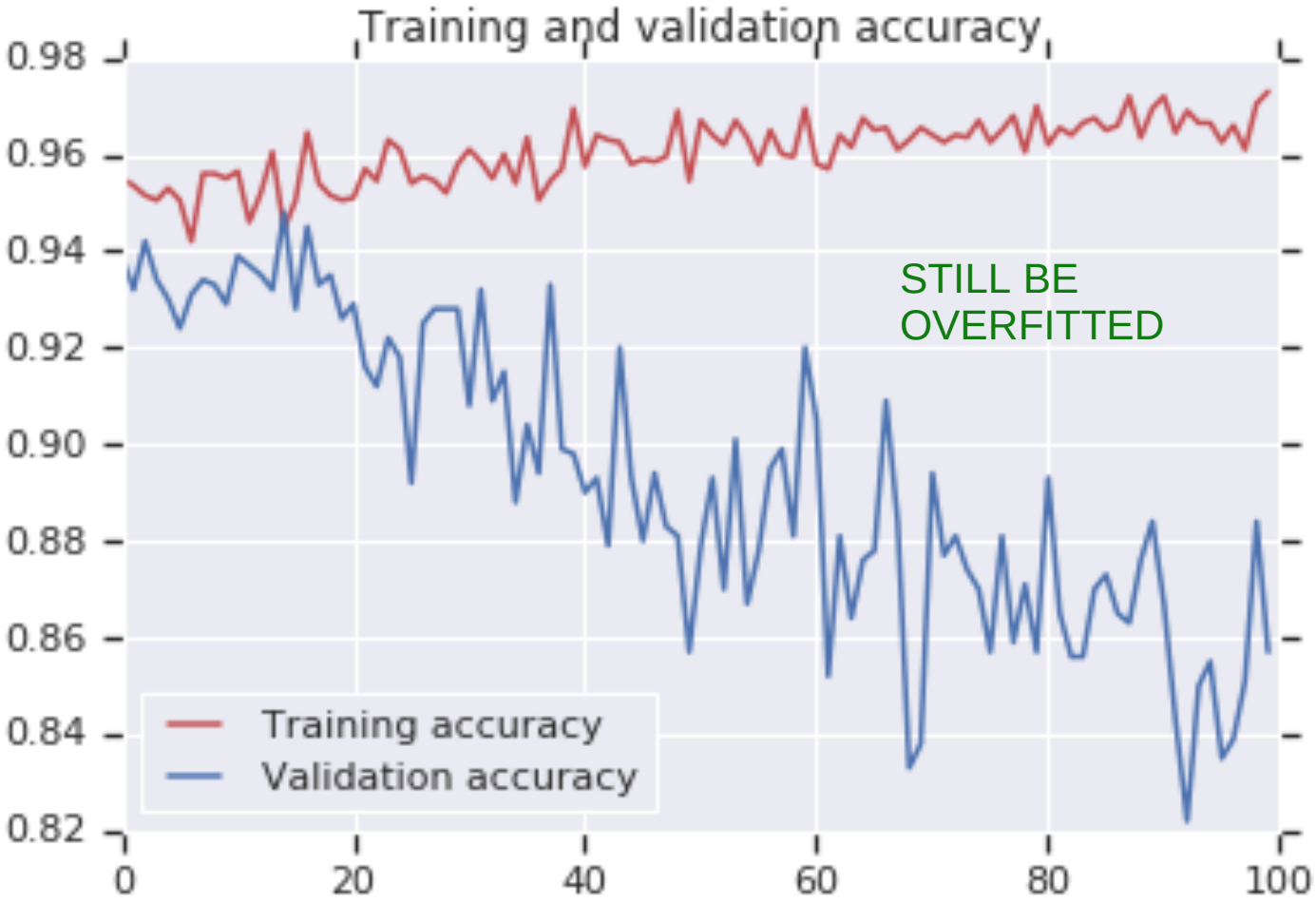
=> Create your own model with all set up layers and pre-train model

```
from tensorflow.keras.optimizers import RMSprop

x = layers.Flatten()(last_output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dense  (1, activation='sigmoid')(x)

model = Model( pre_trained_model.input, x)
model.compile(optimizer = RMSprop(lr=0.0001),
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

```
# Add our data-augmentation parameters to ImageDataGenerator
train_datagen = ImageDataGenerator(rescale = 1./255.,
                                   rotation_range = 40,
                                   width_shift_range = 0.2,
                                   height_shift_range = 0.2,
                                   shear_range = 0.2,
                                   zoom_range = 0.2,
                                   horizontal_flip = True)
```

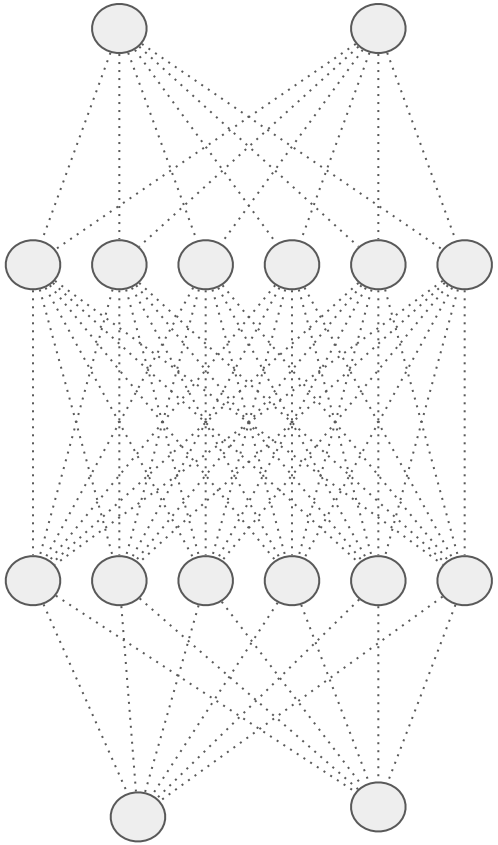
```
train_generator = train_datagen.flow_from_directory(
                  train_dir,
                  batch_size = 20,
                  class_mode = 'binary',
                  target_size = (150, 150))
```

```
history = model.fit(
        train_generator,
        validation_data = validation_generator,
        steps_per_epoch = 100,
        epochs = 100,
        validation_steps = 50,
        verbose = 2)
```

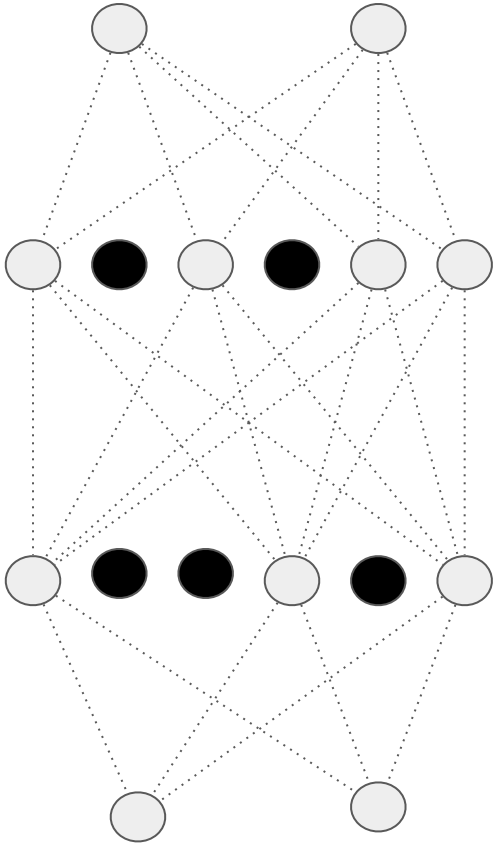

Training and validation accuracy
0.98
0.96
0.94
0.92
0.90
0.88
0.86
0.84
0.82
0
20
40
60
80
100
Training accuracy
Validation accuracy
STILL BE
OVERFITTED

How to improve it?

Using dropout!



However,
dropping out can break the neural network
out of this potential bad habit!

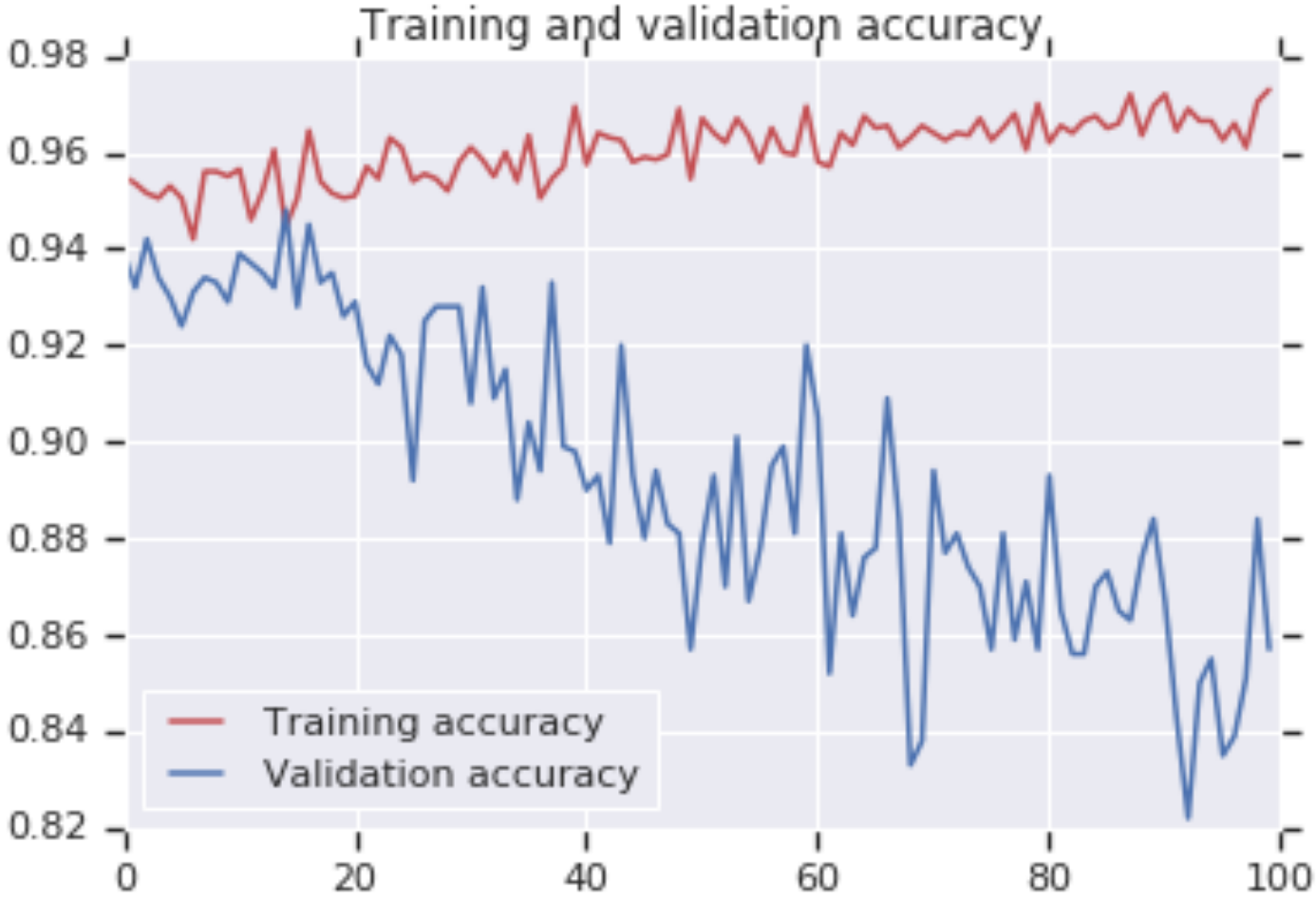


The idea behind it is to remove a random number of neurons in your neural network. This works very well for two reasons: The first is that neighboring neurons often end up with similar weights, which can lead to overfitting, so dropping some out at random can remove this. The second is that often a neuron can over-weigh the input from a neuron in the previous layer and can over specialize as a result.

```
from tensorflow.keras.optimizers import RMSprop

x = layers.Flatten()(last_output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dense  (1, activation='sigmoid')(x)

model = Model( pre_trained_model.input, x)
model.compile(optimizer = RMSprop(lr=0.0001),
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

```
from tensorflow.keras.optimizers import RMSprop

x = layers.Flatten()(last_output)
x = layers.Dense(1024, activation='relu')(x)
x = layers.Dropout(0.2)(x)
x = layers.Dense  (1, activation='sigmoid')(x)

model = Model( pre_trained_model.input, x)
model.compile(optimizer = RMSprop(lr=0.0001),
              loss = 'binary_crossentropy',
              metrics = ['acc'])
```

=> Dropping 20% our neurons


Training and validation accuracy
0.98
0.96
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0.88
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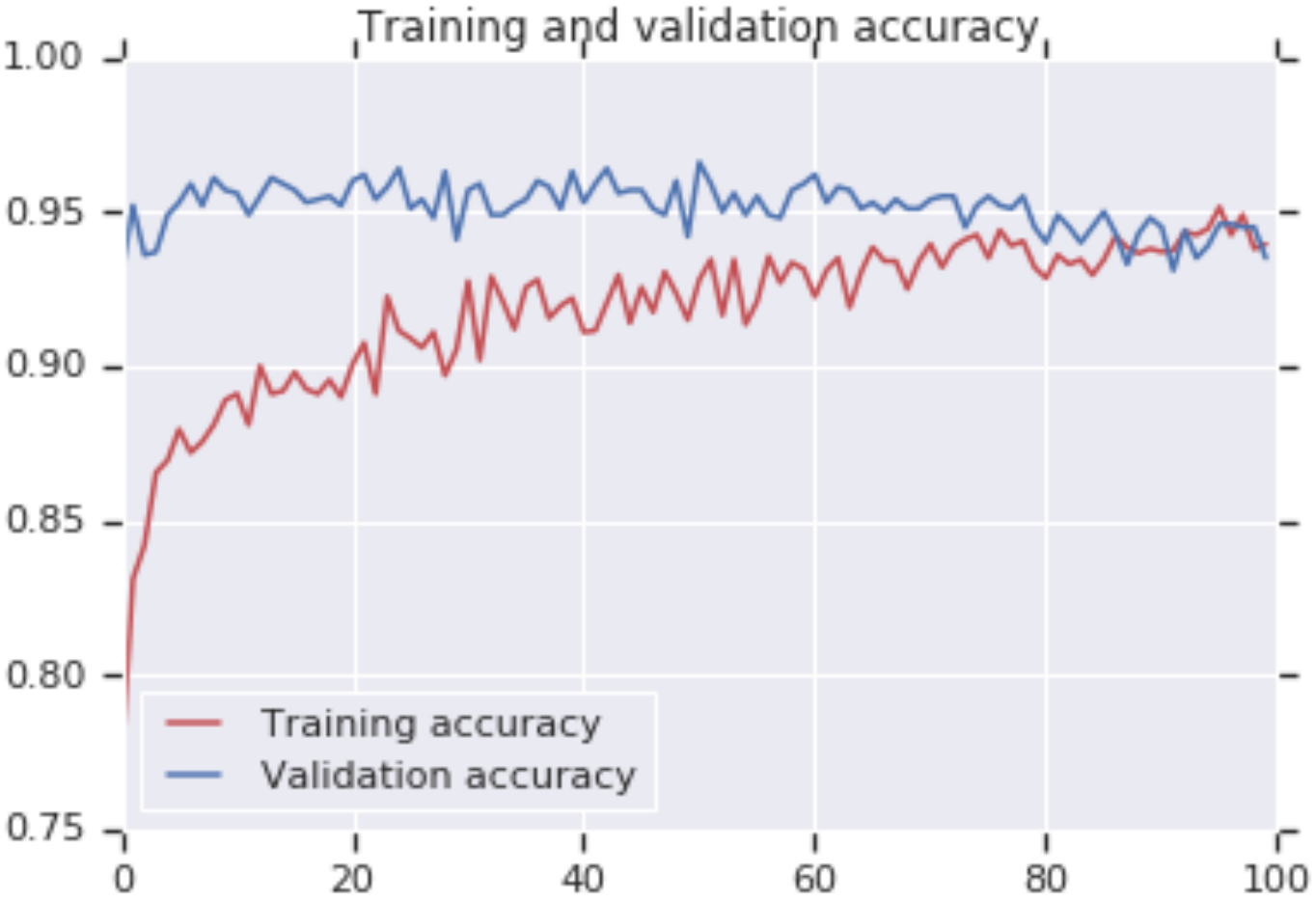
Training and validation accuracy
1.00
0.95
0.90
0.85
0.80
0.75
0
20
40
60
80
100
Training accuracy
Validation accuracy