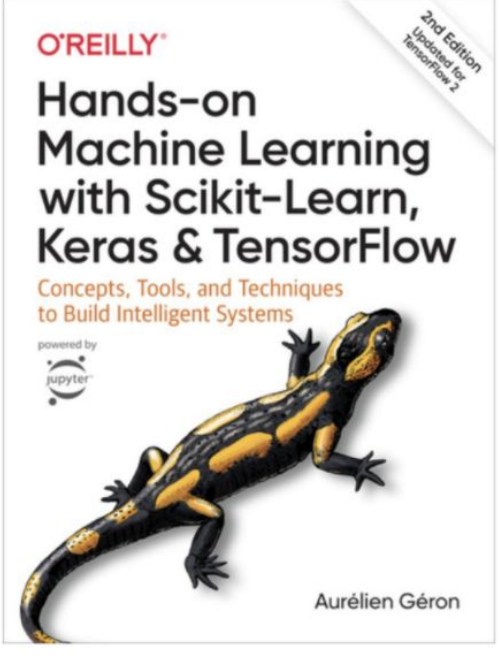
# Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition

★★★★★ 92 reviews

By Aurélien Géron




**TIME TO COMPLETE:**
24h 18m

**TOPICS:**
Machine Learning

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| Chapter | Title |
|---|---|
| 1 | The Machine Learning Landscape |
| 2 | End-to-End Machine Learning Project |
| 3 | Classification |
| 4 | Training Models |
| 5 | Support Vector Machines |
| 6 | Decision Trees |
| 7 | Ensemble Learning and Random Forests |
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| 10 | Introduction to Artificial Neural Networks with Keras |
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| 15 | Processing Sequences Using RNNs and CNNs |
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| 18 | Reinforcement Learning |
| 19 | Training and Deploying TensorFlow Models at Scale |

Chapter 14 : Deep Computer Vision Using Convolutional Neural Networks
Discussion led by George Zoto

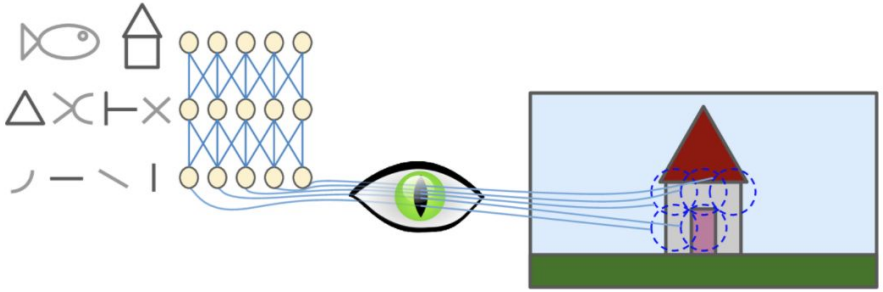
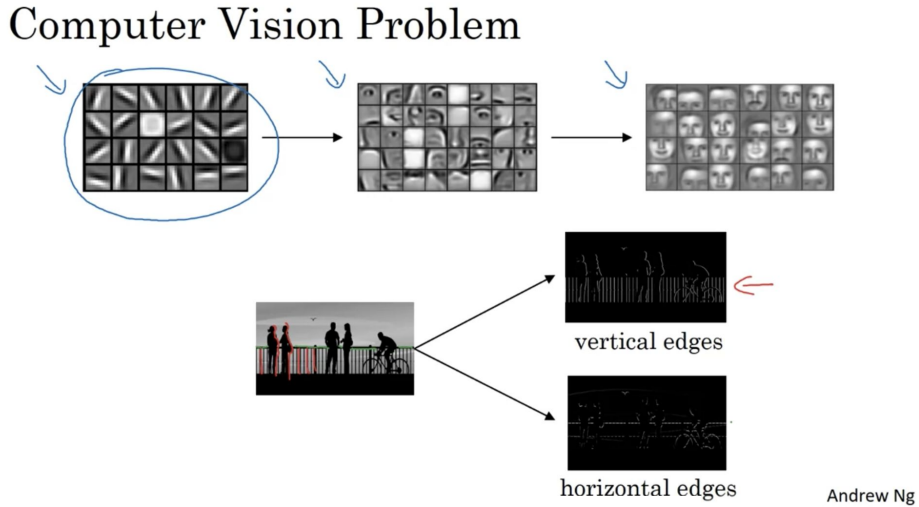
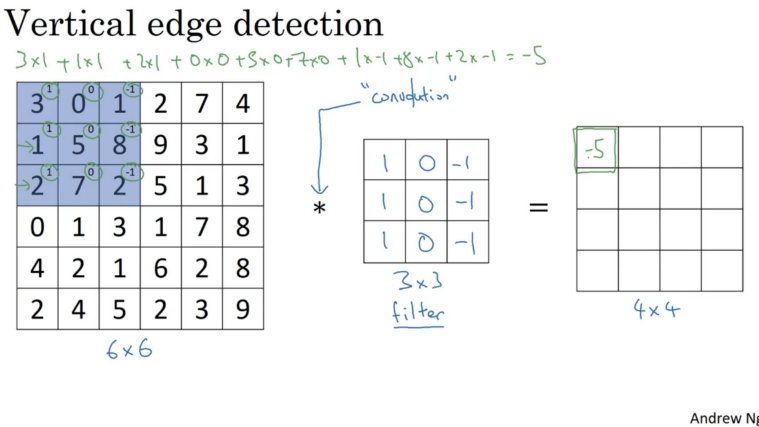
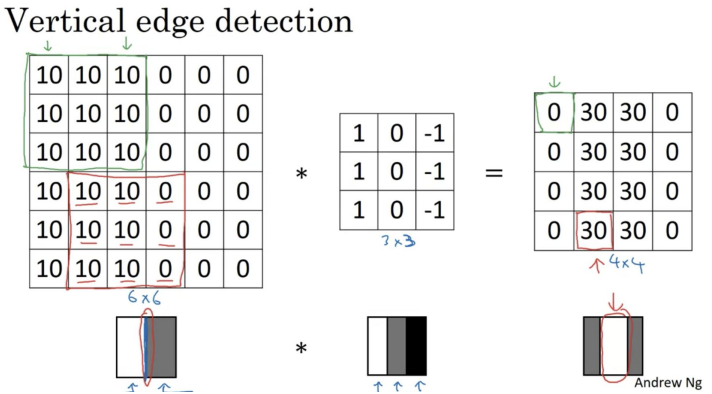


*Figure 14-1. Biological neurons in the visual cortex respond to specific patterns in small regions of the visual field called receptive fields; as the visual signal makes its way through consecutive brain modules, neurons respond to more complex patterns in larger receptive fields.*

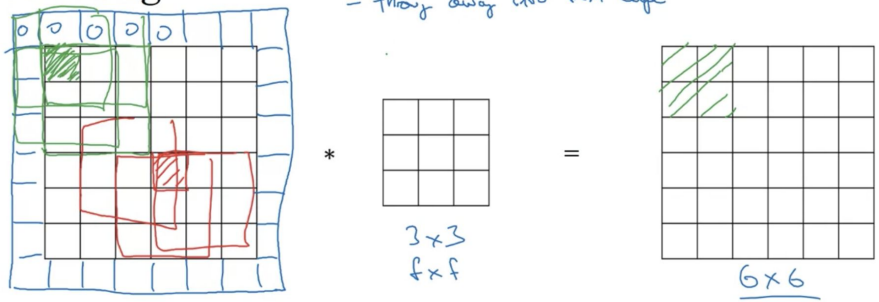



Source: https://www.coursera.org/learn/convolutional-neural-networks/lecture/4Trod/edge-detection-example

# Padding

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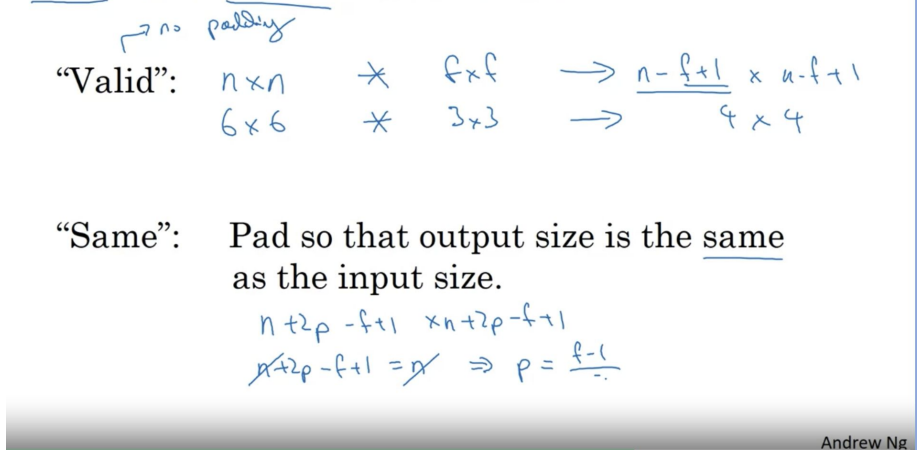
# Valid and Same convolutions

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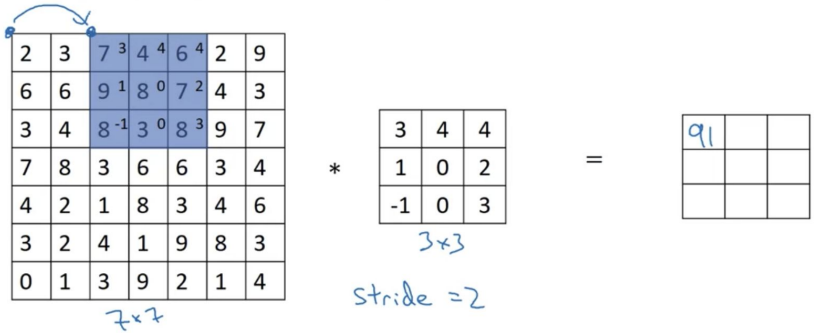
# Strided convolution




# Summary of convolutions

$n \times n$ image $\quad$ $f \times f$ filter

padding $p$ $\quad$ stride $s$

$$\left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor \times \left\lfloor \frac{n+2p-f}{s} + 1 \right\rfloor$$

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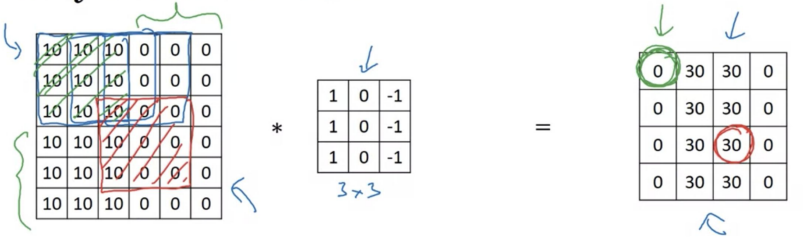
# Enhancing Vision with Convolutional Neural Networks

## Why convolutions

translation invariance




**Parameter sharing:** A feature detector (such as a vertical edge detector) that's useful in one part of the image is probably useful in another part of the image.

→ **Sparsity of connections:** In each layer, each output value depends only on a small number of inputs.

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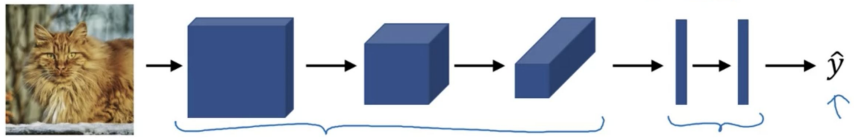
## Putting it together

Training set $(x^{(1)}, y^{(1)}) \ldots (x^{(m)}, y^{(m)})$.

w, b




Cost $J = \frac{1}{m} \sum_{i=1}^{m} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$

Use gradient descent to optimize parameters to reduce $J$

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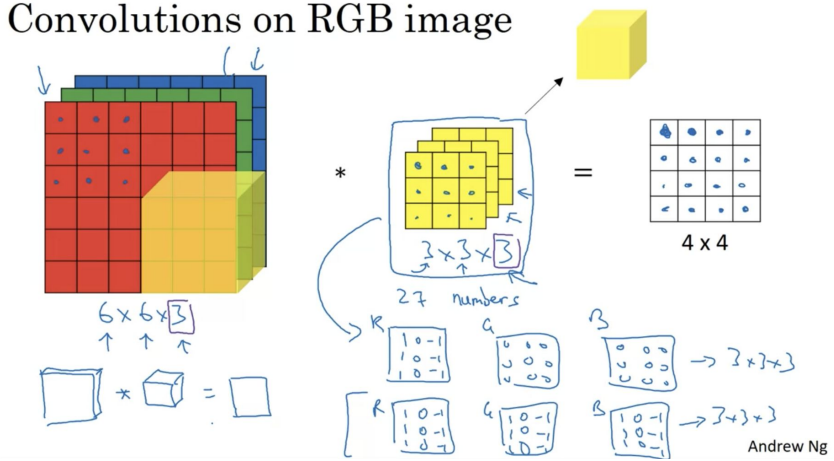
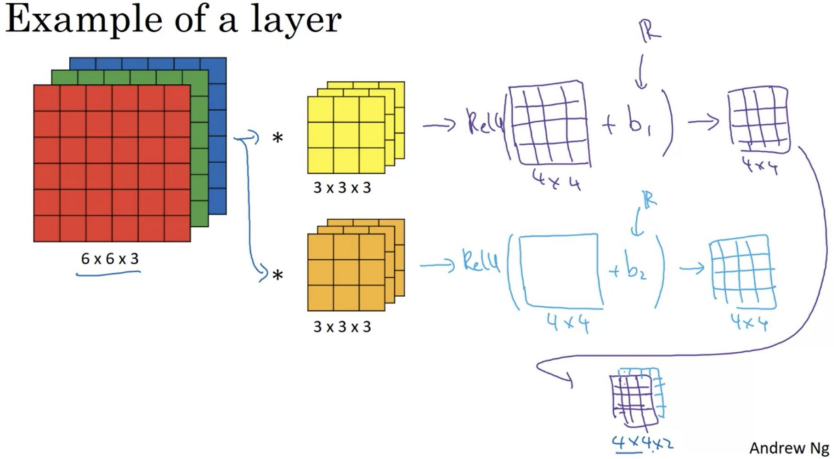
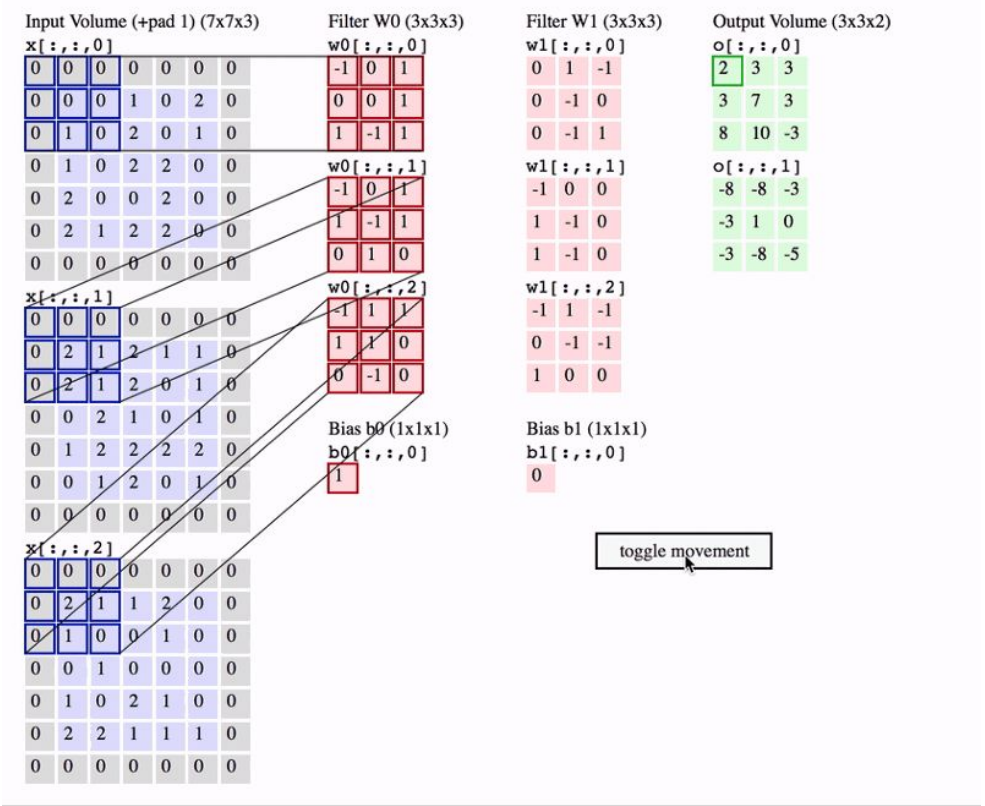
Source: https://www.coursera.org/lecture/convolutional-neural-networks/why-convolutions-Xv7B5

# Content added after Week 1 and 2, based on group feedback




Source: https://www.coursera.org/learn/convolutional-neural-networks
https://images.app.goo.gl/Z4xDvjzi3Gcerpm27

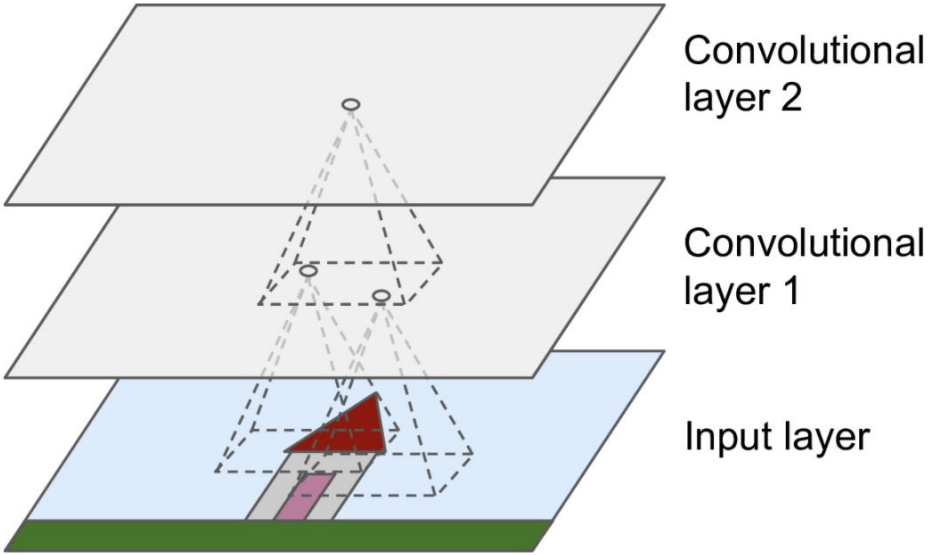



*Figure 14-2. CNN layers with rectangular local receptive fields*

```
model = keras.models.Sequential([
    keras.layers.Conv2D(64, 7, activation="relu", padding="same",
                        input_shape=[28, 28, 1]),
    keras.layers.MaxPooling2D(2),
    keras.layers.Conv2D(128, 3, activation="relu", padding="same"),
    keras.layers.Conv2D(128, 3, activation="relu", padding="same"),
    keras.layers.MaxPooling2D(2),
    keras.layers.Conv2D(256, 3, activation="relu", padding="same"),
    keras.layers.Conv2D(256, 3, activation="relu", padding="same"),
    keras.layers.MaxPooling2D(2),
    keras.layers.Flatten(),
    keras.layers.Dense(128, activation="relu"),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(64, activation="relu"),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(10, activation="softmax")
])
```

```
model.layers
```

```
convolutional.Conv2D
pooling.MaxPooling2D
convolutional.Conv2D
pooling.MaxPooling2D
convolutional.Conv2D
pooling.MaxPooling2D
convolutional.Conv2D
pooling.MaxPooling2D
convolutional.Conv2D
pooling.MaxPooling2D
core.Flatten at 0x7f
core.Dense at 0x7f07
core.Dense at 0x7f07
```

```
model.layers[0].Conv2D
```

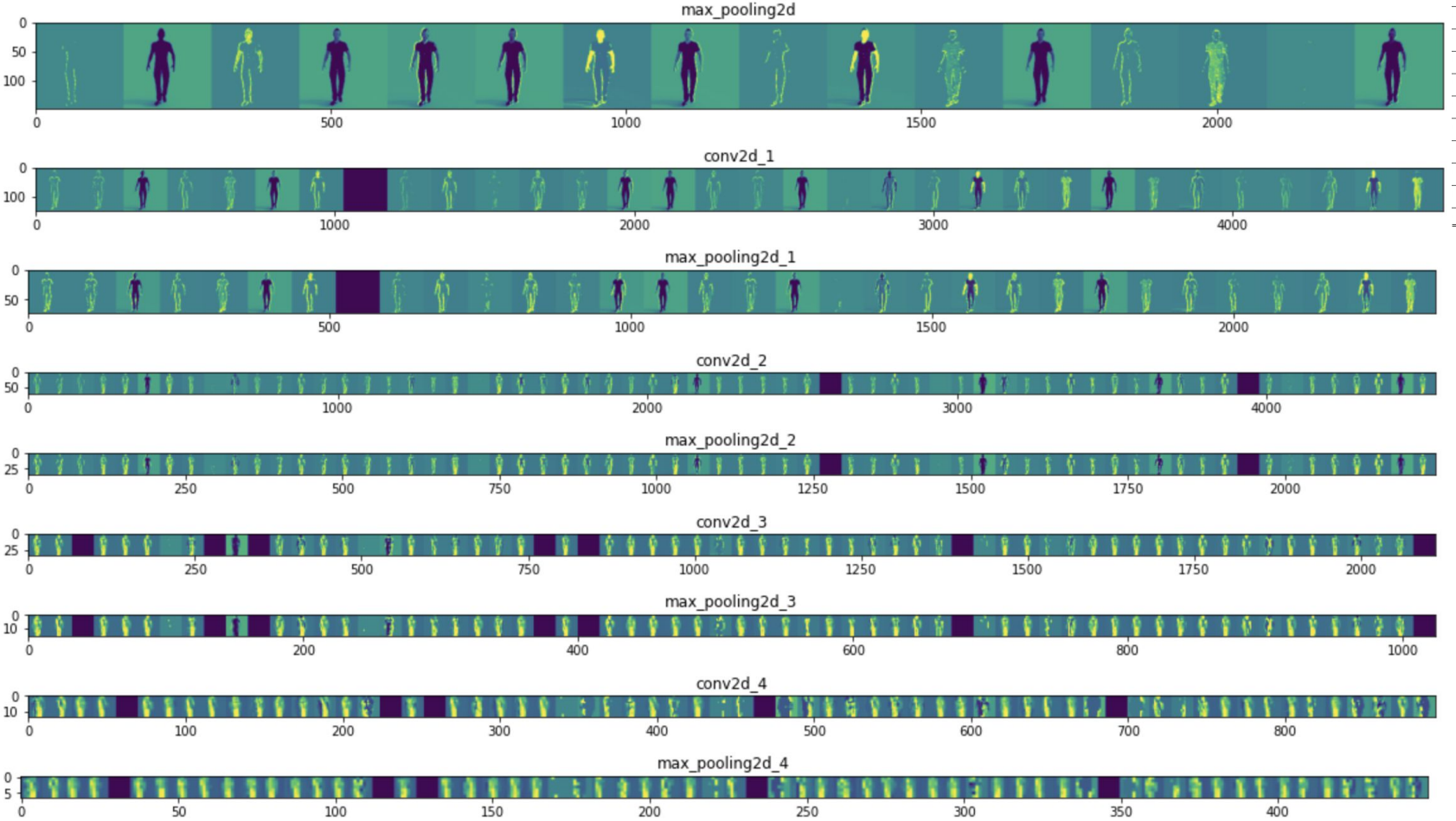
- **valhuman01-00.png**(image/png) -

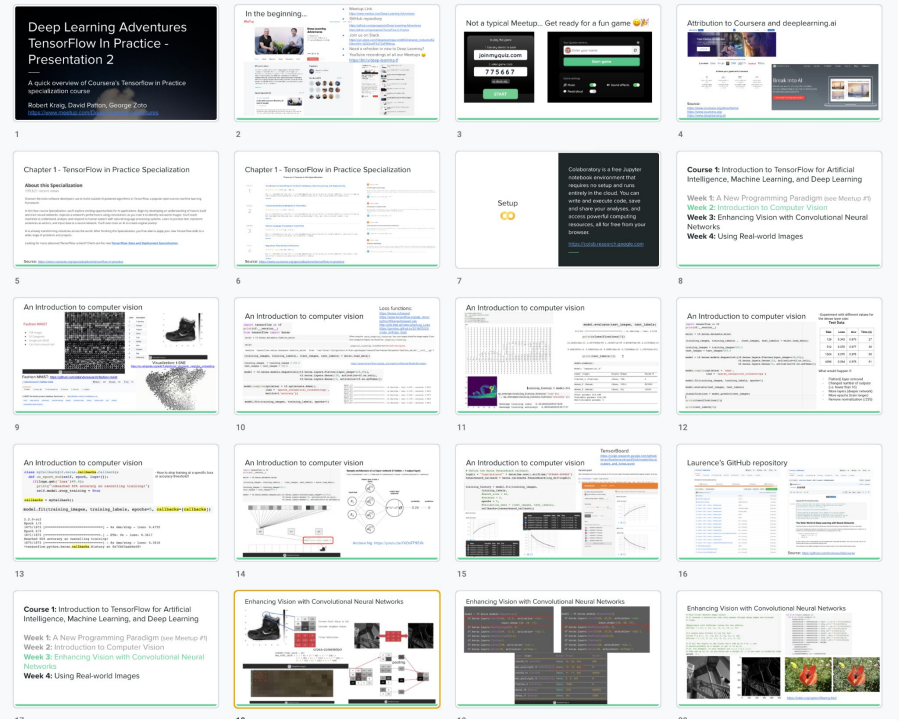
```
Saving valhuman01-00.png to
[1.]
valhuman01-00.png is a human
```

[1.]

```
successive_outputs = [layer.output for layer in model.layers[1:]]
```

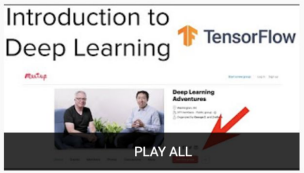
| Layer (type) | Output Shape |
|---|---|
| conv2d (Conv2D) | (None, 298, 298, 16) |
| max_pooling2d (MaxPooling2D) | (None, 149, 149, 16) |
| conv2d_1 (Conv2D) | (None, 147, 147, 32) |
| | 73, 73, 32) |
| | 71, 71, 64) |
| | 35, 35, 64) |
| | 33, 33, 64) |
| | 16, 16, 64) |
| | 14, 14, 64) |
| | 7, 7, 64) |
| | 3136) |
| | 512) |
| | 1) |






[Deep-Learning-Adventures-Tensorflow-In-Practice-Presentation-2]

[http://bit.ly/dla-youtube]

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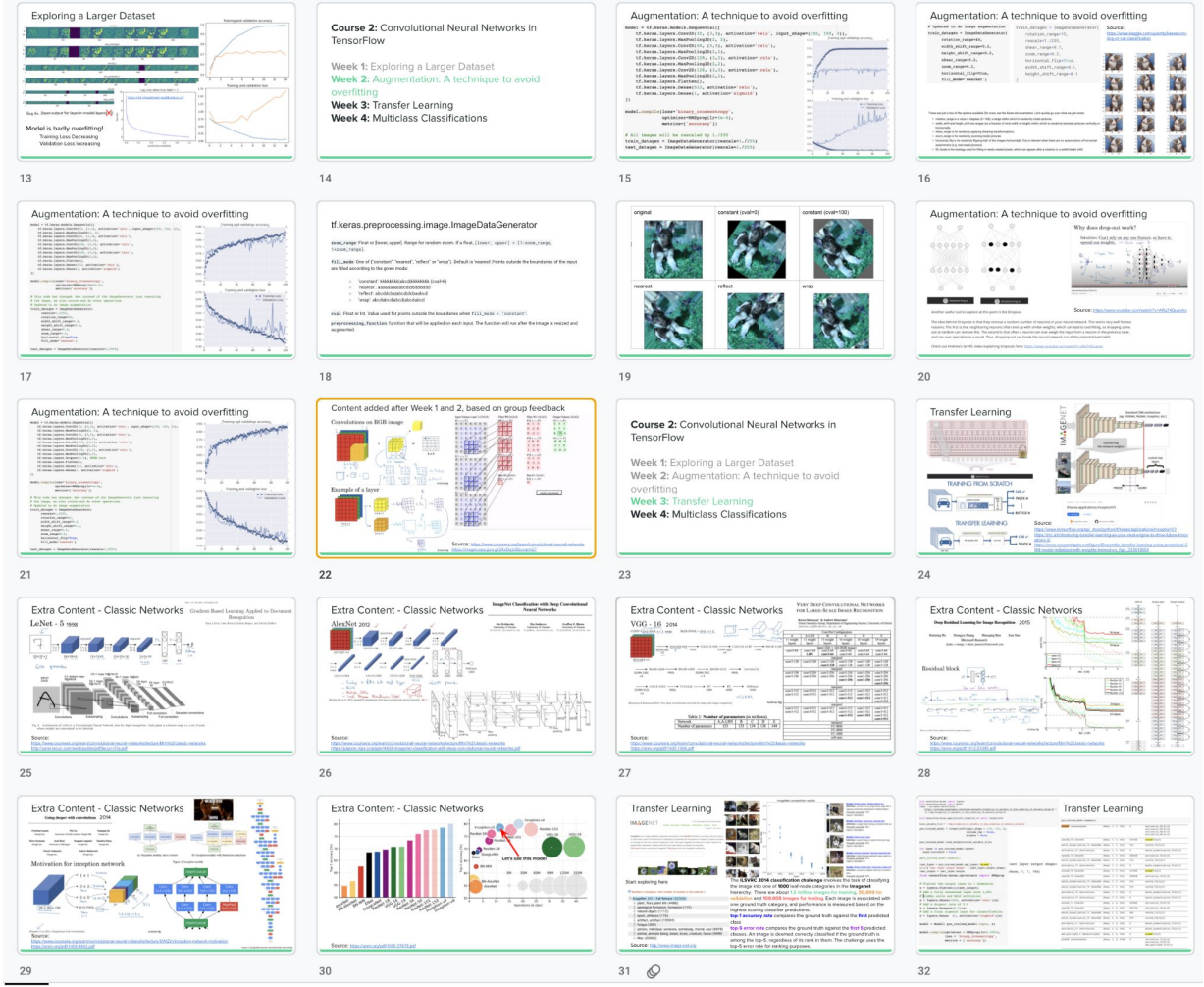


[Deep-Learning-Adventures-Tensorflow-In-Practice-Presentation-3]

http://bit.ly/dla-youtube

ILSVRC challenge

*Table 14-1. LeNet-5 architecture*

| Layer | Type | Maps | Size | Kernel size | Stride | Activation |
|---|---|---|---|---|---|---|
| Out | Fully connected | – | 10 | – | – | RBF |
| F6 | Fully connected | – | 84 | – | – | tanh |
| C5 | Convolution | 120 | 1 × 1 | 5 × 5 | 1 | tanh |
| S4 | Avg pooling | 16 | 5 × 5 | 2 × 2 | 2 | tanh |
| C3 | Convolution | 16 | 10 × 10 | 5 × 5 | 1 | tanh |
| S2 | Avg pooling | 6 | 14 × 14 | 2 × 2 | 2 | tanh |
| C1 | Convolution | 6 | 28 × 28 | 5 × 5 | 1 | tanh |
| In | Input | 1 | 32 × 32 | – | – | – |

*Table 14-2. AlexNet architecture*

| Layer | Type | Maps | Size | Kernel size | Stride | Padding | Activation |
|---|---|---|---|---|---|---|---|
| Out | Fully connected | – | 1,000 | – | – | – | Softmax |
| F10 | Fully connected | – | 4,096 | – | – | – | ReLU |
| F9 | Fully connected | – | 4,096 | – | – | – | ReLU |
| S8 | Max pooling | 256 | 6 × 6 | 3 × 3 | 2 | `valid` | – |
| C7 | Convolution | 256 | 13 × 13 | 3 × 3 | 1 | `same` | ReLU |
| C6 | Convolution | 384 | 13 × 13 | 3 × 3 | 1 | `same` | ReLU |
| C5 | Convolution | 384 | 13 × 13 | 3 × 3 | 1 | `same` | ReLU |
| S4 | Max pooling | 256 | 13 × 13 | 3 × 3 | 2 | `valid` | – |
| C3 | Convolution | 256 | 27 × 27 | 5 × 5 | 1 | `same` | ReLU |
| S2 | Max pooling | 96 | 27 × 27 | 3 × 3 | 2 | `valid` | – |
| C1 | Convolution | 96 | 55 × 55 | 11 × 11 | 4 | `valid` | ReLU |
| In | Input | 3 (RGB) | 227 × 227 | – | – | – | – |

ILSVRC challenge

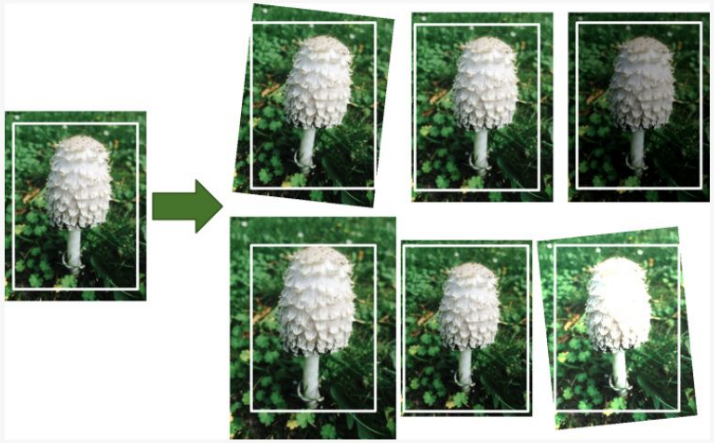

*Figure 14-12. Generating new training instances from existing ones*

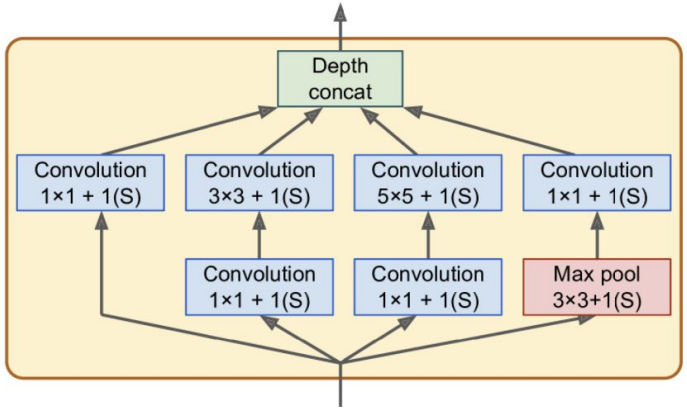


*Figure 14-13. Inception module*

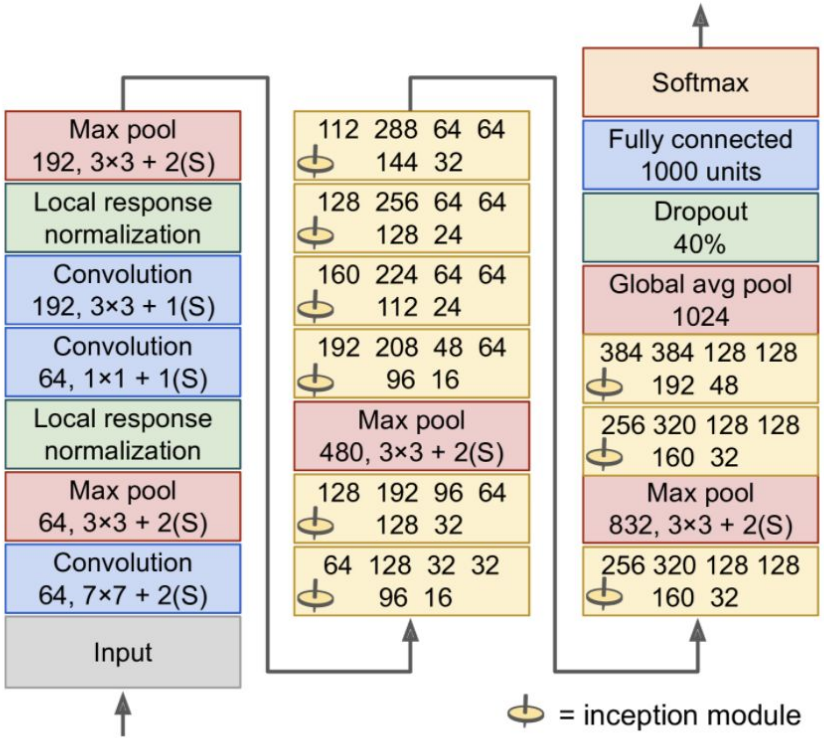


*Figure 14-14. GoogLeNet architecture*

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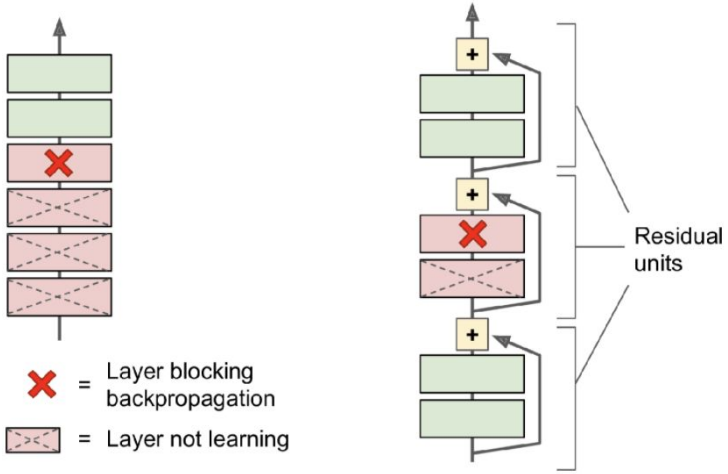



*Figure 14-16. Regular deep neural network (left) and deep residual network (right)*

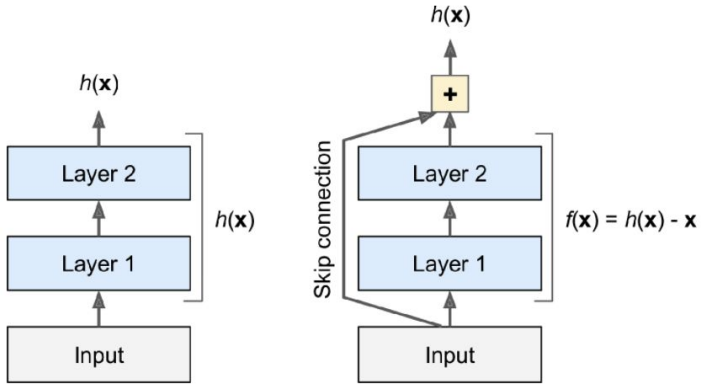



*Figure 14-15. Residual learning*

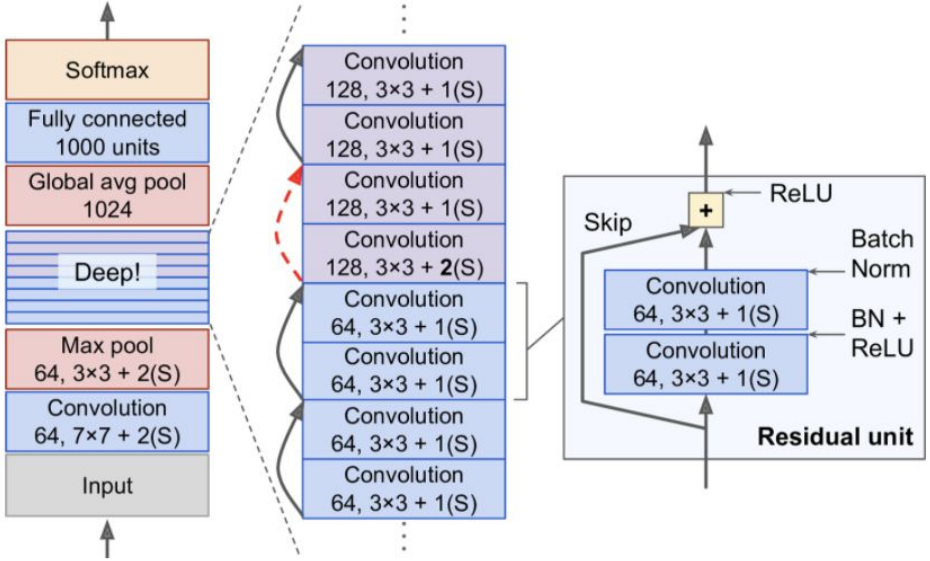



*Figure 14-17. ResNet architecture*

ILSVRC challenge

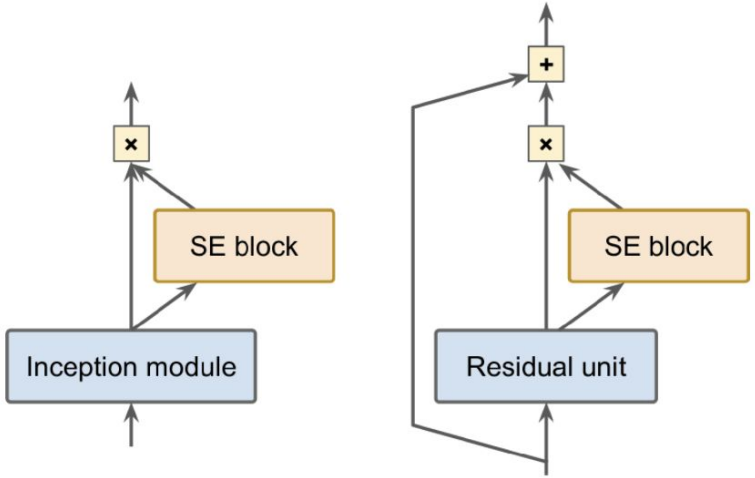



*Figure 14-20. SE-Inception module (left) and SE-ResNet unit (right)*

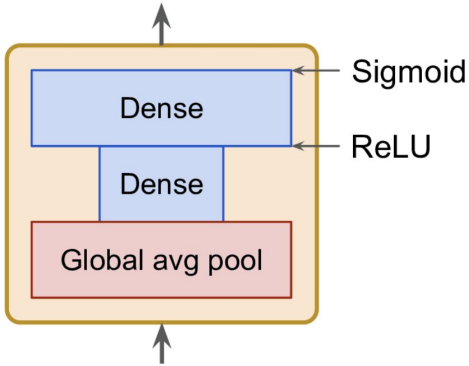



*Figure 14-22. SE block architecture*

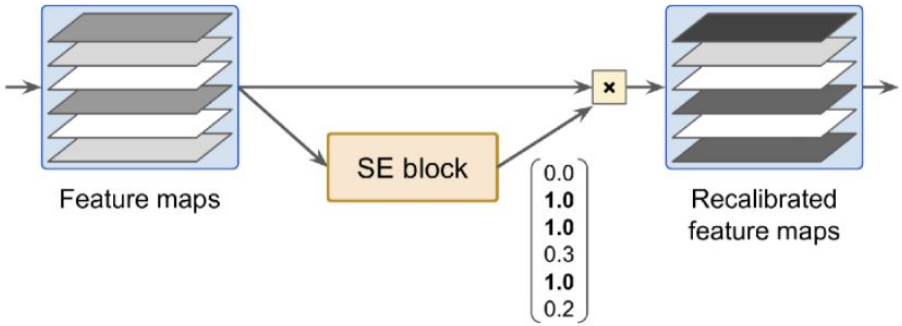



*Figure 14-21. An SE block performs feature map recalibration*

```
model = keras.applications.resnet50.ResNet50(weights="imagenet")

base_model = keras.applications.xception.Xception(weights="imagenet",
                                                  include_top=False)
avg = keras.layers.GlobalAveragePooling2D()(base_model.output)
output = keras.layers.Dense(n_classes, activation="softmax")(avg)
model = keras.Model(inputs=base_model.input, outputs=output)


optimizer = keras.optimizers.SGD(lr=0.2, momentum=0.9, decay=0.01)
model.compile(loss="sparse_categorical_crossentropy", optimizer=optimizer,
              metrics=["accuracy"])
history = model.fit(train_set, epochs=5, validation_data=valid_set)
```

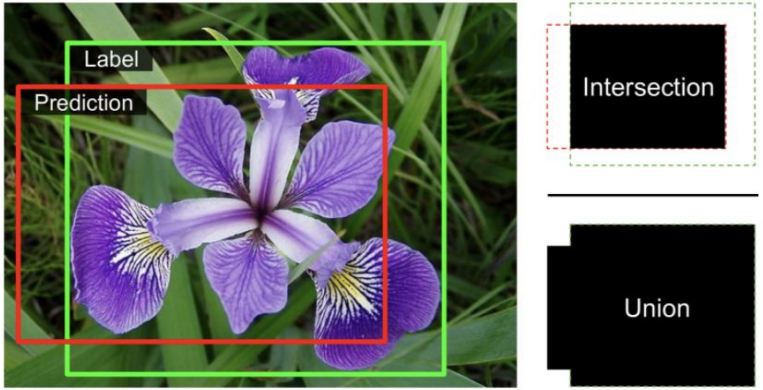



*Figure 14-23. Intersection over Union (IoU) metric for bounding boxes*

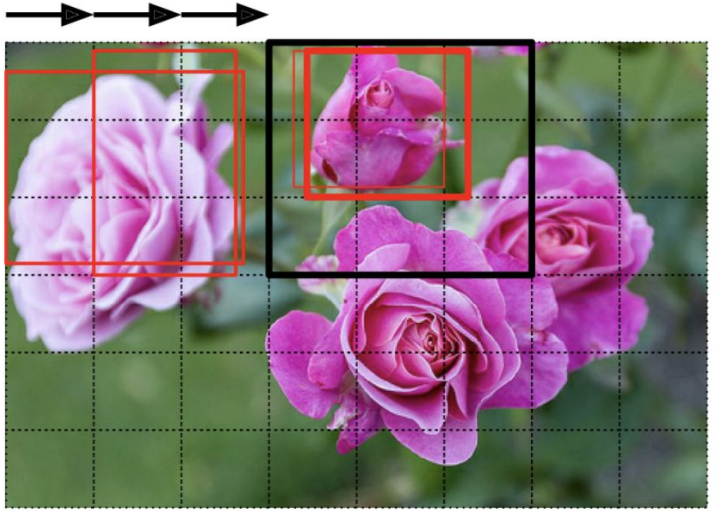


*Figure 14-24. Detecting multiple objects by sliding a CNN across the image*

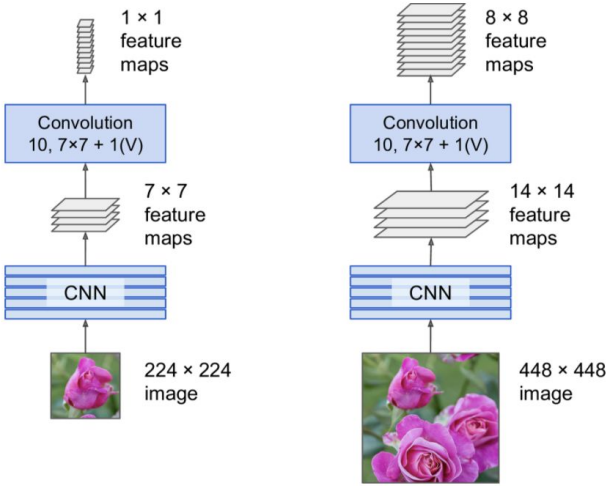
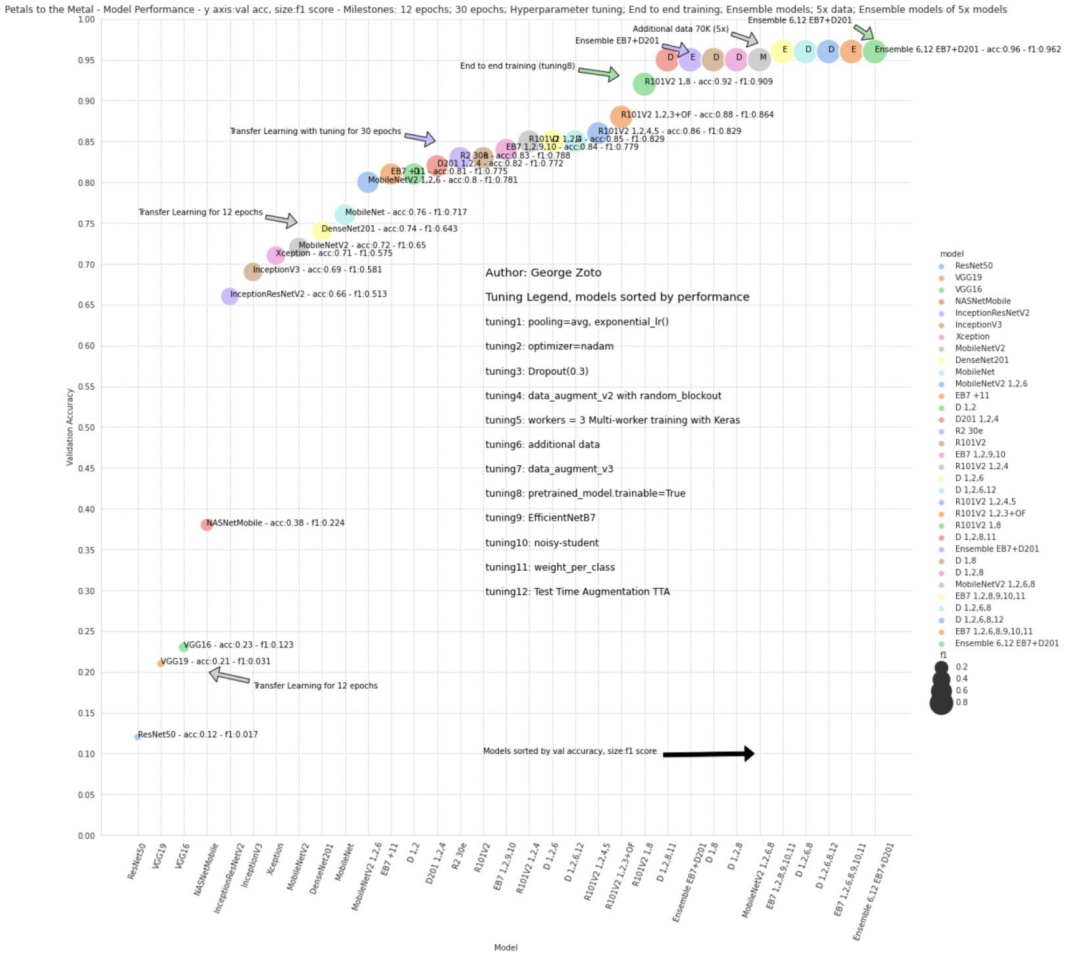
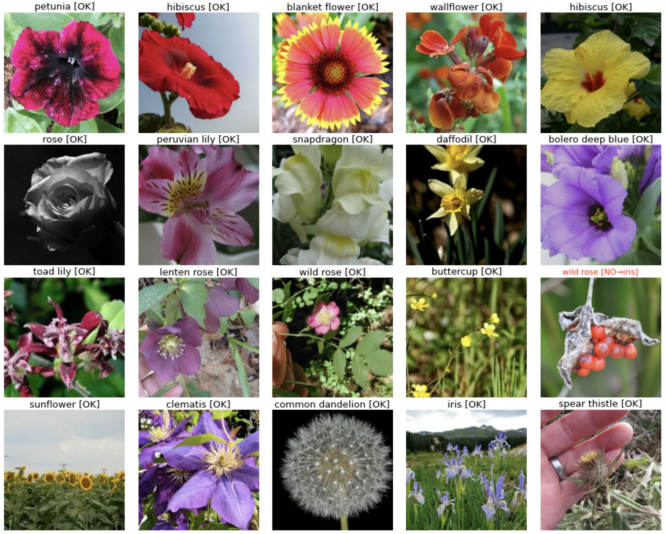



*Figure 14-25. The same fully convolutional network processing a small image (left) and a large one (right)*


*Figure 14-26. Semantic segmentation*



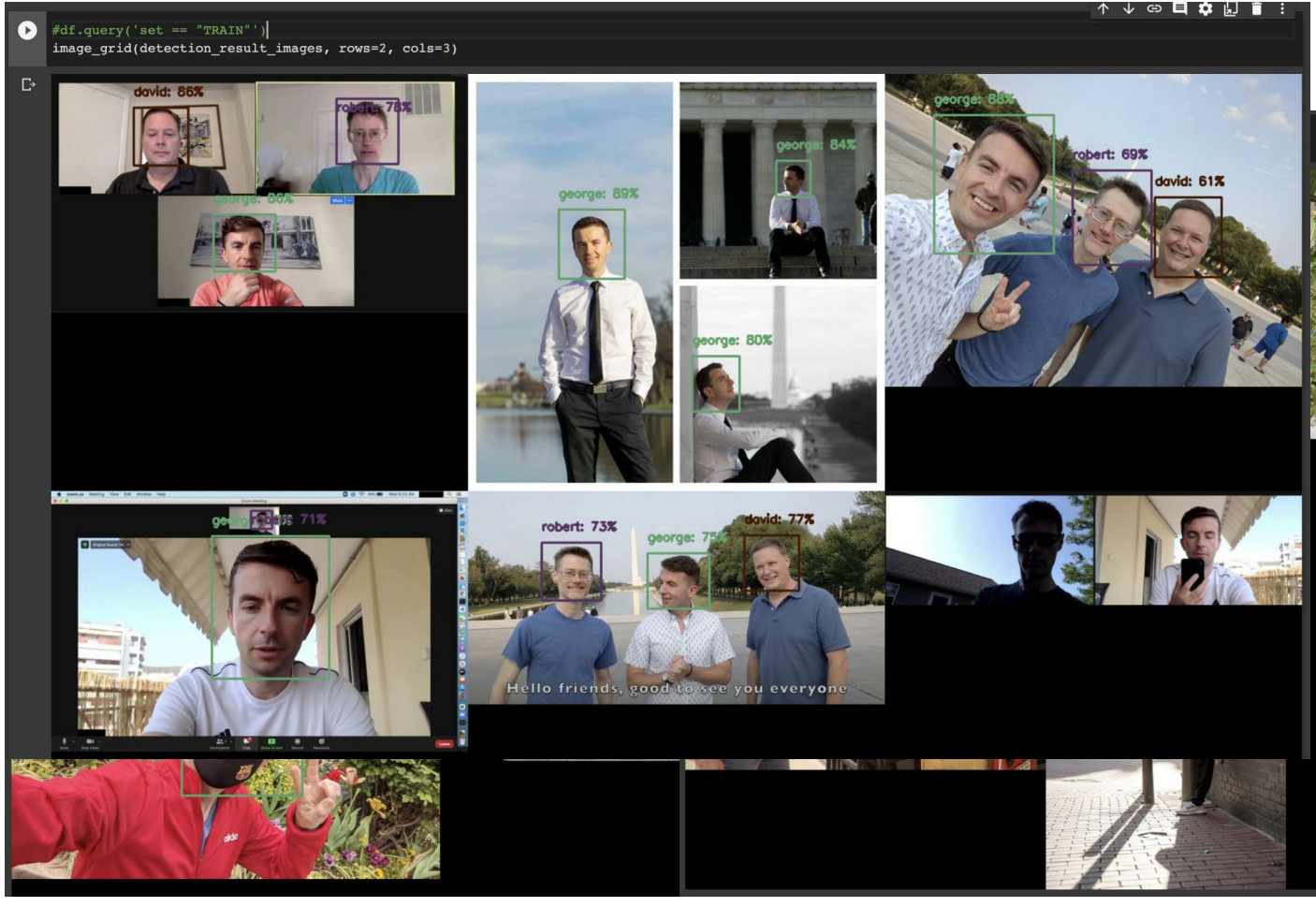

[Computer Vision - Petals to the Metal 🌻🌸🌹]



# Colab Demo

Deep Learning Adventures

Animated - Best viewed as a presentation



# Android App Demo

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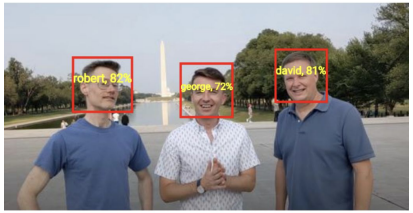
Deep Learning Adventures

Custom Object Detection App

Select a preset image or take a new photo

Take photo

Deep Learning Adventures




Select a preset image or take a new photo

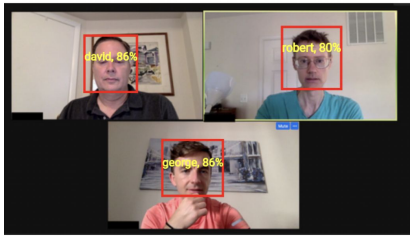
Take photo

Deep Learning Adventures

Select a preset image or take a new photo

Take photo

Deep Learning Adventures

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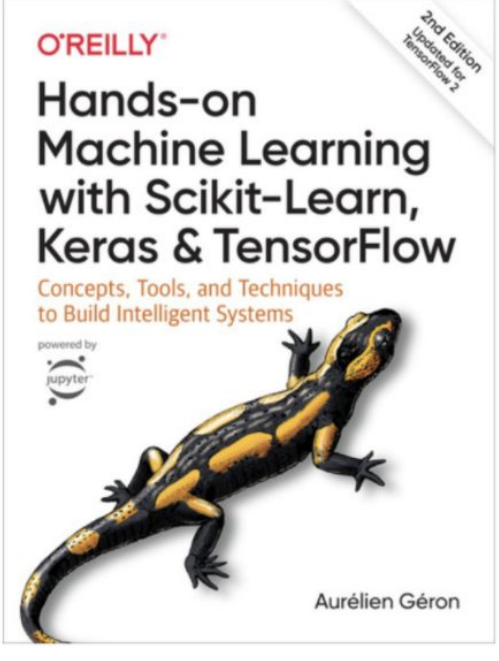
# Useful Resources

- Long list coming up, see live presentation for now

# Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow, 2nd Edition

★★★★★ 92 reviews

By Aurélien Géron

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24h 18m

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| Chapter | Title |
|---|---|
| 1 | The Machine Learning Landscape |
| 2 | End-to-End Machine Learning Project |
| 3 | Classification |
| 4 | Training Models |
| 5 | Support Vector Machines |
| 6 | Decision Trees |
| 7 | Ensemble Learning and Random Forests |
| 8 | Dimensionality Reduction |
| 9a | Unsupervised Learning Techniques: Clustering |
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| 10 | Introduction to Artificial Neural Networks with Keras |
| 11 | Training Deep Neural Networks |
| 12 | Custom Models and Training with TensorFlow |
| 13 | Loading and Preprocessing Data with TensorFlow |
| 14 | Deep Computer Vision Using Convolutional Neural Networks |
| 15 | Processing Sequences Using RNNs and CNNs |
| 16 | Natural Language Processing with RNNs and Attention |
| 17 | Representation Learning and Generative Learning Using Autoencoders and GANs |
| 18 | Reinforcement Learning |
| 19 | Training and Deploying TensorFlow Models at Scale |

Chapter 14 : Deep Computer Vision Using Convolutional Neural Networks
Discussion led by George Zoto