

# Artificial intelligence

Deep Learning: CNNs and application to image classification

- Convolutional Neural Networks (CNN)
- pre-trained models and transfer Learning
- **Kaggle competition: Cats vs. Dogs classification**

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# Convolutional Neural Networks (CNN)

A convolutional neural network (CNN) (aka ConvNet)  
is a feedforward (sequential) neural network + filters or ‘kernels’

# Digital image processing

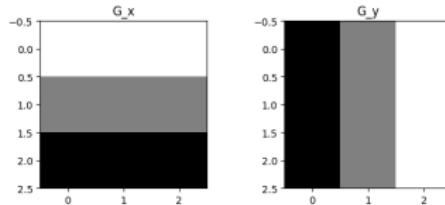
Prewitt edge detector (1970) is a  $3 \times 3$  ‘kernel’ used to estimate the first derivative

$$G_x = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 0 & 0 \\ -1 & -1 & -1 \end{bmatrix}$$

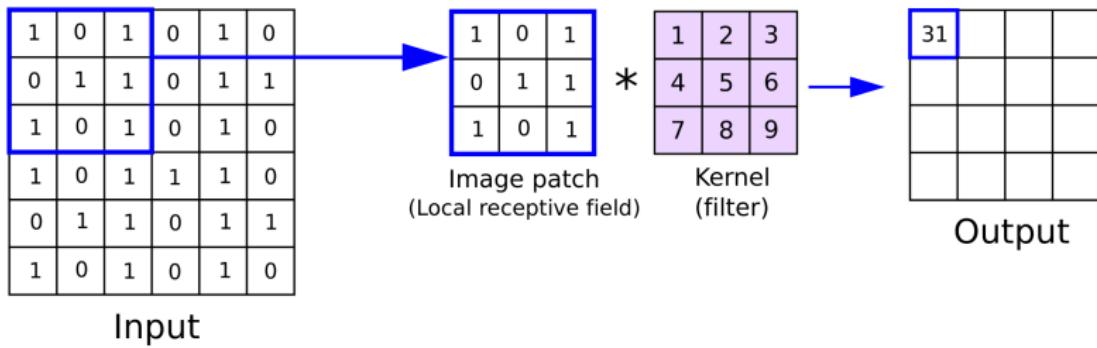
and

$$G_y = \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

and as greyscale plots



## The convolution operation (written as $*$ or $\otimes$ )



## Results for Prewitt:



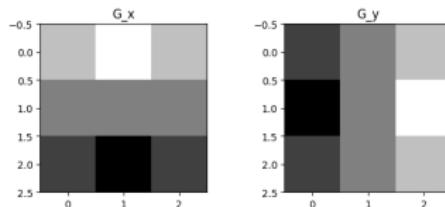
Another edge detector is the Sobel  $3 \times 3$  ‘kernel’

$$G_x = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

and

$$G_y = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

and as greyscale plots



# Practical session

Apply the Prewitt  $G_y$  kernel by hand to the following image:

0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1
0	0	0	0	1	1	1	1

(Notice that we shall loose the 'outer ring' of the original image pixels in the new image.

To avoid this we could apply 'padding' to the original image before convolution.)

Let us try the Prewitt filter ourselves on a couple of images:

[notebook\\_CNN\\_Prewitt.ipynb](#)

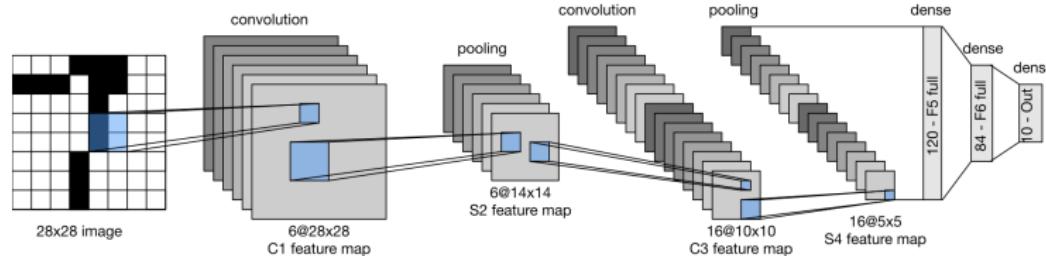
CNN approach:

rather than use specific filters, we now learn the best filters for our problem

# Optical character recognition (OCR)

Recognizing digits and letters.

LeNet-1 (1989) LeNet-5 (1998) by Yann LeCun *et. al* for handwritten character recognition



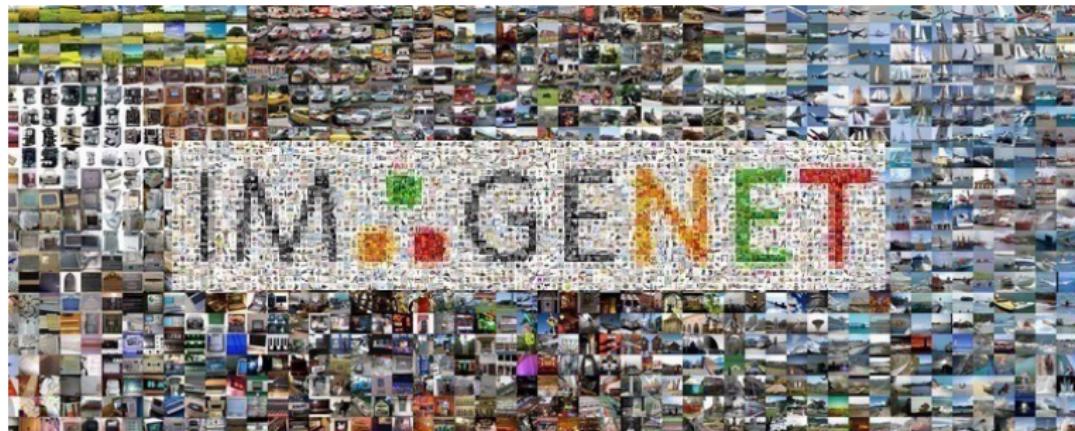
```
model = models.Sequential()
model.add(layers.Conv2D(6, (5, 5), activation='relu', input_shape=(28, 28, 1)))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Conv2D(16, (5, 5), activation='relu'))
model.add(layers.MaxPooling2D((2, 2)))
model.add(layers.Flatten())      # go from 2D to 1D
model.add(layers.Dense(120, activation='relu'))
model.add(layers.Dense(84, activation='relu'))
model.add(layers.Dense(n_classes, activation='softmax'))

# Compile the model
model.compile(optimizer='adam',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

(Source: [LeNet-5 - A complete guide](#))

# Image classification

The ImageNet competition (2010-2017)

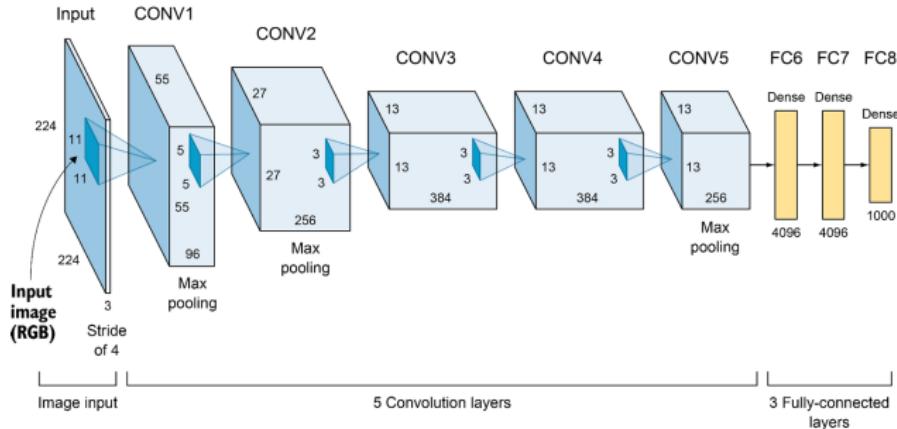


The ImageNet dataset has over 1.2 million images with 1,000 classes/categories ([paper](#)).

In 2012 a CNN called [AlexNet](#) scored a huge 10% better than rivals on the [ImageNet competition](#)

This work by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton ignited the current AI revolution.

## The AlexNet architecture:



AlexNet is a **sequential** model.

## AlexNet as a Keras model:

```
model = keras.models.Sequential([
    keras.layers.Conv2D(filters=96, kernel_size=(11,11), strides=(4,4), activation='relu', input_shape=(128,128,
    keras.layers.BatchNormalization(),
    keras.layers.MaxPool2D(pool_size=(3,3), strides=(2,2)),
    keras.layers.Conv2D(filters=256, kernel_size=(5,5), strides=(1,1), activation='relu', padding="same"),
    keras.layers.BatchNormalization(),
    keras.layers.MaxPool2D(pool_size=(3,3), strides=(2,2)),
    keras.layers.Conv2D(filters=384, kernel_size=(3,3), strides=(1,1), activation='relu', padding="same"),
    keras.layers.BatchNormalization(),
    keras.layers.Conv2D(filters=384, kernel_size=(1,1), strides=(1,1), activation='relu', padding="same"),
    keras.layers.BatchNormalization(),
    keras.layers.Conv2D(filters=256, kernel_size=(1,1), strides=(1,1), activation='relu', padding="same"),
    keras.layers.BatchNormalization(),
    keras.layers.MaxPool2D(pool_size=(3,3), strides=(2,2)),
    keras.layers.Flatten(),
    keras.layers.Dense(4096, activation='relu'),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(4096, activation='relu'),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(n_classes, activation='softmax')
])
```

## 8 October 2024: Geoffrey Hinton wins Nobel Prize



Scientific Background to the Nobel Prize in Physics 2024

**“FOR FOUNDATIONAL DISCOVERIES AND INVENTIONS  
THAT ENABLE MACHINE LEARNING  
WITH ARTIFICIAL NEURAL NETWORKS”**

The Nobel Committee for Physics

As well as the layers we saw before for ANN

- **Flatten** - a **reshaping layer**
- **Dense** - a **fully connected layer**

we now have these two new **layers**

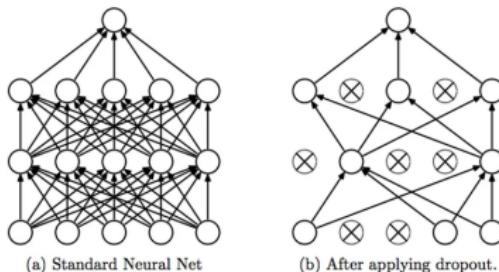
- **BatchNormalization** - a **normalization layer**
- **Dropout** - a **regularization layer**

A batch normalization layer can speed up training by re-scaling each (mini)-batch individually

```
layers.BatchNormalization(),
```

(Paper: "*Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift*" (2015))

## Dropout layers:



we can randomly drop out some fraction of a layer's input units. Note that the weights of the remaining neurons are multiplied by the rate so as to compensate for the now missing neurons.

```
# apply 30% dropout to the next layer  
layers.Dropout(rate=0.3),
```

(Paper: "Dropout: A Simple Way to Prevent Neural Networks from Overfitting" (2014))

and we also now have two new **2-dimensional layers**

- Conv2D - a convolution layer
- MaxPool2D - a pooling layer

# The convolutional layer (**Conv2D**) is what makes a CNN a CNN

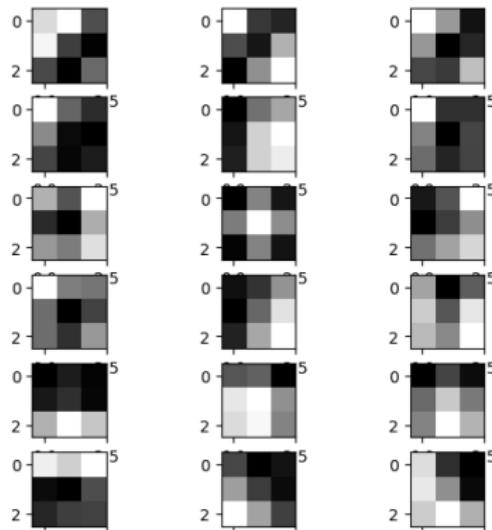
(This is the first Conv2D layer of AlexNet)

```
layers.Conv2D(filters=96,  
              kernel_size=(3,3),  
              padding="valid",  
              strides=(1, 1),  
              dilation_rate=(1, 1),),
```

options:

- filters - the number of kernels that the layer will learn
- kernel size - the shape of the filters
- padding
- strides (see animation)
- dilation (see animation)

## example of some $3 \times 3$ filters learned by a CNN



See the 64 filters of the first layer of the VGG-16 model:  
[notebook\\_CNN\\_VGG16\\_filters.ipynb](#)

we can also visualize the results of a `Conv2D` operation

`notebook_CNN_VGG16_feature_maps.ipynb`

## Padding examples

102	13	0	30	97	102	
13	11	12	101	0	63	
3	17	19	4	100	13	
97	19	3	2	16	104	
102	12	2	101	0	3	
0	2	3	3	7	5	

P=0

0	0	0	0	0	0	0	0	0	0
0	102	13	0	30	97	102	0		
0	13	11	12	101	0	63	0		
0	3	17	19	4	100	13	0		
0	97	19	3	2	16	104	0		
0	102	12	2	101	0	3	0		
0	0	2	3	3	7	5	0		
0	0	0	0	0	0	0	0		

P=1

0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
0	0	102	13	0	30	97	102	0	0
0	0	13	11	12	101	0	63	0	0
0	0	3	17	19	4	100	13	0	0
0	0	97	19	3	2	16	104	0	0
0	0	102	12	2	101	0	3	0	0
0	0	0	2	3	3	7	5	0	0
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0

P=2

for example

```
model.add(ZeroPadding2D((1,1)))
```

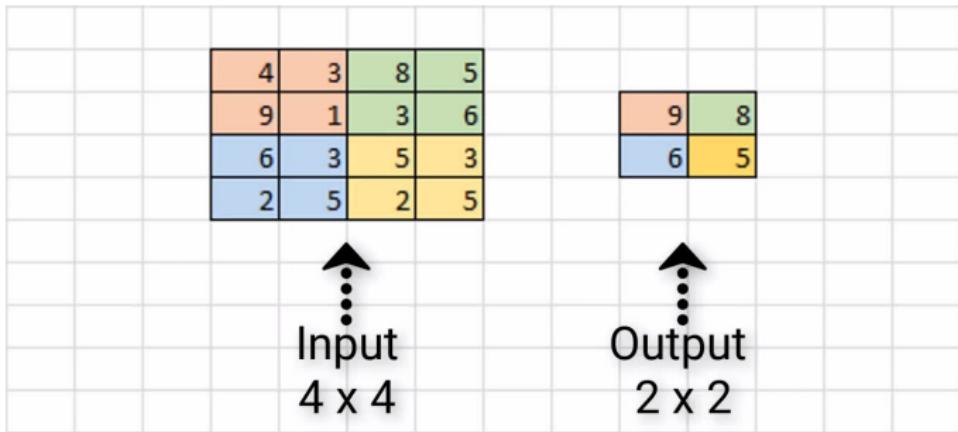
Condense (downsample) using a **maximum pooling layer**

```
layers.MaxPool2D(pool_size=(2, 2))
```

MaxPool is usually added after a convolution layer.

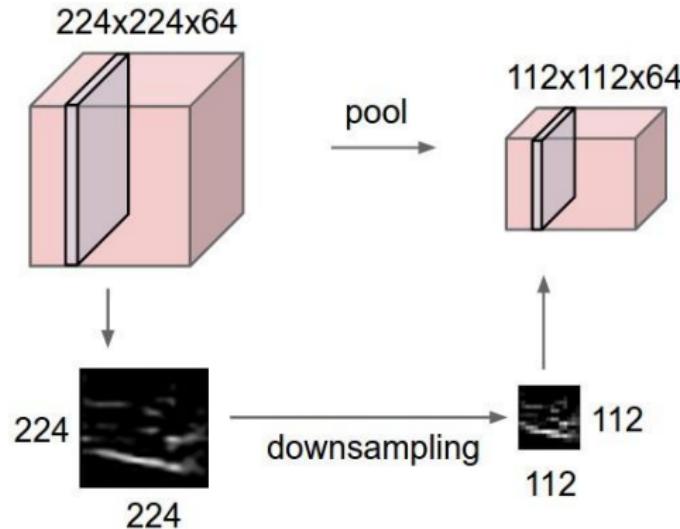
MaxPool basically shrinks an image (array) using the maximum value.  
The size of the sliding window is defined by **pool\_size**, and the **stride** defaults to the pool size.

```
MaxPool2D(pool_size=(2, 2))
```



also there is average pooling:

```
layers.AveragePooling2D(pool_size=(2, 2))
```



## max pooling

(446, 450)



(223, 225)



(111, 112)



(55, 56)



## average pooling

(446, 450)



(223, 225)



(111, 112)



(55, 56)



{Why do we do this?

- smaller images mean less computation
- reduce noise, thus less potential for 'overfitting'

# Practical session

Adapt your MNIST ANN model

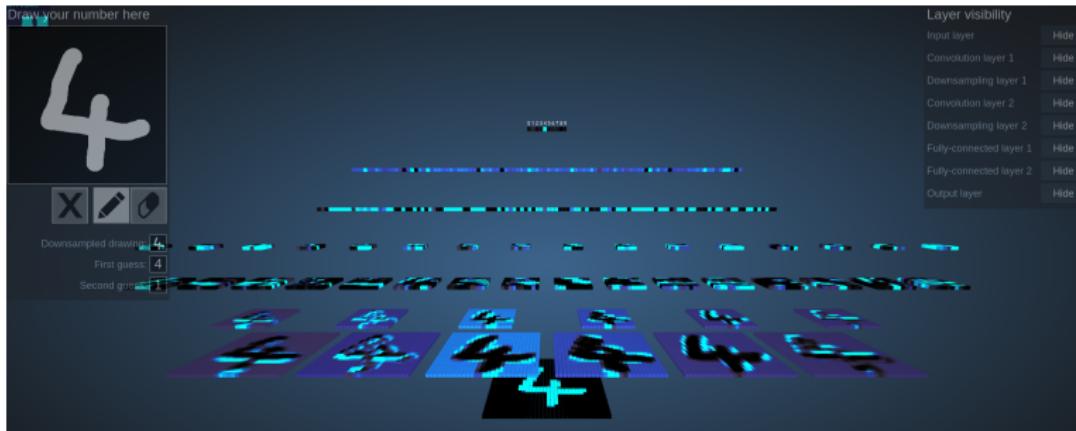
[`notebook\_ANN\_Keras\_MNIST.ipynb`](#)

to now be a CNN model, based on the Keras “[Simple MNIST convnet](#)” page.

To do: Compare the learning curves and the accuracy (better still, the [MCC](#)) score between the ANN and the CNN models.

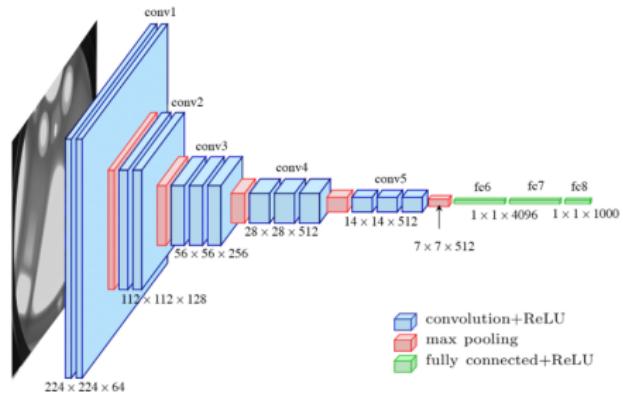
Notice that we had no flatten layer  
our CNN was working with 2D data

## Interactive: 2D convolutional network visualization



This is now the CNN version (for more information see the [paper](#)).

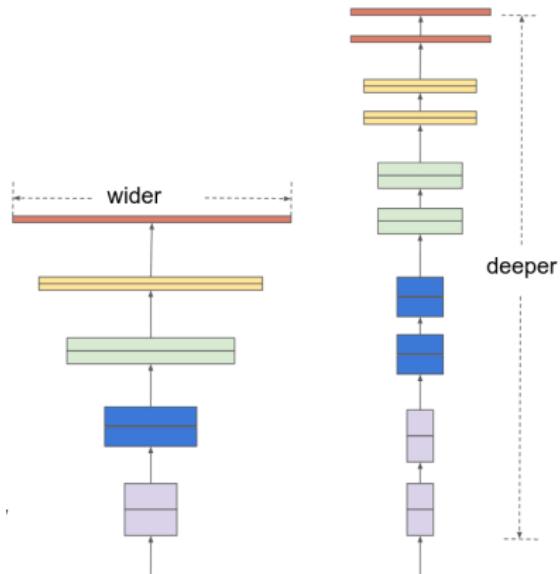
# The VGG (Visual Geometry Group) VGG-16 architecture from 2014:



(VGG-16 model source example)

(Paper: "Very Deep Convolutional Networks for Large-Scale Image Recognition")

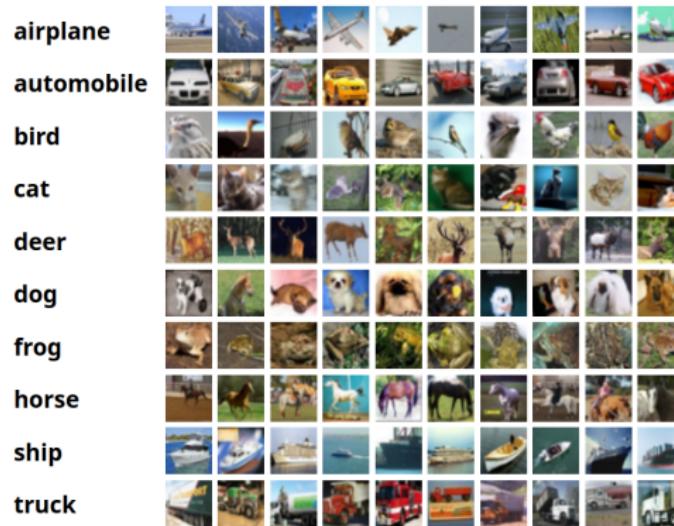
# Neural networks: wide vs deep?



(Paper: "EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks")

# Colour images: CIFAR-10

The [CIFAR-10](#) dataset (2009)



## Getting the CIFAR-10 data using Keras

```
(x_train, y_train), (x_test, y_test) = keras.datasets.cifar10.load_data()
```

the CIFAR images now have red, green, and blue blue channels  
(stored in row-major order)

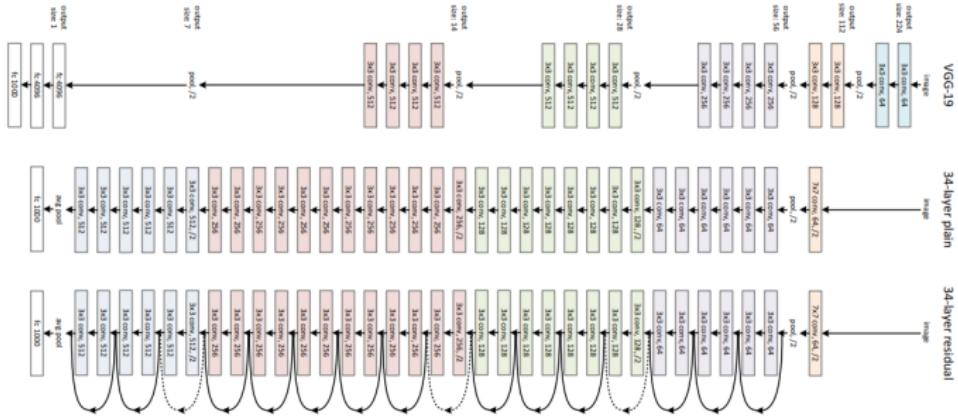
```
image_size = (32, 32)
input_shape = image_size + (3,)
```

# Practical session

Let us take a look at CIFAR-10

[notebook\\_CNN\\_Keras\\_CIFAR10.ipynb](#)

# The Residual Network (ResNet) architecture:



won the 2015 edition of the ImageNet Challenge. ResNet is no longer sequential, having 'residual blocks'.

(Paper: "[Deep Residual Learning for Image Recognition](#)")

“The difference in ResNetV1 and ResNetV2 rests in the structure of their individual building blocks. In ResNetV2, the batch normalization and ReLU activation precede the convolution layers, as opposed to ResNetV1 where the batch normalization and ReLU activation are applied after the convolution layers.”

2017 was the last year of the 2D [ImageNet challenge](#)

2D object detection and image classification is now a ‘solved problem’;  
computers essentially outperform humans.

# Data augmentation

The more data we train on, the better the model.

In classification we can make use of symmetry to perform label-invariant transformations, for example we can **randomly flip** some of our images:

```
keras.layers.RandomFlip(mode="horizontal_and_vertical",)
```



...but only within reason

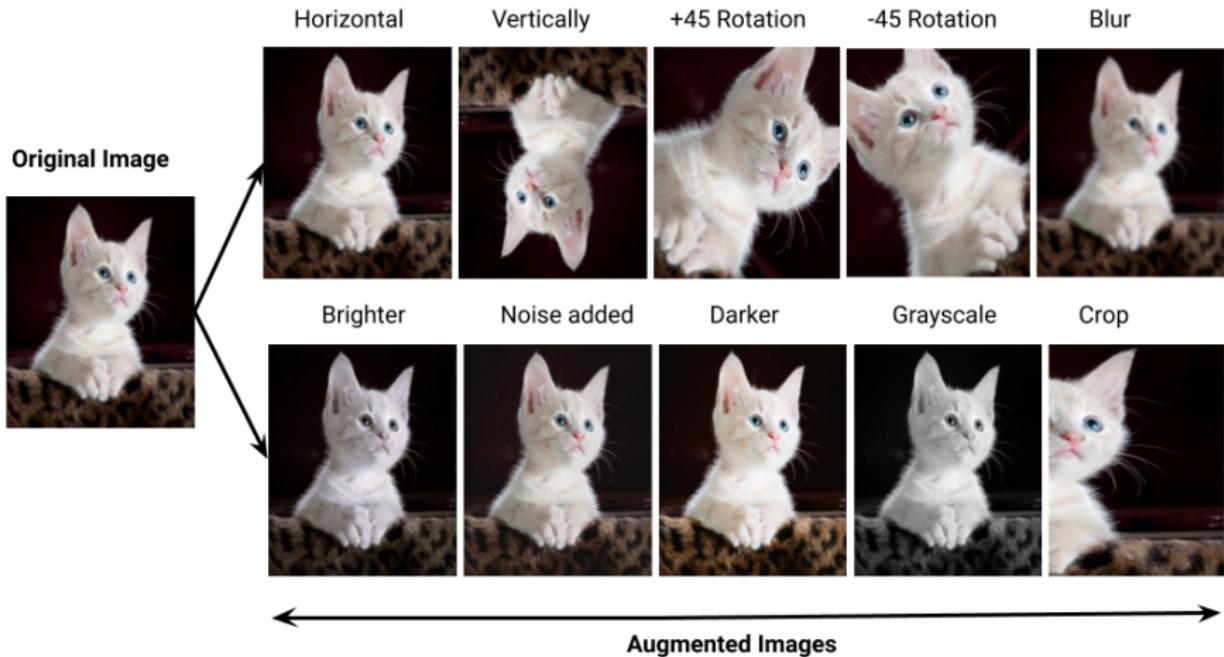


Keras provides a number of such [transformations](#) that can be applied to (mini-)batches as a layer in ones sequence:

## Image augmentation layers

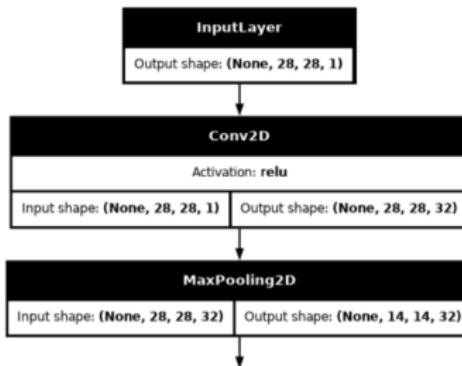
- RandomCrop layer
- RandomFlip layer
- RandomTranslation layer
- RandomRotation layer
- RandomZoom layer
- RandomContrast layer
- RandomBrightness layer

See also the [albumentations](#) package



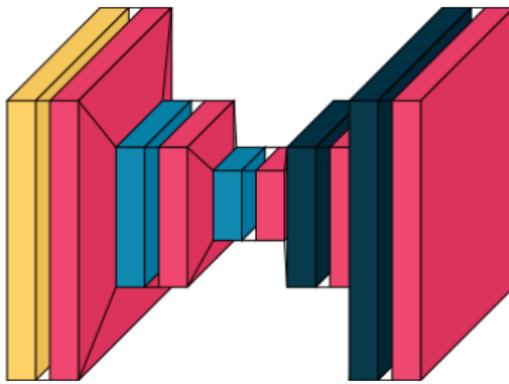
We shall now see two ways of visualizing our neural network architecture:

```
keras.utils.plot_model(model,  
                      show_shapes=True,  
                      show_layer_activations=True,)
```



and the [visualkeras](#) package

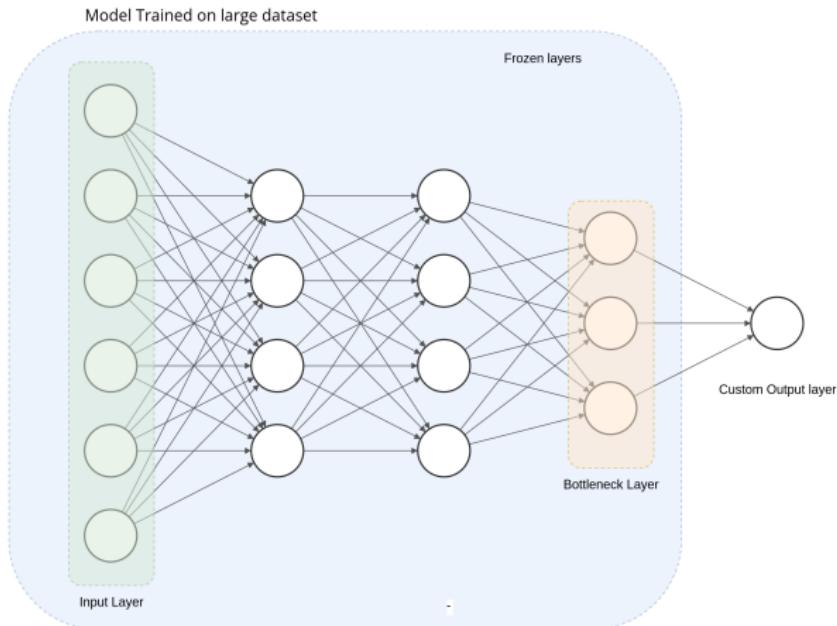
```
!pip install -q visualkeras  
import visualkeras  
visualkeras.layered_view(model)
```



# Transfer learning

“Transfer learning consists of taking features learned on one problem, and leveraging them on a new, similar problem. For instance, features from a model that has learned to identify racoons may be useful to kick-start a model meant to identify tanukis.

Transfer learning is usually done for tasks where your dataset has too little data to train a full-scale model from scratch.”



Freezing the layers of a pre-training model avoids destroying any of the information it contains during future training rounds.

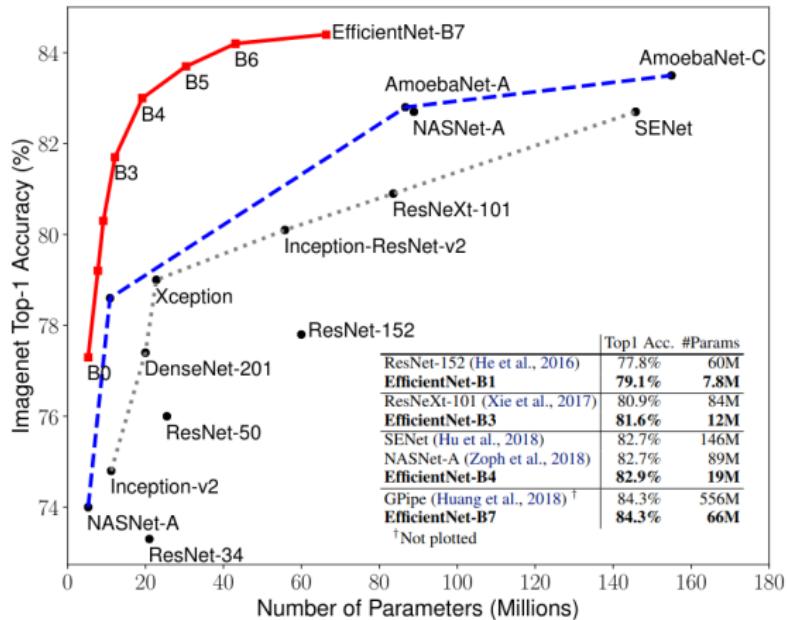
# Pre-trained models

Keras provides many **models** along with pre-trained weights

The screenshot shows the 'Models' section of the Kaggle website. At the top, there are buttons for 'New Model' and 'Your Model'. Below that is a search bar with the placeholder 'Search Models' and a dropdown menu with filters: 'All Filters', 'Clear All', 'Image Classification', 'Keras', 'Organization Models', 'Data Type', 'Language', and a sorting dropdown set to 'Hotness'. A message '8 Results (70 Variations)' is displayed. The results list includes:

- EfficientNetV2**: Implements the EfficientNetV2 architecture. Keras: 12 Variants - 17 Notebooks.
- PolGennas**: An implementation of the PolGennas model. This Keras 3 implementation will run on Jupyter, TensorFlow and PyTorch. Keras: 2 Variants - 10 Notebooks.
- ResNetV2**: Implements the ResNetV2 architecture. Keras: 10 Variants - 19 Notebooks.
- DenseNet**: Implements the DenseNet architecture. Keras: 12 Variants - 17 Notebooks.
- ResNetV1**: Implements the ResNet architecture. Keras: 8 Variants - 17 Notebooks.
- MobileNetV3**: Implements the MobileNetV3 architecture. Keras: 12 Variants - 8 Notebooks.
- VitDot**: A ViT image encoder that uses a multi-head transformer encoder and Keras: 10 Variants - 8 Notebooks.
- RetinaNet**: A RetinaNet implementation using the Retinanet meta-architecture. Keras: 10 Variants - 1 Notebooks.

Pre-trained Keras image classification models on Kaggle, of particular note are **ResNetV2** and **EfficientNetV2**.



Keras also provides a VGG-16 model pre-trained on the imagenet data:

```
from keras.applications.vgg16 import VGG16

base_model = VGG16(
    include_top=False,
    weights="imagenet",
    input_tensor=None,
    input_shape=(32, 32, 3),
    pooling=None,
    classes=10,
    classifier_activation="softmax",
    name="vgg16",
)
```

([source code](#))

then

```
for layer in base_model.layers:  
    layer.trainable = False  
  
model = Sequential()  
model.add(base_model) # for example use a VGG16 base model here  
model.add(Flatten())  
model.add(Dense(512, activation='relu'))  
model.add(Dense(n_classes, activation='softmax'))
```

Keras has a ResNet for imagenet too.

```
model = keras_cv.models.ImageClassifier.from_preset(  
    "resnet50_imagenet",  
    n_classes=2)
```

For binary classification set num\_classes=2

For example, to instantiate a ‘base’ model (here `Xception`) having pre-trained weights and biases:

```
base_model = keras.applications.Xception(  
    weights='imagenet',  
    input_shape=(150, 150, 3),  
    include_top=False)  
  
base_model.trainable = False  
  
base_model.summary()
```

# Fine-tuning

Fine-tuning consists of unfreezing the entire model you obtained above (or part of it), and re-training it on the new data with a very low learning rate (for example 0.00001). This can potentially achieve meaningful improvements, by incrementally adapting the pretrained features to the new data.

# (Very) highly recommended reading

Keras manual: [Transfer learning & fine-tuning](#)

# Kaggle competition

Binary image classification competition:  
Is the photo of a cat or of a dog?

