# Master SIF - REP (Part 7)
# Basics of deep learning

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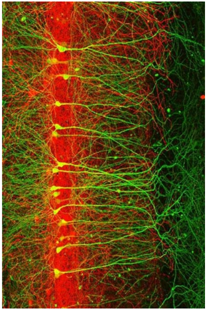
# Outline

# Outline

# The artificial neuron

- The human brain contains around 80 billion neurons.
  - Mouse≈75 million neurons;
  - Cat≈1 billion neurons;
  - Chimpanzee≈7 billion neurons.
- A neuron is a nerve cell that is the basic building block of the nervous system.
- Neurons are specialized to transmit information throughout the body.

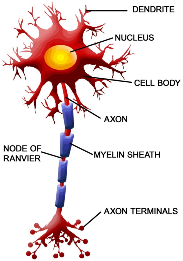


Courtesy of Erik Bloss, Janelia Research Campus

# The artificial neuron

There are three basic parts of a neuron: the dendrites, the cell body, and the axon.

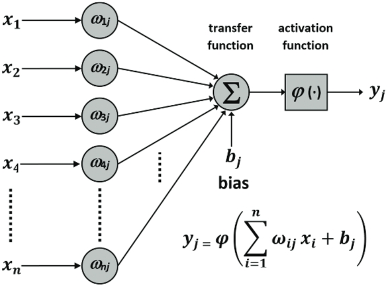
- the dentrites receive information from sensory receptors or other neurons.
- the cell body processes incoming information.
- the axon: each neuron has one axon that transmit the information to the following cell.



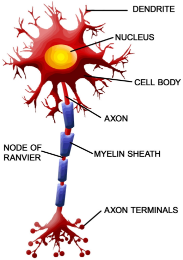

From http://www.interactive-biology.com/3247/the-neuron-external-structure-and-classif

# The artificial neuron

A common scheme of a single neuron (perceptron (McCulloch and Pitts, 1943, Rosenblatt, 1958)):




Adapted from (Álvarez et al., 2017)




From http://www.interactive-biology.com/3247/the-neuron-external-structure-and-classif

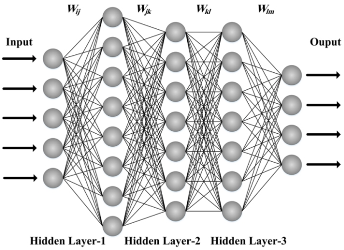
The basic model for a neuron $j$, defined for a generic input $\boldsymbol{x} \in \mathcal{R}^n$:

- performs the weighted linear activation, $\boldsymbol{w}_i \in \mathcal{R}^n$;
- use an activation function $\varphi$, for simulating the firing rate of the cell (e.g. sigmoid function, hyperbolic tangent function).

# The artificial neuron

From a perceptron to a neural network:

- One perceptron outputs one decision;
- For multiple decisions (e.g. digit classification), stack as many outputs as the possible outcomes into a layer $\Rightarrow$ Neural Network;
- Use one layer as input to the next layer (Multi-layer perceptron).




Adapted from (Hosseini and Samanipour, 2015)

Humm, a number of weights to train...

Note that a neural network without an activation function boils down to a simple linear regression model.

# The artificial neuron

A few words on backprogation algorithm:

- Measure the prediction error or loss $z$, error between the actual data and the prediction $\Rightarrow$ loss function;
- Optimize weights to reduce loss $\Rightarrow$ partial derivative of the loss w.r.t the weights;
- Backpropagate the loss, layer by layer, until all neuron weights have been improved (non-convex optimization by gradient descent):

$$(\boldsymbol{w}_i)^{t+1} = (\boldsymbol{w}_i)^t - \eta \frac{\partial z}{\partial (\boldsymbol{w}_i)^t} \tag{1}$$

  where $\boldsymbol{w}_i$ represents the weights of the $i^{th}$ layer, $\eta$ the learning rate (small positive value) and $t$ the time index.
- Repeat until convergence

# The artificial neuron



Limitations of deep neural networks at that time:

- Lack of processing power (1958-1998), no GPU...
- Lack of data, no super big annotated datasets
- Limited performance due to the limited training ability (processing power and data), models do not generalize well.

After a long AI winter, from 1998-2006, the deep neural networks come back with an amazing success.

# Outline

# The big picture



A family of parametric, non-linear and hierarchical representation learning functions, which are massively optimized with batch/stochastic/mini-batch gradient descent to encode domain knowledge, i.e. domain invariances, stationarity.

$$\hat{y}_L\left(x;\theta_{1,\ldots,L}\right) = h_L\left(h_{L-1}\left(\ldots h_1\left(x;\theta_1\right),\theta_{L-1}\right),\theta_L\right) \tag{2}$$

- $x$, input; $\theta_l$, parameters for layer $l$, $\hat{y}_l = h_l(x,\theta_l)$, a (non)linear function.

Given training corpus $\{X,Y\}$, find optimal parameters to minimize the loss:

$$\theta^* \leftarrow \arg\min_{\theta} \sum_{(x,y)\subseteq(X,Y)} \Phi\left(y;\hat{y}_L\left(x;\theta_{1,\ldots,L}\right)\right) \tag{3}$$

with $\Phi$ the chosen loss function.

Adapted from *Introduction to deep learning and neural networks*, UVA deep learning course - Efstrations GAVVE.

# End-to-end learning

Given training corpus $\{X, Y\}$, find optimal parameters to minimize the loss:

$$\theta^* \leftarrow \arg\min_{\theta} \sum_{(x,y) \subseteq (X,Y)} \Phi\left(y; \hat{y}_L\left(x; \theta_{1,\ldots,L}\right)\right) \tag{4}$$

- A pipeline of successive modules
- Each module's output is the input for the next module
- Modules produce features of higher and higher abstractions
- Features are also learned from data!
  - hand-crafted feature extraction are no more required, such as SIFT, SURF, HoG....
  - they are very compact and specific for the task at hand
  - time spent for designing features now spent for designing architectures!

Adapted from *Introduction to deep learning and neural networks*, UVA deep learning course - Efstrations GAVVE.

# Different types of deep neural network



- Deep (5-20 layers) vs Shallow (1-2 layers) neural network;
- Supervised vs Unsupervised:
  - Unsupervised learning infers a function that describes the structure of unlabeled data ($\Rightarrow$ Autoencoders, Deep Belief Nets, Generative Adversarial Networks, Self-organizing map);
  - Supervised learning.
    Given a bunch of input data $X$ and labels $Y$, we are learning a function $f : X \rightarrow Y$ that maps $X$ (e.g. images) to $Y$ (e.g. class label). The function will be able to predict $Y$ from novel input data with a certain accuracy if the training process converged.
    - Convolution Neural Network, appropriate for visual data
    - Recurrent Neural Network, appropriate for text, sound, series

# Outline

# Basic building operators of CNNs

## Convolution layer (1/6)

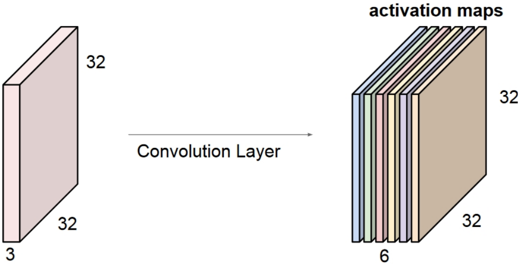
### Convolution Layer

The **convolution operator** aims to extract features from the input image. It preserves the spatial relationship between pixels by learning image features using small chunk of input data (as a neuron would do in our visual cortex).

- Input: a 2D map
- Output: Convolved Feature or Activation Map or the Feature Map
- Parameters: a $N \times N$ kernel or filter (the same across all locations)
  - Example:
    $1000 \times 1000$ images, 100 convolution filters, kernel size $10 \times 10$
    $\Rightarrow 10 * 10 * 100 = 10k$ parameters to learn...
- Filters always extend the full depth of the input volume:
  - Example:
    $32 \times 32 \times 3$ images with $5 \times 5 \times 3 \Rightarrow 75$ parameters to learn ($+1$ for the bias).

Here are the hyper-parameters:

- The depth: the number of filters we use for the convolution operation.
  Increasing the depth $\Rightarrow$ more feature maps are extracted.
  - Example:
    $32 \times 32 \times 3$ images with 6 filters $5 \times 5 \times 3 \Rightarrow 6 \times (75 + 1)$ parameters to learn.




with stride=1, pad=2

Adapted from Standford course http://cs231n.stanford.edu

# Basic building operators of CNNs

## Convolution layer (3/6)

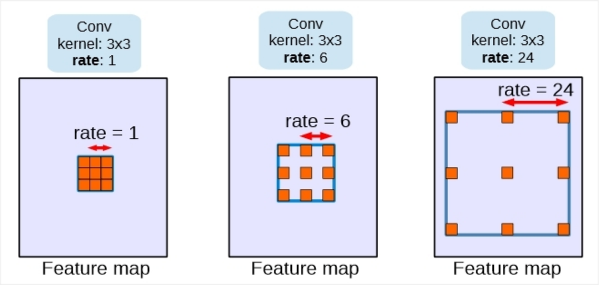
Here are the hyper-parameters:

- The stride: the stride is the number of pixels by which we slide our filter matrix over the input matrix.
  - stride=1, no decimation
  - stride=2, decimation of 2...
- Padding: padding pads the input volume around the border (zero padding).
  - if stride=1, we can pad the volume with $\frac{N-1}{2}$ to be sure to keep the same output resolution as the input one ($N$ is the size of the convolutional kernel)
- Causal or not: a convolution is called causal if the filter output does not depend on future inputs (e.g. audio (Van Den Oord et al., 2016)).

# Basic building operators of CNNs

## Convolution layer (4/6)

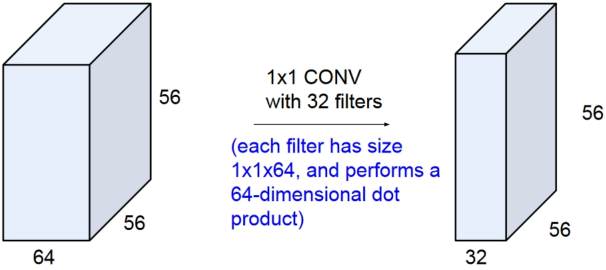
- Dilatation rate (A trous convolution):
  - Used to expand the receptive field without loss of resolution or coverage (Yu and Koltun, 2015)
  - Multi-scale information without losing resolution (stride=1!!)




Extracted from (Chen et al., 2017)

➡ the particular case of the $1 \times 1$ convolution:

- use to reduce the dimension of the input volume (not the spatial dimension!)
- a $1 \times 1$ convolution with one layer produces only one layer in output, no matter the number of layer in input.




Adapted from Standford course http://cs231n.stanford.edu

# Basic building operators of CNNs

## Convolution layer (6/6)

- 3D convolution (e.g. spatial convolution over volumes):

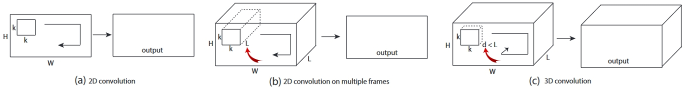



Figure 1. **2D and 3D convolution operations**. a) Applying 2D convolution on an image results in an image. b) Applying 2D convolution on a video volume (multiple frames as multiple channels) also results in an image. c) Applying 3D convolution on a video volume results in another volume, preserving temporal information of the input signal.

Adapted from (Tran et al., 2015)

- We can specify the strides of the convolution along each spatial dimension (spatial ($\times 2$), temporal);
- The kernel size is defined by the depth, height and width of the 3D convolution window.

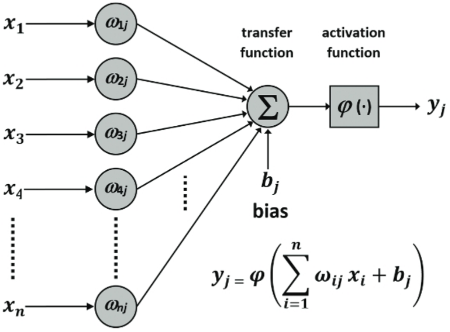
- In (Tran et al., 2015), they showed that the C3D network can model appearance and motion information simultaneously!!
- Video saliency (Ding and Fang, 2017), audio-visual saliency (Tavakoli et al., 2019), trajectory, motion...

# Basic building operators of CNNs

## Activation layer(1/7)

### Activation layer

The **activation operator** aims to simulate the firing rate of the cell.




Adapted from (Álvarez et al., 2017)

# Basic building operators of CNNs

## Activation layer(2/7)

- Sigmoid: $\varphi(x) = \frac{1}{1+e^{-x}}$
- Tanh: $\varphi(x) = tanh(x)$
- Relu (Krizhevsky et al., 2012): $\varphi(x) = \max(0, x)$
- Leaky-Relu (Maas et al., 2013):

$$\varphi(x) = \max(0.01 \times x, x)$$

- PRelu (Parametric Rectifier) (He et al., 2015):

$$\varphi(x) = \max(\alpha \times x, x)$$

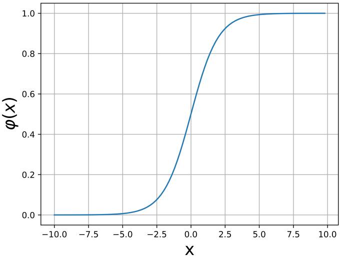
- ELU (Exponential Linear Units) (Clevert et al., 2015):

$$\varphi(x) = \begin{cases} x & \text{if } x > 0, \\ \alpha\left(exp(x) - 1\right) & \text{if } x \leq 0. \end{cases}$$

- Swish (Ramachandran et al., 2017)(seems to be the best now):

$$\varphi(x) = \frac{x}{1 + e^{-x}}$$

- Sigmoid: $\varphi(x) = \frac{1}{1+e^{-x}}$

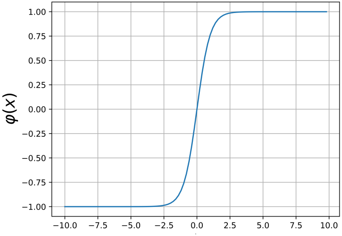



- Output numbers in the range $[0, 1]$
- Vanishing gradients, i.e. kills gradients when saturated
- Outputs are not zero-centered
- Exp() is computationally expensive

# Basic building operators of CNNs

## Activation layer(4/7)

- tanh: $\varphi(x) = tanh(x)$

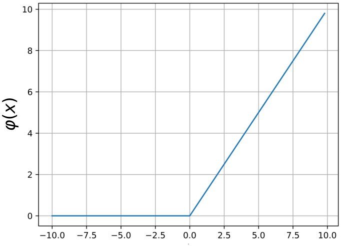



- Output numbers in the range $[0, 1]$
- Vanishing gradients, i.e. kills gradients when saturated
- Outputs are zero-centered

# Basic building operators of CNNs

## Activation layer(5/7)

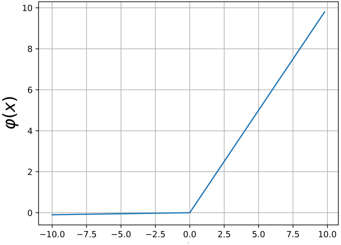
- Relu: $\varphi(x) = \max(0, x)$




- ✓ No saturation for $x > 0$
- ✓ Very simple, and computationally efficient
- ✓ Converge faster than sigmoid and tanh
- ✗ No zero-centered

Transforms
T. Maugey
Introduction
The big picture of deep neural network
Deep Convolutional Neural Network
Convolutional Layer
Activation Layer
Pooling layer
Fully-Connected Layer
Loss functions
Training
VGG network
ResNet
MobileNet
Auto-encoder
Generative Adversarial Networks

- Weakly Relu: $\varphi(x) = \max(0.01 \times x, x)$

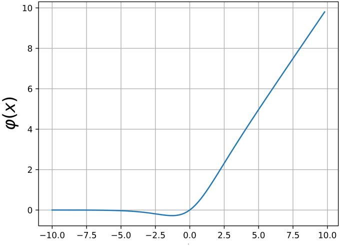



- ✔ No saturation for $x > 0$ and small positive slope, when $x \leq 0$
- ✔ Very simple, and computationally efficient
- ✔ Converge faster than sigmoid and tanh
- ✘ No zero-centered

# Basic building operators of CNNs

## Activation layer(7/7)

- Swish: $\varphi(x) = \frac{x}{1+e^{-x}}$




- A subtle mixture between sigmoid, and weakly-Relu

# Basic building operators of CNNs

## Pooling layer (1/3)

### Pooling Layer

The **pooling operator** aims to map a subregion of the input into a single number in order to reduce the size of the representation (to speed up the computation) and to make features detection more robust.

Two types of pooling operators are widely used:

- max pooling maps a subregion to its maximum value;
- average pooling maps a subregion to its maximum value

```
MaxPooling2D(pool_size=(2, 2), strides=None,
    padding='valid', data_format=None)
```

- global average pooling.

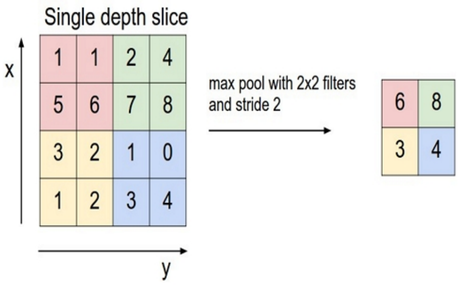
No parameters to learn!!

# Basic building operators of CNNs

## Pooling layer (2/3)

Here are the hyper-parameters:

- Kernel size: the size of the subregion of the input that will be mapped to a single value;
- The stride: same as the convolutional layer.




Max pooling is the most used: if a specific feature is in the original input volume, there will be a high activation value, the max pooling can catch it!

- 2D Global Average Pooling:
  - It consists in taking an average of every incoming feature map;
  - It is therefore independent of the size of the input image;
  - Reduce the number of parameters (cf. fully connected).

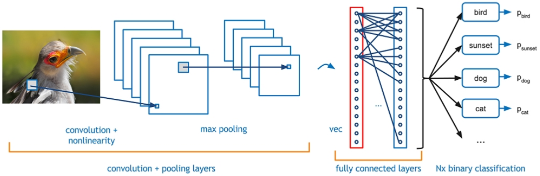
  For example, with a $15 \times 15 \times 8$ incoming tensor of feature maps, we take the average of each $15 \times 15$ matrix slice, giving an 8 dimensional vector.
- Same concept for 2D Global Max Pooling.

# Basic building operators of CNNs

## Fully-Connected Layer (1/2)

### Fully-Connected Layer

In a fully connected layer, each neuron is connected to every neuron in the previous layer, and each connection has it's own weight. This is a totally general purpose connection pattern and makes no assumptions about the features in the data. It's also very expensive in terms of memory (weights) and computation (connections).




From https://adeshpande3.github.io/A-Beginner's-Guide-To-Understanding-Convolutional-Neural-Networks/

can hence be computed with a matrix multiplication

# Basic building operators of CNNs

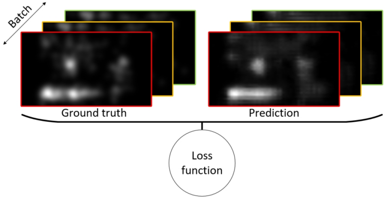
## Fully-Connected Layer (2/2)

```
model = Sequential()
# Dense(64) is a fully-connected layer with 64
    hidden units.
# in the first layer, you must specify the expected
    input data shape:
# here, 20-dimensional vectors.
model.add(Dense(64,activation='relu',input_dim=20))
```

```
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))
```

# Loss functions for dense prediction (1/4)

- Loss function $\mathcal{L}(S, \hat{S})$ for a dense prediction between $S$ and $\hat{S}$ map




- Taxonomy of loss functions:
  - Pixel-based loss functions
  - Probability distribution-based loss functions
  - Task-dependent loss functions (e.g. saliency metrics)

# Loss functions for dense prediction (2/4)

➡ Pixel-based loss functions ($S, \hat{S} \in [0,1]$):

$$\mathcal{L}(S,\hat{S})_{MSE} = \frac{1}{N}\sum_{j=1}^{N}(S_j - \hat{S}_j)^2$$

(He et al., 2018)

$$\mathcal{L}(S,\hat{S})_{EAD} = \frac{1}{N}\sum_{j=1}^{N}\Big(exp(|S_j - \hat{S}_j|) - 1\Big)$$

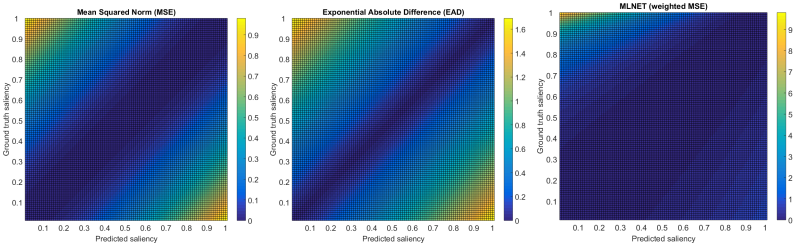
(Cornia et al., 2016)

$$\mathcal{L}(S,\hat{S})_{MLNET} = \frac{1}{N}\sum_{j=1}^{N}\frac{1}{\alpha - S_j}(S_j - \hat{S}_j)^2, \alpha = 1.1$$

MSE: Mean Squared Error; EAD: Exponential Absolute Difference; MLNET: Weighted MSE

# Loss functions for dense prediction (3/4)

➡ Pixel-based loss functions ($S, \hat{S} \in [0,1]$):




From left to right: MSE, EAD, MLNET

MSE: Mean Squared Error; EAD: Exponential Absolute Difference; MLNET: Weighted MSE

# Loss functions for dense prediction (4/4)

- Probability distribution-based loss functions ($\sum_i S_i = \sum_i \hat{S}_i = 1$):

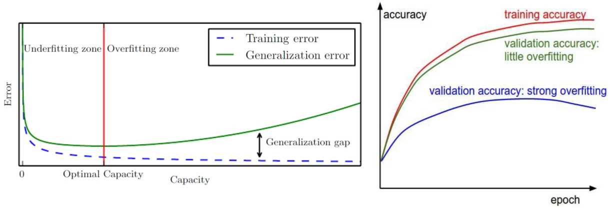
$$\mathcal{L}(S,\hat{S})_{Bhat} = -ln\left(\sum_{j=1}^{M}\sqrt{S_j\hat{S}_j}\right) \quad (5)$$

$$\mathcal{L}(S,\hat{S})_{KL} = \sum_{j=1}^{M} S_j log\left(\frac{S_j}{\hat{S}_j}\right) \quad (6)$$

Bhat: Bhattacharyya distance; KL: Kullback-Leibler divergence.

# Training (1/3)

- Overfitting (network size, amount of data, gap between training and test performance (generalization))




Adapted from M. Tekalp, tutorial EUSIPCO 2018, *Deep Learning for image and video processing*.

To prevent overfitting:

- Weight-decay
- Drop out

When the data set is too small:

- Pre-training on generic datasets;
- Data augmentation (Random crop, horizontal/vertical flip, rotations, synthetic data generation).

# Training (2/3)



- Kernel initializers:
  - Zeros, Ones, Constant
  - Random Normal, Random Uniform: initialization with a normal ($\mu$, $\sigma$ and seed) / uniform distribution ($minval$, $maxval$ and seed);
  - Le Cun Uniform (LeCun et al., 2012): initialization from a uniform distribution within $[-limit, limit]$ with $limit = \sqrt{\frac{3}{N}}$, N is the number of input channels of the layer.
  - glorot_normal (Glorot and Bengio, 2010): initialization from a normal distribution centered on 0 with $\sigma = \sqrt{\frac{2}{N+M}}$, M is the number of output channels of the layer.

Many variants!

But all you need is a good init (Mishkin and Matas, 2015).

Not convinced by these initializers, make your own initializer!

# Training (3/3)

Not convinced by these initializers, make your own initializer!

```
from keras import backend as K
def my_init(shape, dtype=None):
    return K.random_normal(shape, dtype=dtype)
model.add(Dense(64, kernel_initializer=my_init))
```

# Outline

# Visual Geometry Group (VGG) network (1/5)

➡ CNN for image classification (Simonyan and Zisserman, 2014):

- Given an input image, VGG network aims to find object name in the image
- It can detect up to 1000 different objects
- It takes input image of size $224 \times 224 \times 3$ (RGB image)

Built using:

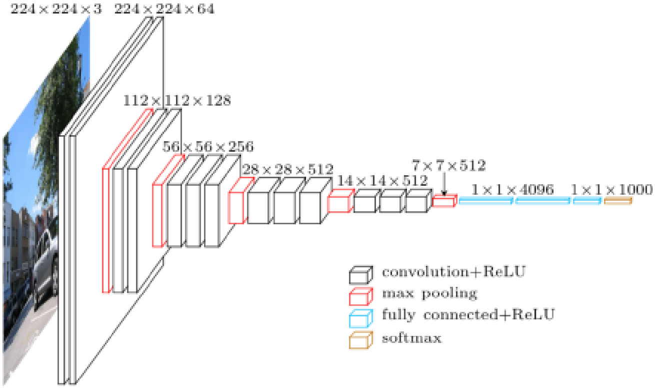
- Convolutions layers (used only $3 \times 3$ size)
- Max pooling layers (used only $2 \times 2$ size)
- Fully connected layers at end
- Total 16 layers
- Trained with Imagenet, $\approx$ 16 Million images,1000 classes (Deng et al., 2009)

Model size: 528MB

Hummm, 138 millions of parameters.

# Visual Geometry Group (VGG) network (2/5)

- CNN for image classification:




Architecture of VGG16

# Visual Geometry Group (VGG) network (3/5)



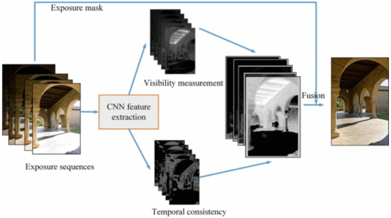

- Convolution using 64 filters
- Convolution using 64 filters + Max pooling
- Convolution using 128 filters
- Convolution using 128 filters + Max pooling
- Convolution using 256 filters
- Convolution using 256 filters
- Convolution using 256 filters + Max pooling
- Convolution using 512 filters
- Convolution using 512 filters
- Convolution using 512 filters + Max pooling
- Convolution using 512 filters
- Convolution using 512 filters
- Convolution using 512 filters + Max pooling
- Fully connected with 4096 nodes
- Fully connected with 4096 nodes
- Output layer with Softmax activation with 1000 nodes

# VGG-like convnet

```python
import numpy as np
import keras
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras.optimizers import SGD

# Generate dummy data
x_train = np.random.random((100, 100, 100, 3))
y_train = keras.utils.to_categorical(np.random.randint(10, size=(100, 1)), num_classes=10)
x_test = np.random.random((20, 100, 100, 3))
y_test = keras.utils.to_categorical(np.random.randint(10, size=(20, 1)), num_classes=10)

model = Sequential()
# input: 100x100 images with 3 channels -> (100, 100, 3) tensors.
# this applies 32 convolution filters of size 3x3 each.
model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(100, 100, 3)))
model.add(Conv2D(32, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))

model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(10, activation='softmax'))

sgd = SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='categorical_crossentropy', optimizer=sgd)

model.fit(x_train, y_train, batch_size=32, epochs=10)
score = model.evaluate(x_test, y_test, batch_size=32)
```

# Visual Geometry Group (VGG) network (5/5)

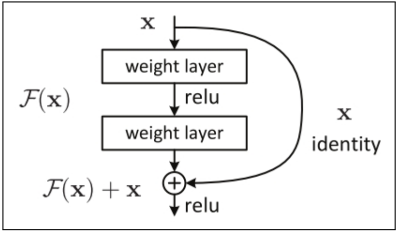
- A number of applications with the deep features:
  - Multi-Exposure Fusion with CNN features (Li and Zhang, 2018):




  - Deep Features to Classify Skin Lesions (Kawahara et al., 2016).
  - Image retrieval (Babenko and Lempitsky, 2015).
  - Image saliency (Cornia et al., 2016, Kümmerer et al., 2014, 2016).

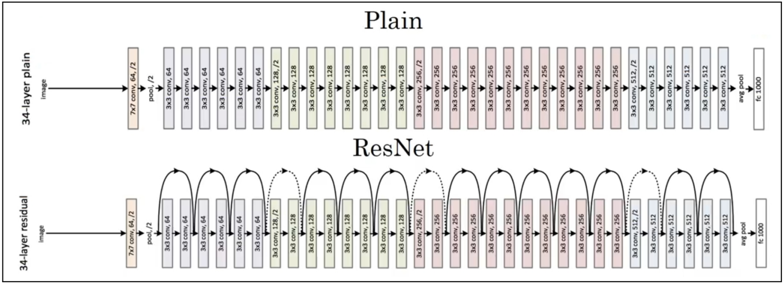
# ResNet (1/2)

- Going deeper and deeper, but increasing network depth does not work by simply stacking layers together:
  - vanishing gradient problem;
  - too small gradient $\Rightarrow$ performance saturation.
- ResNet (He et al., 2016) ($> 29000$ citations...):
  - Skip connections or short cut connections;
  - Identity function, adding new layers do not hurt the ability to train the network.



# ResNet (2/2)

➡ ResNet (He et al., 2016):




Wonderful explanations in 7 minutes:

https://www.youtube.com/watch?v=ZILIbUvp5lk

# MobileNet (1/2)



- MobileNet (Howard et al., 2017):
  - efficient models for mobile and embedded vision applications;
  - light weight deep neural networks;
  - main novelty is based on a depthwise Separable Convolutions=depthwise + pointwise convolution.

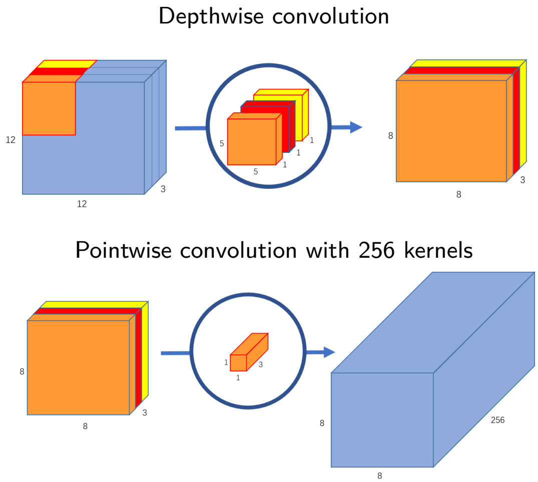
If we assume an image with 3 channels and a convolution kernel of $5 \times 5$ size:

- For a classic 2d convolution: we actually do $5 \times 5 \times 3 = 75$ multiplications.
- Depthwise convolution: Instead of 1 kernel, we use 3 kernels of shape $5 \times 5 \times 1$.
- Pointwise Convolution: To get the final map, we use 1D convolution of size $1 \times 1 \times 3$ to mix together the different channels.

The number of multiplication significantly decreases!!

# MobileNet (2/2)

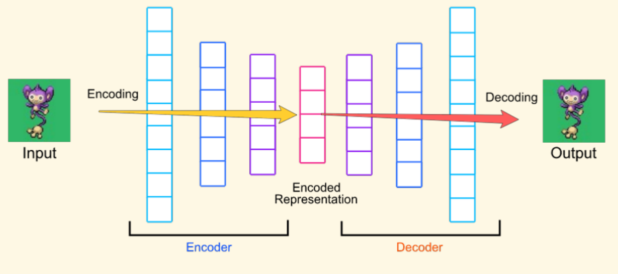
- MobileNet (Howard et al., 2017):




From https://towardsdatascience.com/a-basic-introduction-to-separable-convolutions-b99ec3102728

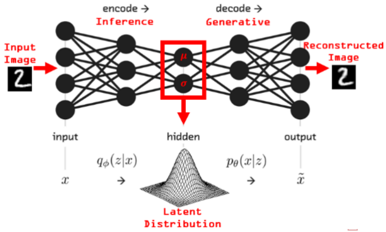
# Auto-encoders

- Encoder network: receives the original image and generates a compact representation (latent code)
- Decoder network: reconstructs the original image from the compact representation, with as much fidelity as possible
- Both networks are iteratively trained with some loss function



# Variational auto-encoders

- Same as auto-encoder but with a constraint on the encoding network, that forces it to generate latent vectors that follow a unit gaussian distribution
- Generating new images: sample a latent vector from the unit gaussian and pass it into the decoder
- Includes two separate losses:
  - Generative loss: mean squared error that measures the reconstructed images quality
  - Latent loss: KL divergence that measures how closely the latent variables match a unit gaussian

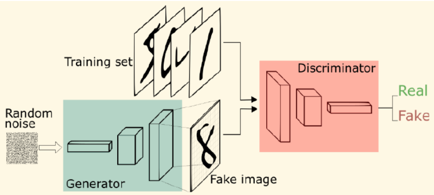


# Generative Adversarial Neural Networks

Generative Adversarial Neural Networks (GAN) are a class of unsupervised machine learning algorithms which able to generate high quality images

- Generative model: generates new images with the aim of creating real-looking data instances to fool the discriminator
- Discriminative model: evaluates images estimates the probability of how close an image belongs to the training data set

Both networks are involved in a minmax game, because one of the models tries to minimize the cost while the other tries to maximize it




*StyleGAN*

# Deep neural network behavior

Current research directions:

- Explore new architectures
- Decrease network's complexity
- Understand network's behavior (*e.g.*, https://www.youtube.com/watch?v=jhOu5yhe0rc)

[Moosavi-Dezfooli, S. M., Fawzi, A., Fawzi, O., and Frossard, P. (2017). Universal adversarial perturbations. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1765-1773).]

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