UNIVERSITY OF JYVÄSKYLÄ

Lecture 3: AutoEncoders and Convolutional Neural Networks (CNN)

TIES4911 Deep-Learning for Cognitive Computing for Developers
Spring 2024

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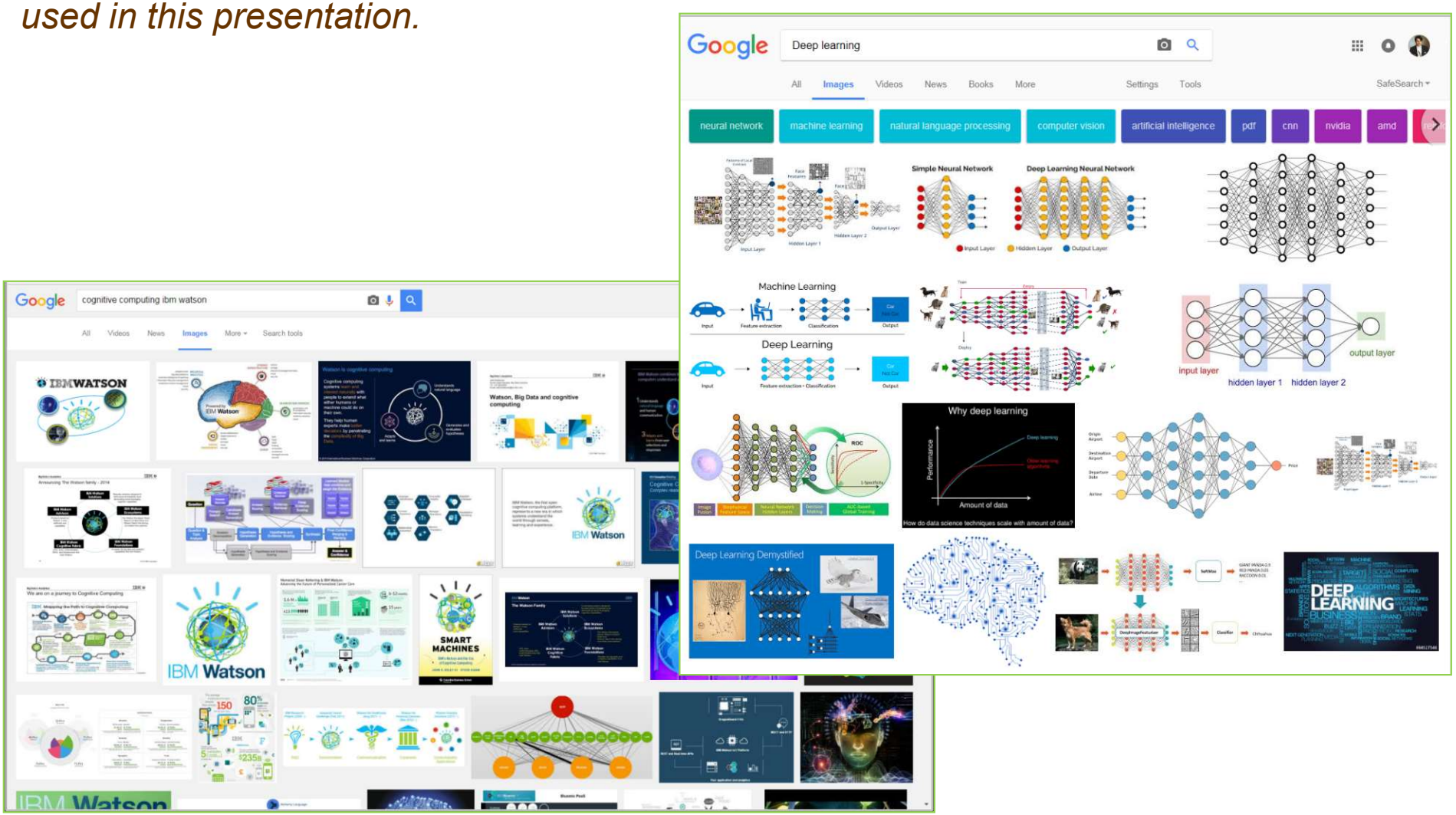
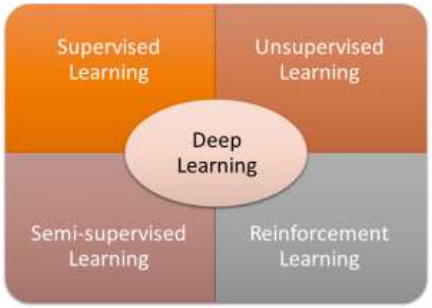
Acknowledgement

I am grateful to all the creators/owners of the images that I found from Google and have used in this presentation.





Deep Learning

UNLABELED data

- *Feature Extraction*
- *Unsupervised Learning*
- *Pattern Recognition*

use Unsupervised Learning (extraction of the patterns from a set of unlabeled data):

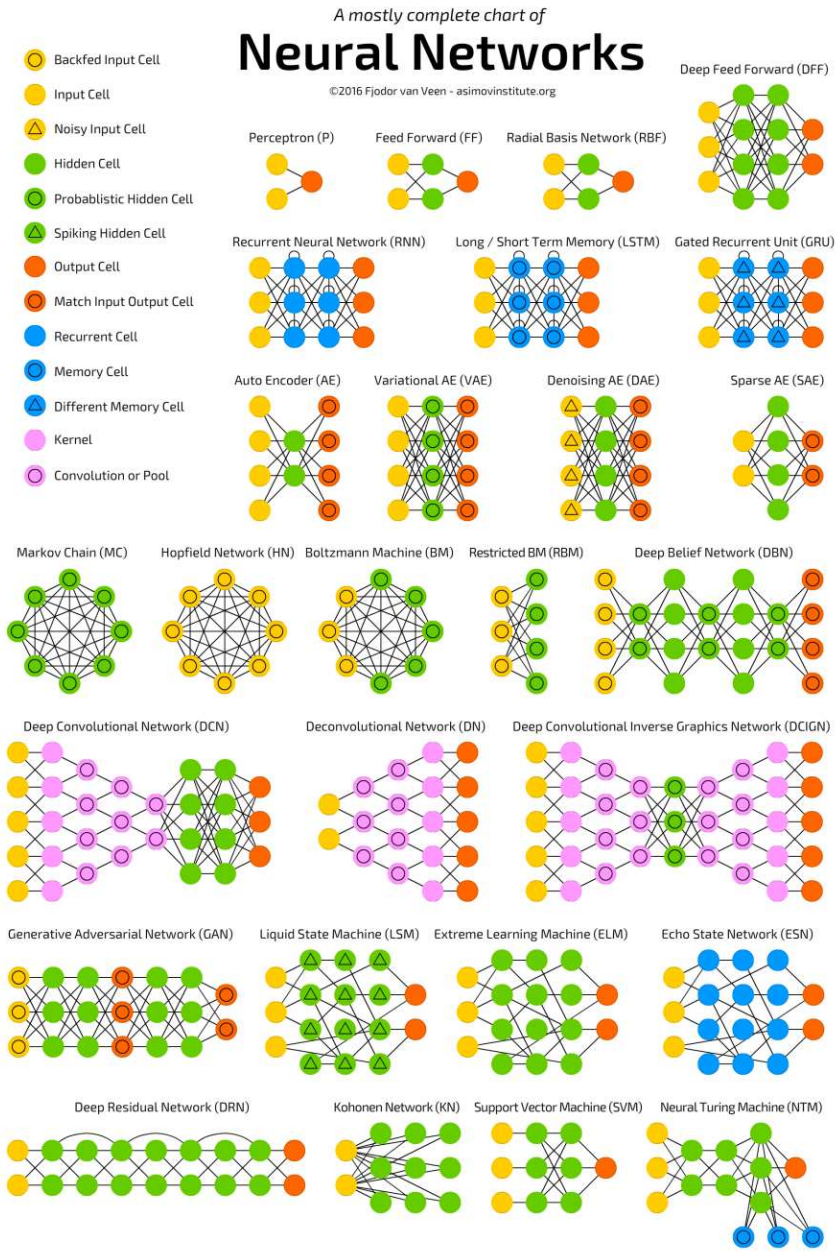
- *Restricted Boltzmann Machine (RBM)*
- *Autoencoders*

LABELED data

- *Supervised Learning*

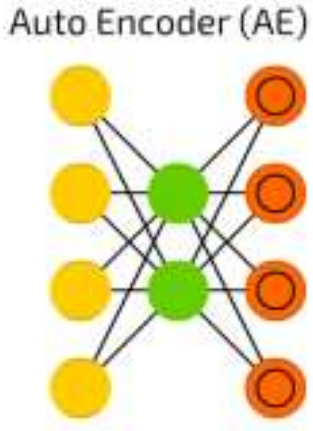
use Supervised Learning to build predictors, classifiers, generators, etc. Depending on application use:

- *Multilayer Perceptrons and Deep Belief Networks for regression and classification tasks.*
- *Convolutional Net (CNN) and Transformers for image and video processing (classification, annotation, generation, etc.)*
- *CNN for object detection/recognition.*
- *Recurrent Neural Net (RNN) and Transformers for sequences or time series analysis including speech recognition/generation and language model-based NLP tasks such as sentiment analysis, parsing, named entity recognition, etc.*



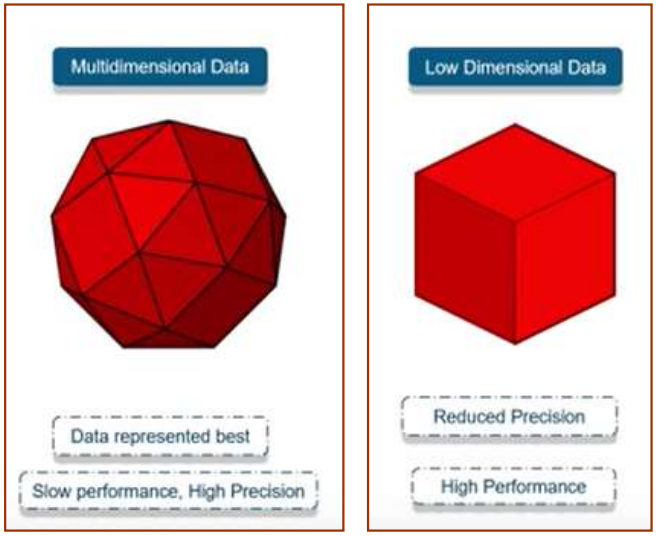
A visual and intuitive understanding of deep learning:
https://www.youtube.com/watch?v=Oqm9vsf_hvU

Autoencoders

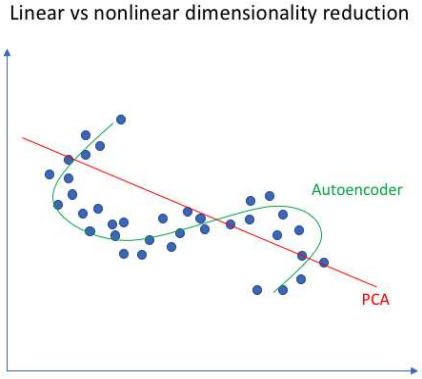


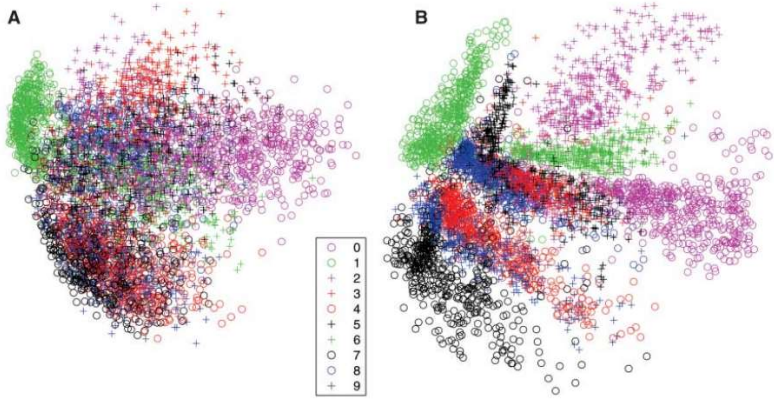
Autoencoders in Deep Learning

Data compression *and* ***Dimensionality reduction*** *help us to increase the performance by converting our data into a smaller representation that we can recreate to a degree of quality.*



Autoencoders *outperform linear dimensionality reduction approaches (e.g.* ***Principle Component Analysis (PCA)****) applying non-linear transformations using multiple layers and non-linear activation functions…*

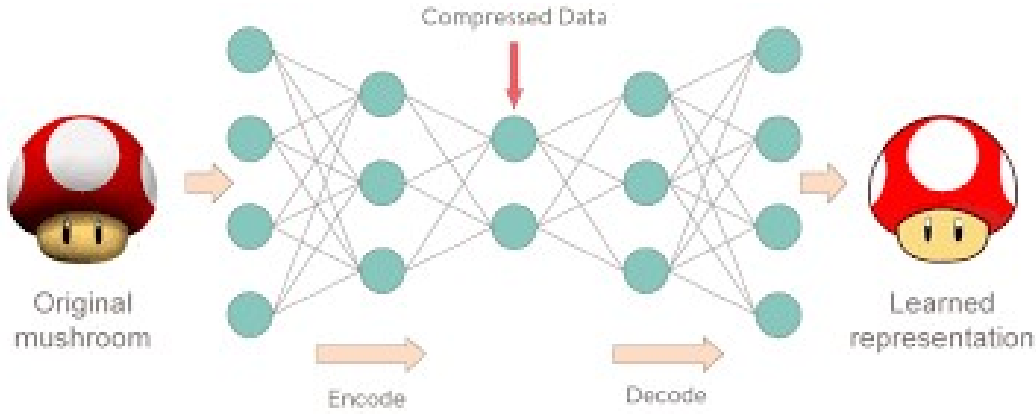




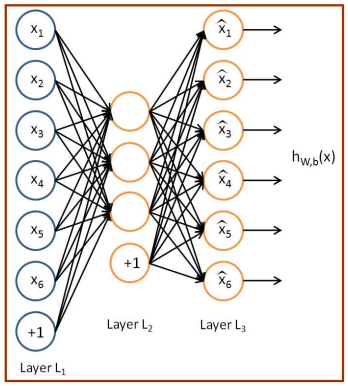
Relevant links:
https://www.youtube.com/watch?v=nTt_ajul8NY
http://www.deeplearningbook.org/contents/autoencoders.html
https://stats.stackexchange.com/questions/190148/building-an-autoencoder-in-tensorflow-to-surpass-pca

Autoencoders in Deep Learning

Autoencoders *are an important family of neural networks that are designed to recognize inherent patterns in data and sort of encode their own structure. Autoencoder is a neural net that takes a set of typically unlabeled inputs, and after encoding them, tries to reconstruct them as accurately as possible. As a result, the net decides which of the data features are the most important, essentially acting as a feature extraction engine.*



Autoencoders are typically very shallow, and are usually comprised of an input layer, an output layer and a hidden layer. However, there are deep autoencoders that are extremely useful tools for dimensionality reduction.



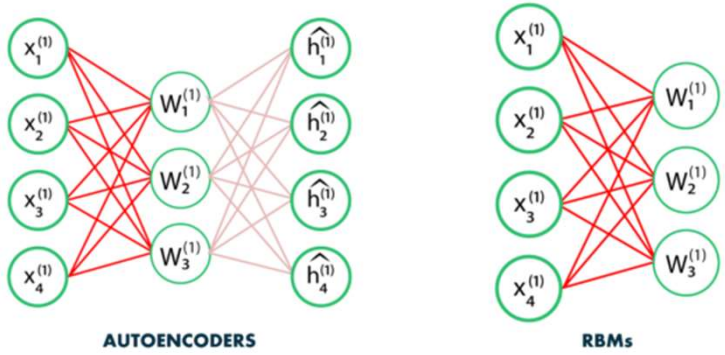
Autoencoder training parameters:

- ***Code size*** *– size of compressed data (number of nodes in the middle layer)*
- ***Number of Layers*** *– could be as deep as you wish*
- ***Loss Function*** *– mean square error or binary cross entropy (if the input values in the range [0,1])*
- ***Number of Nodes per Layers*** *– usually layers structure is symmetric for encoder and decoder, and number of nodes decrease the "code" (compressed data)*

Relevant links:
https://www.youtube.com/watch?v=nTt_ajul8NY
http://www.deeplearningbook.org/contents/autoencoders.html

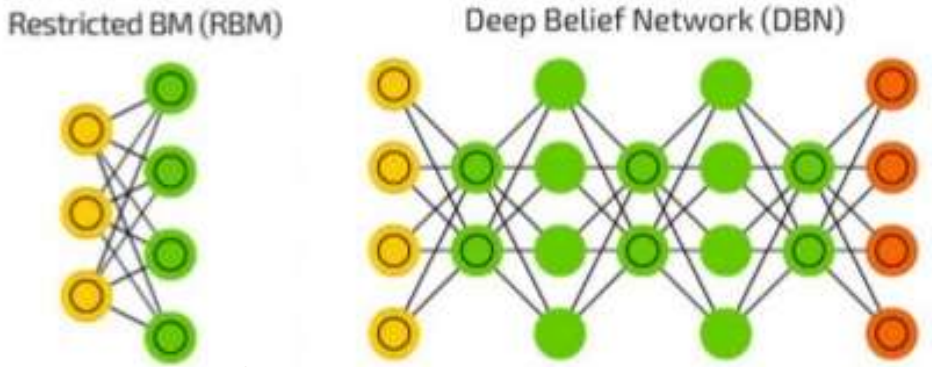
Deep Learning

Restricted Boltzmann Machine (RBM) *(is a very popular example of an autoencoder) allows automatically find patterns in data by reconstructing the input. It makes decisions about which input features are important and how they should be combined to form patterns. An RBM is an example of an autoencoder with only two layers.*



Deep Belief Net (DBN) *could be considered as a stack (a combination) of several RBMs that detect patterns based on unlabeled data and need relatively small amount of labeled data to organize them for classification purpose.*

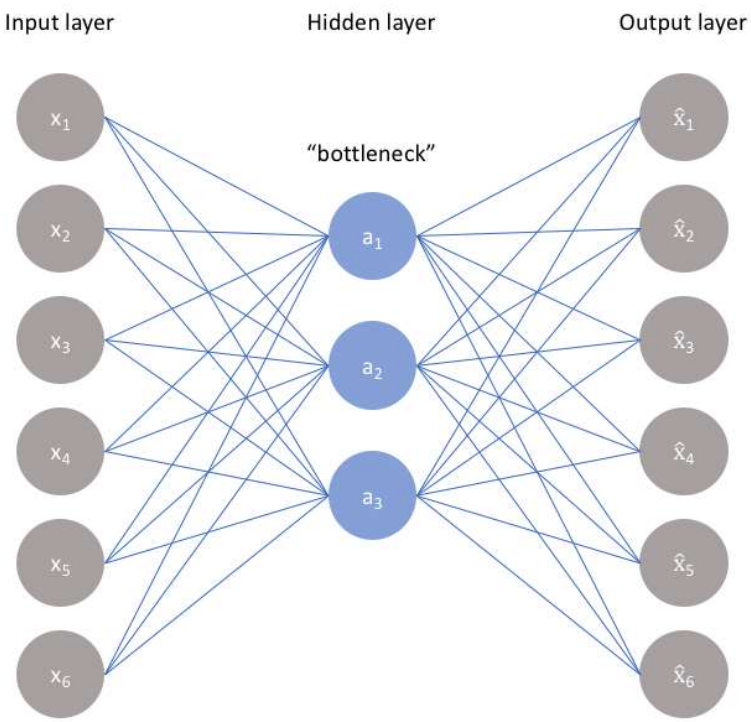
Each RBM layer learns the entire input. After this initial training, the RBMs have created a model that can detect inherent patterns in the data. To finish training, we need to introduce labels to the patterns and fine-tune the net with supervised learning.



- *DBN only needs a small labelled data set, which is important for real-world applications.*
- *the training process can also be completed in a reasonable amount of time through the use of GPUs.*
- *the resulting net will be very accurate compared to a shallow net*

Relevant links:
https://www.edureka.co/blog/restricted-boltzmann-machine-tutorial/
https://medium.com/@batuhanyilmaz1999/detailed-explanation-of-deep-belief-neural-networks-dbn-with-implementation-in-python-and-45353c82922d

Autoencoders in Deep Learning



Loss function *(usually consists of two terms: one encourage the model to be sensitive to the inputs (**reconstruction loss**), another one discourages memorization/overfitting (added **regularizer**).*

$$\mathcal{L}(x, \hat{x}) + regularizer$$

*For **binary inputs** calculate distance as cross-entropy (sum of Bernoulli cross-entropies):*

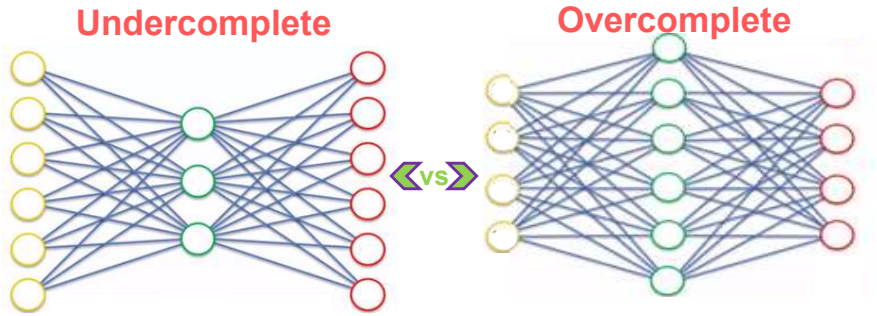
$$l(f(\mathbf{x})) = -\sum_k (x_k \log(\hat{x}_k) + (1 - x_k) \log(1 - \hat{x}_k))$$

*For **real-values inputs** use a linear activation function at the output and calculate distance as sum of squared differences (squared Euclidian distance):*

$$l(f(\mathbf{x})) = \frac{1}{2} \sum_k (\hat{x}_k - x_k)^2$$

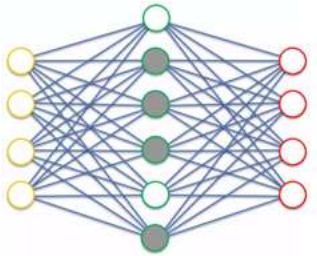
Relevant links:
https://www.jeremyjordan.me/autoencoders/
https://www.youtube.com/watch?v=xTU79Zs4XKY
https://www.youtube.com/watch?v=EehRcPo1M-Q
https://keras.io/api/layers/regularizers/

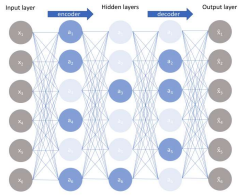
Autoencoders in Deep Learning



Overcomplete Hidden Layers *– a concept in which autoencoders may recognize more features, having a hidden layer that is equal to the number of inputs nodes or greater. However, it might bring a huge problem when trained and make it useless…*

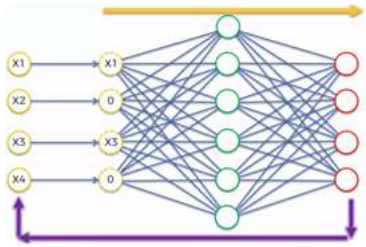
Both types of autoencoders can be shallow or deep...

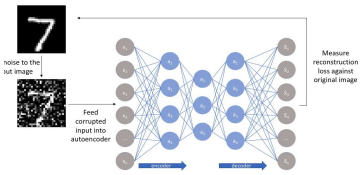




Sparse autoencoders *– is an approach towards regularization via regularization of the activations, not the weights of a network. They offer an alternative method for introducing an information bottleneck without requiring a reduction in the number of nodes at the hidden layers. Here loss function supposed to penalize activations within a layer.*

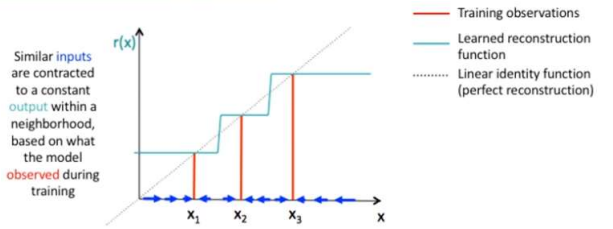
Denoising autoencoders *– is an approach towards developing a generalizable model by slightly corrupting the input data but still maintaining the uncorrupted data as a target output.*





Contractive autoencoders *add a penalty to the backpropagation of the autoencoder preventing it from cheating. Here we explicitly encouraging the model to learn an encoding in which similar inputs have similar encodings.*

Denoising autoencoders make the reconstruction function (ie. decoder) resist small but finite-sized perturbations of the input, while contractive autoencoders make the feature extraction function (ie. encoder) resist infinitesimal perturbations of the input. Jacobian of encoder added to loss function prevent the encoder from copying the input…

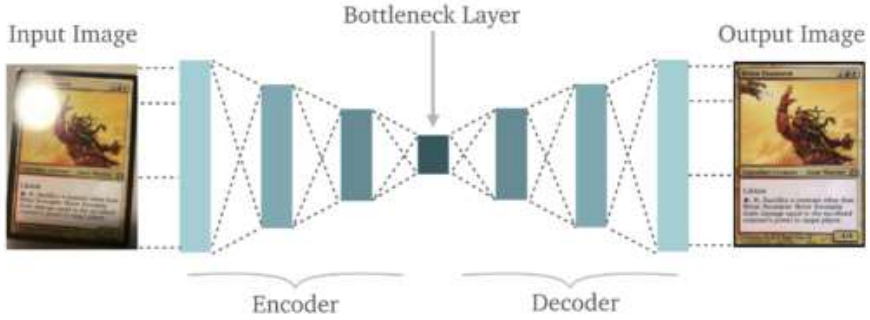


Autoencoders *learn how to compress the data based on attributes (ie. correlations between the input feature vector) discovered from data during training, these models are typically* ***only capable of reconstructing data similar to the class of observations of which the model observed during training.***

Relevant links:
https://www.jeremyjordan.me/autoencoders/
https://medium.com/aimonks/contractive-autoencoders-an-insight-into-enhanced-feature-learning-d3d3bd103d88

Autoencoders Use-cases

- *Data compression and dimensionality reduction*
- *Image reconstruction*
- *Image coloring*
- *Feature variation and Denoising*
- *Generating higher resolution images*
- *Image search and information retrieval*
- *Anomaly detection*
- *…*



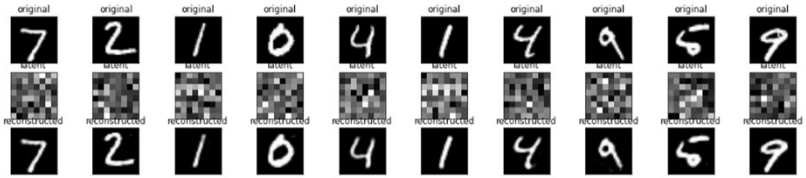
Relevant links:
https://www.edureka.co/blog/autoencoders-tutorial/

Autoencoders

Reconstruction on MNIST dataset…

```
import matplotlib.pyplot as plt
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras import layers, losses
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Model
# size of encoded representations
latent_dim = 64# compression (vs. the input is 784)
# define autoencoder class
class Autoencoder(Model):
  def __init__(self, latent_dim):
    super(Autoencoder, self).__init__()
    self.latent_dim = latent_dim
    # model that maps an input to its latent/encoded representation
    self.encoder = tf.keras.Sequential([
      layers.Flatten(),
      layers.Dense(latent_dim, activation='relu'),      ])
    # model that maps an encoded representation to reconstructed
    self.decoder = tf.keras.Sequential([
      layers.Dense(784, activation='sigmoid'),
      layers.Reshape((28, 28))      ])
  def call(self, x):
    encoded = self.encoder(x)
    decoded = self.decoder(encoded)
    return decoded
# model that maps an input to its reconstruction
autoencoder = Autoencoder(latent_dim)
# configure the model
autoencoder.compile(optimizer='adam',
                    loss=losses.MeanSquaredError())
```

```
# read dataset
(x_train, _), (x_test, _) = mnist.load_data()
# normalize all values between 0 and 1
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
#fit autoencoder
autoencoder.fit(x_train, x_train, epochs=10, shuffle=True,
                validation_data=(x_test, x_test))
# encode and decode some digits, taking them from the *test* set
encoded_imgs = autoencoder.encoder(x_test).numpy()
decoded_imgs = autoencoder.decoder(encoded_imgs).numpy()
# visualise the results
n = 10 # how many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
  # display original
  ax = plt.subplot(3, n, i + 1)
  plt.imshow(x_test[i])
  plt.gray()
  # display latent code
  ax = plt.subplot(3, n, i + 1 + n)
  plt.imshow(encoded_imgs[i].reshape(8, 8))
  plt.gray()
  # display reconstruction
  ax = plt.subplot(3, n, i + 1 + 2*n)
  plt.imshow(decoded_imgs[i])
  plt.gray()
plt.show()
```



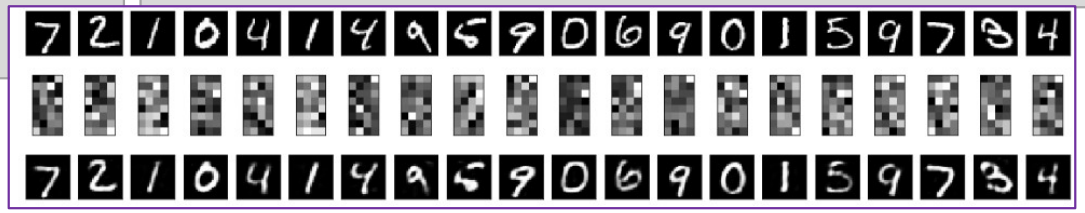
Relevant links:
https://www.tensorflow.org/tutorials/generative/autoencoder

Autoencoders

Reconstruction on MNIST dataset…

```
import numpy as np
from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.models import Model
from tensorflow.keras.datasets import mnist
import matplotlib.pyplot as plt
# size of encoded representations
encoding_dim = 32 # compression (vs. the input is 784)
# input placeholder
input_img = Input(shape=(784,))
# encoded representation of the input
encoded = Dense(encoding_dim, activation='relu')(input_img)
# lossy reconstruction of the input
decoded = Dense(784, activation='sigmoid')(encoded)
# model that maps an input to its reconstruction
autoencoder = Model(input_img, decoded)
# model that maps an input to its encoded representation
encoder = Model(input_img, encoded)
# create a placeholder for an encoded (32-dimensional) input
encoded_input = Input(shape=(encoding_dim,))
# retrieve the last layer of the autoencoder model
decoder_layer = autoencoder.layers[-1]
# decoder model
decoder = Model(encoded_input, decoder_layer(encoded_input))
# configure the model
autoencoder.compile(optimizer='adam', loss='mse')
# read dataset
(x_train, _), (x_test, _) = mnist.load_data()
# normalize all values between 0 and 1 and flatten
# the 28x28 images into vectors of size 784.
```

```
x_train = x_train.astype('float32') / 255.
x_test = x_test.astype('float32') / 255.
x_train = x_train.reshape((len(x_train), np.prod(x_train.shape[1:])))
x_test = x_test.reshape((len(x_test), np.prod(x_test.shape[1:])))
#fit autoencoder
autoencoder.fit(x_train, x_train, epochs=50, batch_size=256,
shuffle=True, validation_data=(x_test, x_test))
# encode and decode some digits, taking them from the *test* set
encoded_imgs = encoder.predict(x_test)
decoded_imgs = decoder.predict(encoded_imgs)
# visualise the results
n = 20 # how many digits we will display
plt.figure(figsize=(20, 4))
for i in range(n):
    # display original
    ax = plt.subplot(3, n, i + 1)
    plt.imshow(x_test[i].reshape(28, 28))
    plt.gray()
    # display code
    ax = plt.subplot(3, n, i + 1 + n)
    plt.imshow(encoded_imgs[i].reshape(8, 4))
    plt.gray()
    # display reconstruction
    ax = plt.subplot(3, n, i + 1 + 2*n)
    plt.imshow(decoded_imgs[i].reshape(28, 28))
    plt.gray()
plt.show()
```



Relevant links:
https://blog.keras.io/building-autoencoders-in-keras.html

Autoencoders

Different architectures of the models…

```
### Vanila Net
def getVanilaAE():
    # input layer
    input_layer = Input(shape=(784,))
    # latent view
    latent_view   = Dense(64, activation='relu')(input_layer)
    # output layer
    output_layer  = Dense(784, activation='sigmoid')(latent_view)
    # model
    model = Model(input_layer, output_layer)

    return model
```

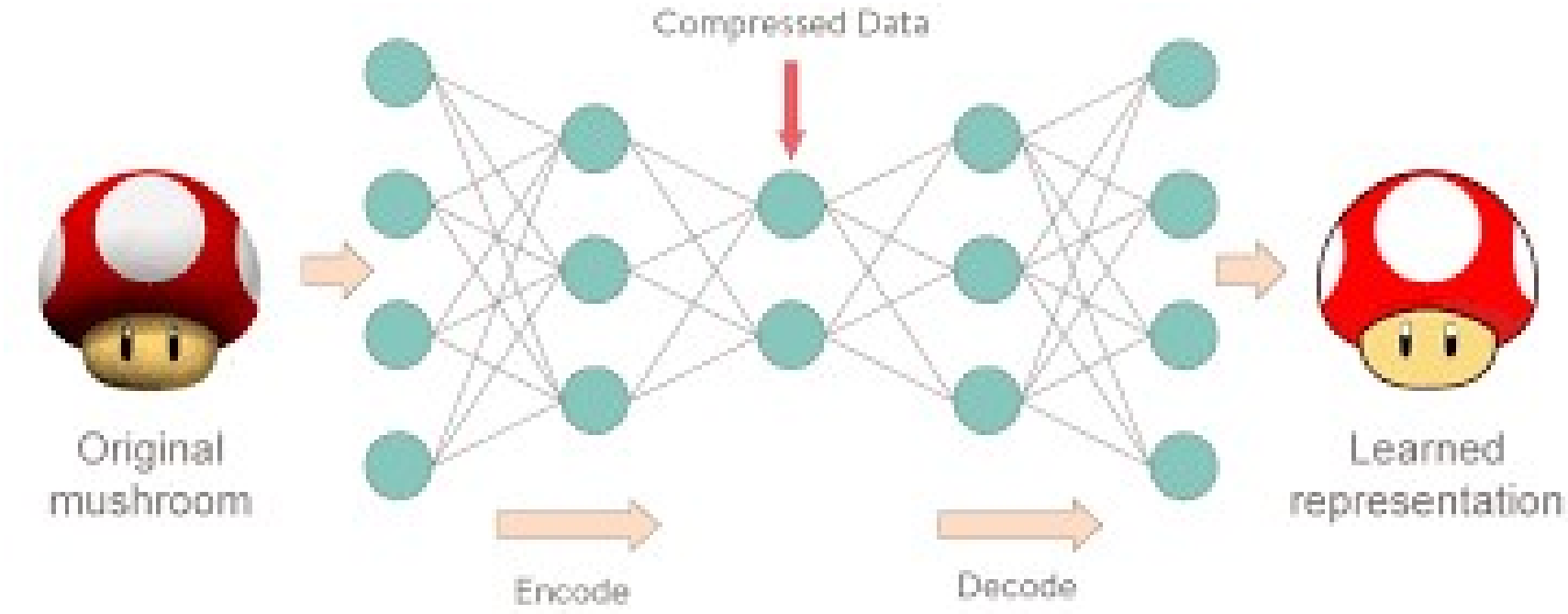
```
### Deep Net
def getDeepAE():
    # input layer
    input_layer = Input(shape=(784,))
    # encoding architecture
    encode_layer1 = Dense(512, activation='relu')(input_layer)
    encode_layer2 = Dense(256, activation='relu')(encode_layer1)
    encode_layer3 = Dense(128, activation='relu')(encode_layer2)
    # latent view
    latent_view   = Dense(64, activation='relu')(encode_layer3)
    # decoding architecture
    decode_layer1 = Dense(128, activation='relu')(latent_view)
    decode_layer2 = Dense(256, activation='relu')(decode_layer1)
    decode_layer3 = Dense(512, activation='relu')(decode_layer2)
    # output layer
    output_layer  = Dense(784, activation='sigmoid')(decode_layer3)
    # model
    model = Model(input_layer, output_layer)

    return model
```

```
### Sparse Deep Net
def getDeepAE():
    # input layer
    input_layer = Input(shape=(784,))
    # encoding architecture
    encode_layer1 = Dense(1024, activation='relu')(input_layer)
    encode_layer2 = Dense(1024, activation='relu')(encode_layer1)
    # latent view
    latent_view   = Dense(1024, activation='relu',
                          activity_regularizer=regularizers.l1(1e-5))(encode_layer2)
    # decoding architecture
    decode_layer1 = Dense(1024, activation='relu')(latent_view)
    decode_layer2 = Dense(1024, activation='relu')(decode_layer1)
    # output layer
    output_layer  = Dense(784, activation='sigmoid')(decode_layer2)
    # model
    model = Model(input_layer, output_layer)

    return model
```

```
### …
```

Relevant links:
https://towardsdatascience.com/implementing-an-autoencoder-in-tensorflow-2-0-5e86126e9f7
https://learnopencv.com/autoencoder-in-tensorflow-2-beginners-guide/

Autoencoders in Deep Learning



Feature extraction

Reconstruction / Generation

Representation transformation

Convolutional Neural Networks (CNN)

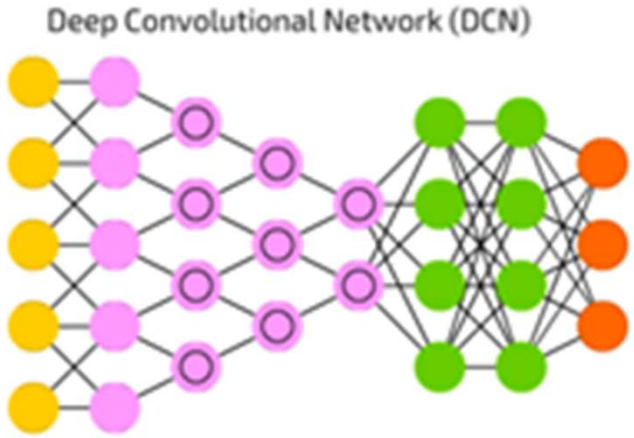


Image Classification

What We See

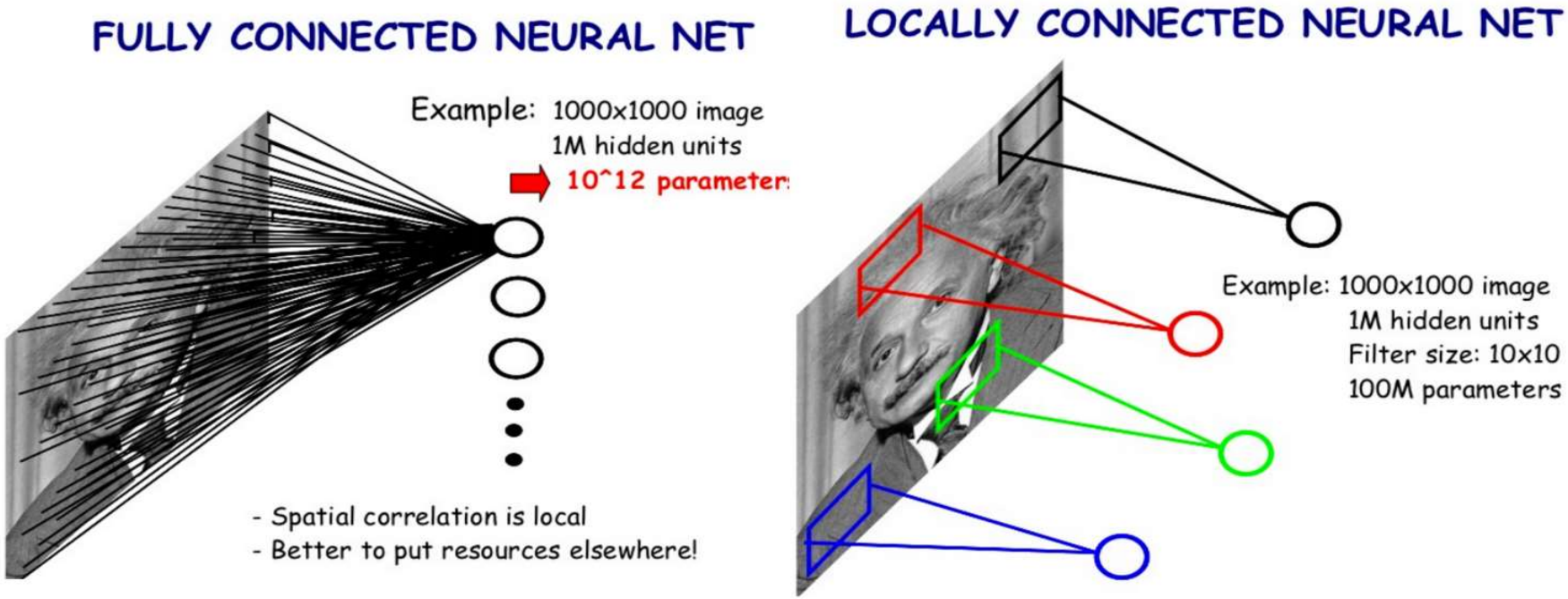
What Computers See

Our expectation: *Computer takes an array of pixels (w x h x 3) with RGB values (0..255) and produces output number(s) that describe the probability of the image being a certain class (.80 for dog, .15 for cat, .05 for car, etc).*

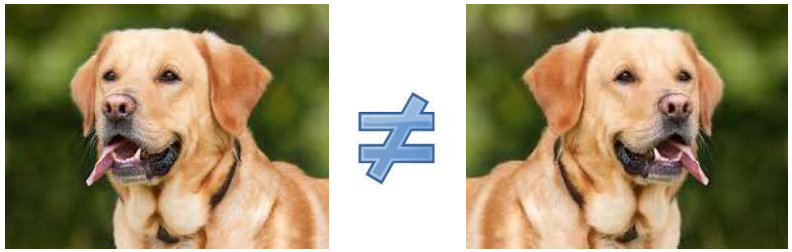
Image Classification

Fully connected DNN *is very rarely used in computer vision tasks…*

- *Too many parameters require too much training data, computation power and time*



- *No generalization, no spatial invariance for images*



CNNs

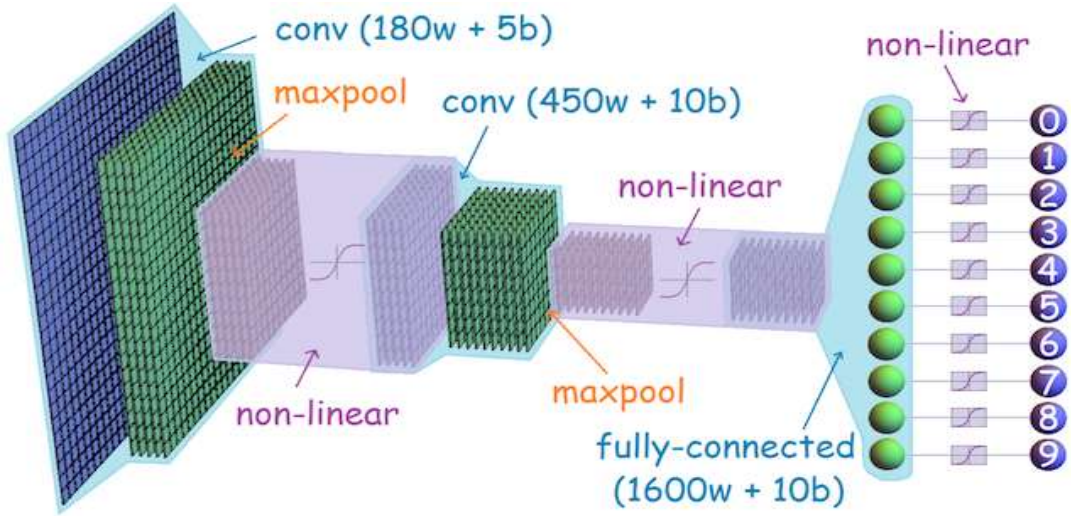
Approach to be used: In a similar way as human classify picture with a dog if it has identifiable features such as paws or 4 legs, the computer suppose to be able perform image classification by looking for low level features such as edges and curves, and then building up to more abstract concepts through a series of convolutional layers. Therefore, we have to train a computer to differentiate between all the images it's given and by figuring out the unique features that make a dog a dog or that make a cat a cat, etc.

Convolutional Neural Networks (CNN) *are probably the most popular deep learning architecture for the moment.*

CNN progressed from 8 layer AlexNet in 2012 towards 152 layer ResNet in 2015 and much further beyond...

Applied for:

- *image related problem*
- *recommender systems*
- *natural language processing*
- *etc.*



The main advantages:

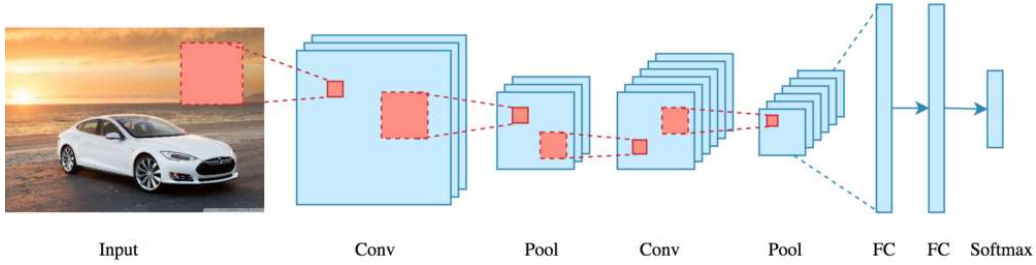
- *Automatic detection of important features without any human supervision (e.g. given many pictures of two different classes it learns distinctive features for each class by itself).*
- *Using special convolution and pooling operations and parameter sharing, CNN becomes computationally efficient and enables models to be run on any device.*

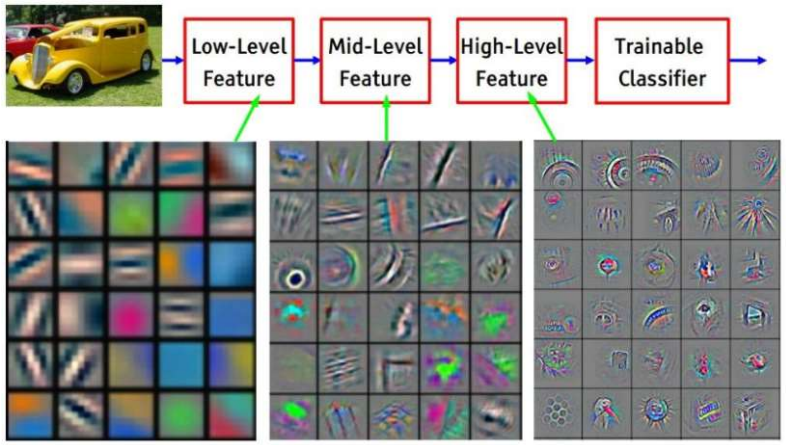
CNNs

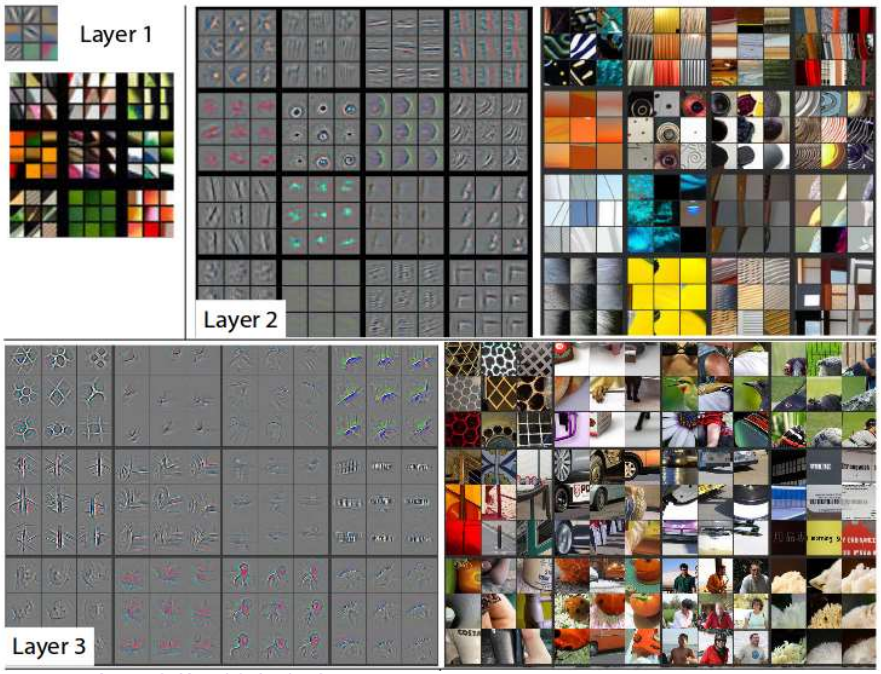
CNN model *is kind of a combination of two components:*

Feature extraction. The convolution + pooling layers perform feature extraction and make possible to detect features like two eyes, four legs, road sign, two wheels, building, face, etc. The convolution layers learn theses complex features by building on top of each other. The first layers detect edges, the next layers combine them to detect shapes, to following layers merge this information to infer complete objects.

Classification. The fully connected layers act as a classifier on top of the extracted features and assign a probability for the input image being a representative of certain class.



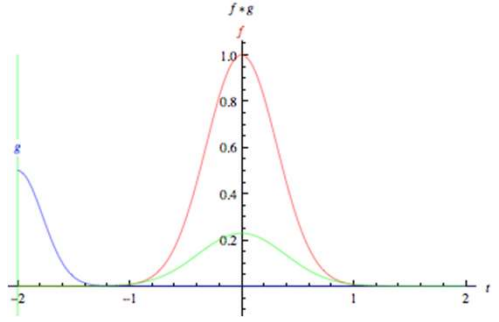




Relevant links:

http://cs231n.stanford.edu/
http://cs231n.github.io/convolutional-networks/
http://www.matthewzeiler.com/wp-content/uploads/2017/07/arxive2013.pdf
https://www.youtube.com/watch?v=AgkfIQ4IGaM
https://towardsdatascience.com/applied-deep-learning-part-4-convolutional-neural-networks-584bc134c1e2
https://www.youtube.com/watch?v=2-OI7ZB0MmU

Convolution

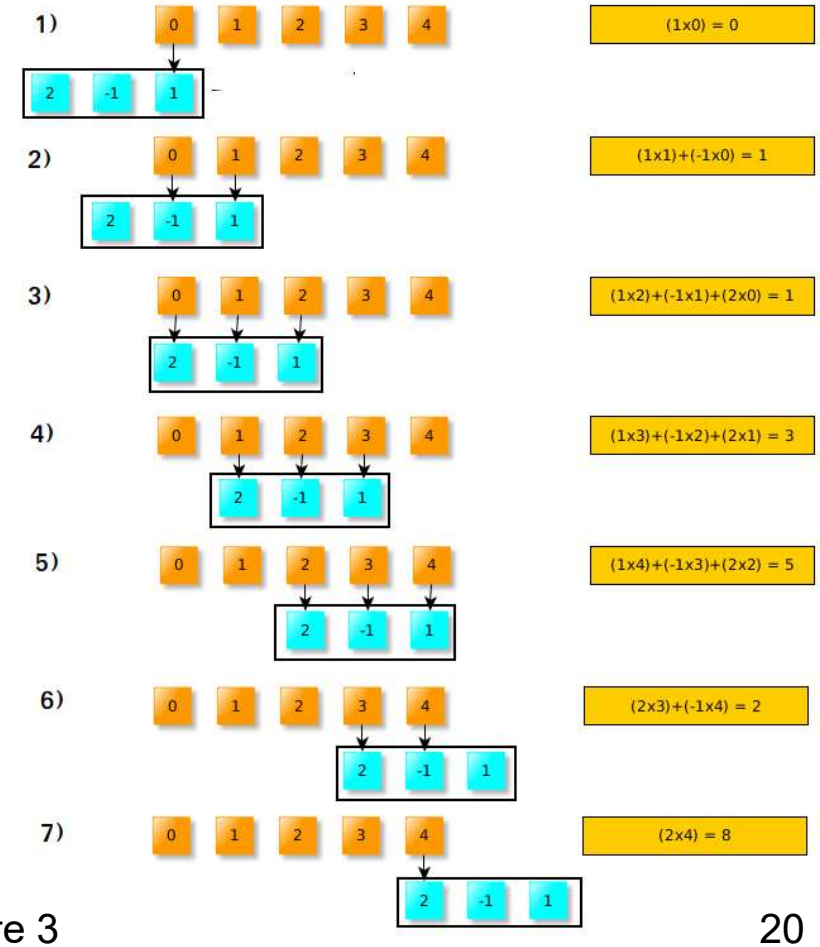


A convolution is an integral that expresses the amount of overlap of one function g as it is shifted over another function f. It therefore "blends" one function with another. In another words, ***Convolution*** *- is a mathematical operation to merge two sets of information.*

Convolution on signal processing is used for the following use cases:

- *Filter signals (1D audio, 2D image processing)*
- *Check how much a signal is correlated to another*
- *Find patterns in signals*


```
In [1]: import numpy as np

In [2]: x = np.array([0,1,2,3,4])

In [3]: w = np.array([1,-1,2])

In [4]: res = np.convolve(x,w)

In [5]: print res
[0 1 1 3 5 2 8]
```



Relevant links:

https://en.wikipedia.org/wiki/Convolution
http://mathworld.wolfram.com/Convolution.html
https://leonardoaraujosantos.gitbooks.io/artificial-inteligence/content/convolution.html

2D Convolution

2D convolutions *are used as image filters, and when you would like to find a specific patch on an image.*

We use a convolution filter on top of the input data to produce a feature map.

$*$

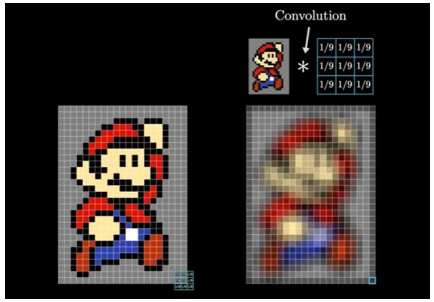
1	0	-1
2	0	-2
1	0	-1

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

Input

1	0	1
0	1	0
1	0	1

Filter / Kernel



Convolution operation on matrixes (images context):

- *slide the filter over the input*
- *do element-wise matrix multiplication and sum the result at every sliding location (receptive field)*

1x1	1x0	1x1	0	0
0x0	1x1	1x0	1	0
0x1	0x0	1x1	1	1
0	0	1	1	0
0	1	1	0	0

Input x Filter

4		

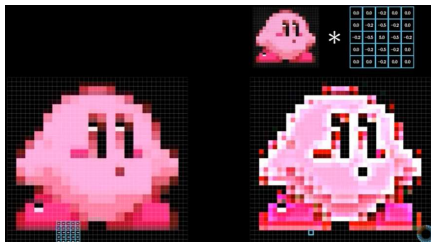
Feature Map

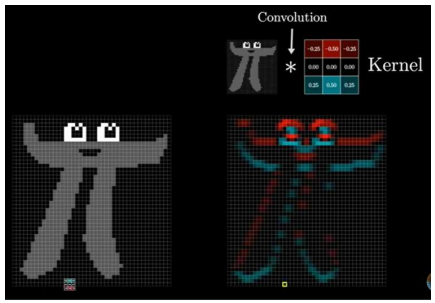
1	1x1	1x0	0x1	0
0	1x0	1x1	1x0	0
0	0x1	1x0	1x1	1
0	0	1	1	0
0	1	1	0	0

Input x Filter

4	3	

Feature Map



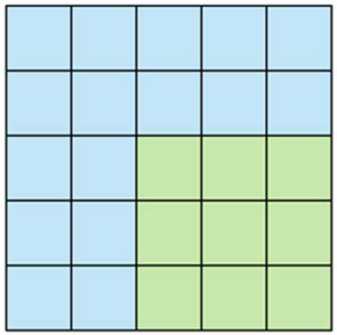


Nice visual explanation of Image Kernels: http://setosa.io/ev/image-kernels/
Convolution – from probability to image processing: https://www.3blue1brown.com/lessons/convolutions

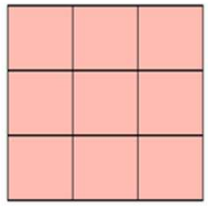
2D Convolution

Stride *specifies how much we move the convolution filter at each step (e.g. stride 1 ([1,1]), stride 2 ([2,2]), etc.). We can have bigger strides if we want less overlap between the receptive fields making the resulting feature map smaller.*

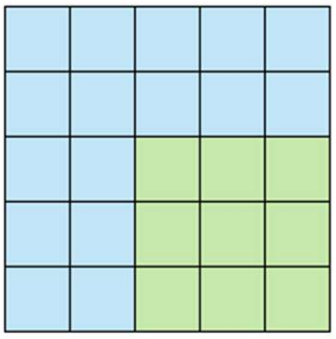
We can use ***padding*** *to maintain the feature map's dimensionality similar to the input by surrounding input with zeros or the values on the edge.*



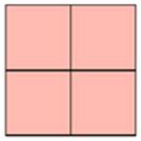
Stride 1



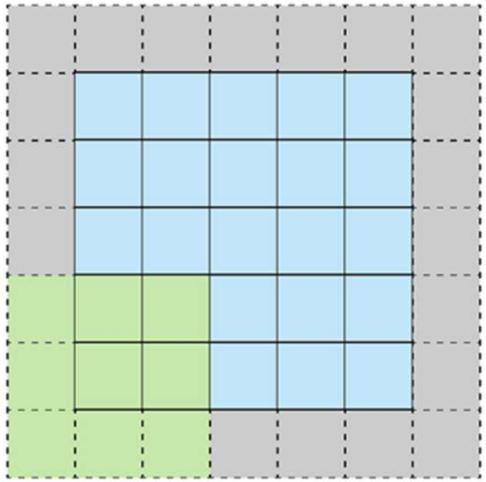
Feature Map



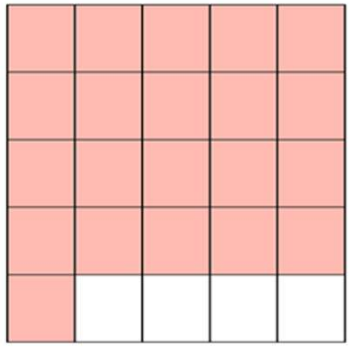
Stride 2



Feature Map



Stride 1 with Padding



Feature Map

TensorFlow

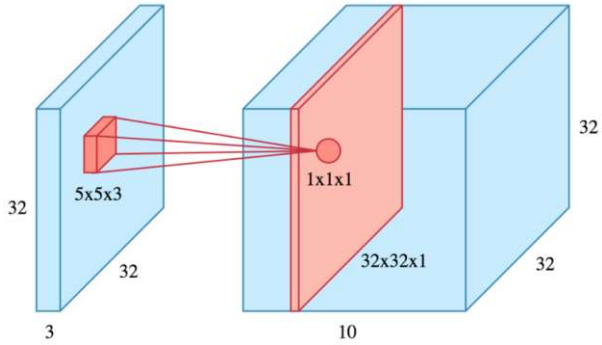
Convolution

```
#Importing
import numpy as np
from scipy import signal
from scipy import misc
import matplotlib.pyplot as plt
from PIL import Image

### Load image of your choice on the notebook
im = Image.open('bird.jpg')  # type here your image's name
# uses the ITU-R 601-2 Luma transform (there are several
# ways to convert an image to grey scale)
image_gr = im.convert("L")
print("\n Original type: %r \n\n" % image_gr)

# convert image to a matrix with values from 0 to 255 (uint8)
arr = np.asarray(image_gr)
print("After conversion to numerical representation: \n\n %r" % arr)

### Activating matplotlib for Ipython
%matplotlib inline

### Plot image
imgplot = plt.imshow(arr)
#you can experiment different colormaps (Greys,winter,autumn)
imgplot.set_cmap('gray')
print("\n Input image converted to gray scale: \n")
plt.show(imgplot)
kernel = np.array([[ 0, 1, 0],
                   [ 1,-4, 1],
                   [ 0, 1, 0], ])
```

```
grad = signal.convolve2d(arr, kernel, mode='same', boundary='symm')
%matplotlib inline
print('GRADIENT MAGNITUDE - Feature map')
fig, aux = plt.subplots(figsize=(10, 10))
aux.imshow(np.absolute(grad), cmap='gray')


type(grad)
grad_biases = np.absolute(grad) + 100
grad_biases[grad_biases > 255] = 255
%matplotlib inline
print('GRADIENT MAGNITUDE - Feature map')
fig, aux = plt.subplots(figsize=(10, 10))
aux.imshow(np.absolute(grad_biases), cmap='gray')
```

2D Convolution

Usually, an image is represented as a 3D matrix with dimensions of height, width and depth (color channels - RGB). In turn, a convolution filter become 3D as well having a specific height and width (e.g. 3x3 or 5x5), and by design covering the entire depth of the input.



Input Volume (+pad 1) (7x7x3)

x[:,:,0]

0	0	0	0	0	0	0
0	1	1	0	2	0	0
0	2	2	2	2	1	0
0	0	0	0	2	1	0
0	2	2	2	2	1	0
0	2	0	2	2	1	0
0	0	0	0	0	0	0

x[:,:,1]

0	0	0	0	0	0	0
0	2	1	0	0	0	0
0	0	2	0	1	0	0
0	1	0	1	2	0	0
0	1	2	0	2	1	0
0	1	2	1	2	2	0
0	0	0	0	0	0	0

x[:,:,2]

0	0	0	0	0	0	0
0	2	1	1	2	2	0
0	1	1	1	0	0	0
0	2	0	1	0	2	0
0	0	2	0	2	1	0
0	0	0	2	1	0	0
0	0	0	0	0	0	0

Filter W0 (3x3x3)

w0[:,:,0]

-1	0	-1
-1	-1	1
-1	0	0

w0[:,:,1]

1	1	0
-1	-1	0
0	1	0

w0[:,:,2]

-1	1	0
-1	0	-1
-1	0	1

Bias b0 (1x1x1)

b0[:,:,0]

1

Filter W1 (3x3x3)

w1[:,:,0]

-1	0	0
0	0	1
0	-1	1

w1[:,:,1]

1	-1	1
0	1	1
0	-1	-1

w1[:,:,2]

0	0	-1
-1	0	-1
1	1	1

Bias b1 (1x1x1)

b1[:,:,0]

0

Output Volume (3x3x2)

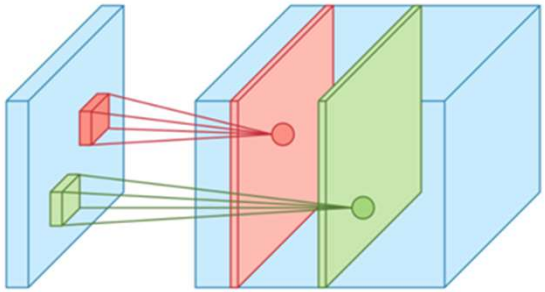
o[:,:,0]

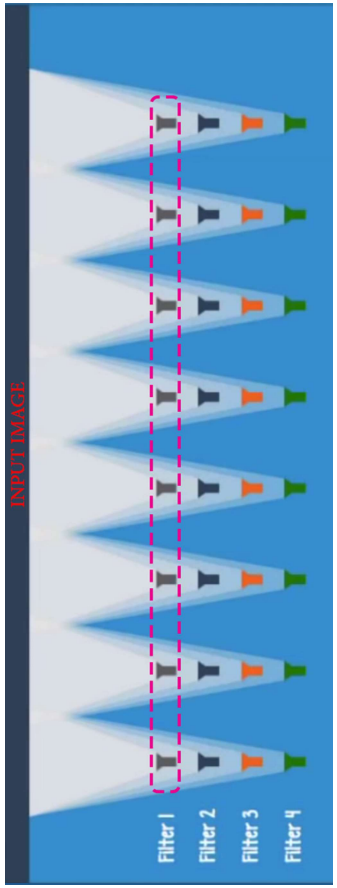
-1	-5	-5
2	-2	-8
-3	-7	-7

o[:,:,1]

3	0	-3
1	8	0
2	4	0

Using different filters, we perform multiple convolutions on an input and stack all the distinct feature maps together forming the final output of the convolution layer. Each of these channels (distinct feature maps) will end up being trained to detect certain key features in the image (e.g. lines, edges or other distinctive shapes).





2D Convolution

To be powerful, neural network (that basically has just been computing linear operations during the conv layers) needs to contain non-linearity. It is achieved by passing the weighted sum of its inputs through an activation function.

*In CNN we pass the result of the convolution operation through **ReLU** activation function, that works far better (comparably to tanh and sigmoid) and makes the network able to train a lot faster (due to the computational efficiency) without making a significant difference to the accuracy. So, the values in the final feature maps are not actually the sums, but the ReLU function applied to them.*

Short summary on Convolution Layer:

There are *4 important hyper-parameters* to decide on:

- Filter size. ***3x3 filters*** *are typically used, but 5x5 or 7x7 are also applicable depending on the application. Even 1x1 filters have sense, since filters are 3D and have a depth dimension as well.*
- Filters amount. *This is the most variable parameter, it's a **power of 2 anywhere between 32 and 1024**. More filters make a model more powerful, but we risk overfitting due to increased number of parameters. One of the strategies is to start with a small number of filters at the initial layers, and progressively increase number of them as go deeper into the network.*
- Stride. *Usually default value is 1 (**stride [1,1]**).*
- Padding. *Usually **use padding**.*

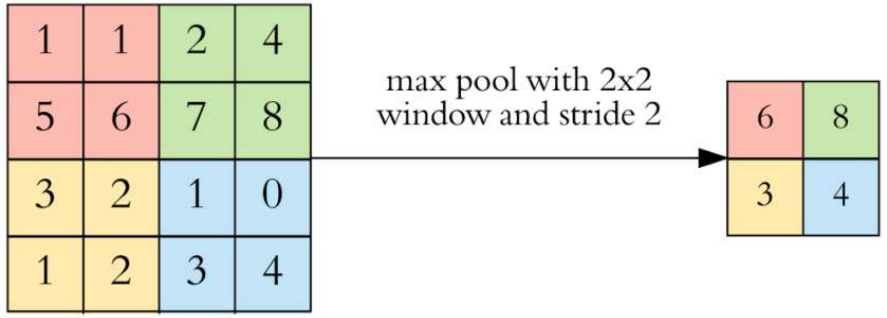
Relevant links:
http://www.cs.toronto.edu/~fritz/absps/reluICML.pdf
https://en.wikipedia.org/wiki/Vanishing_gradient_problem
https://www.quora.com/What-is-the-vanishing-gradient-problem
https://www.youtube.com/watch?v=V9ZYDCnItr0

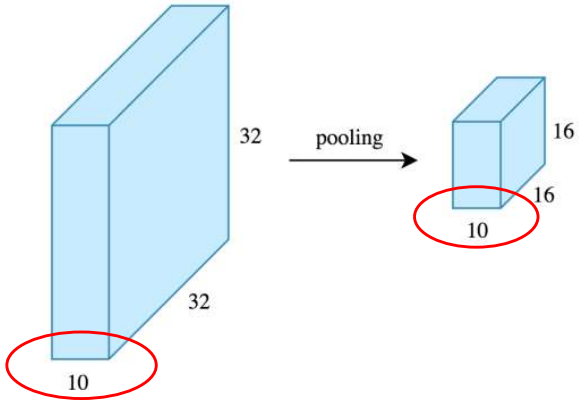
Pooling

To reduce the number of parameters, which both shortens the training time and combats overfitting, we reduce the dimensionality of convolution operation result by performing a ***pooling*** *(sub-sampling) operation. It is also a "sliding window" technique, that applies some sort of statistical function over the values within the window.*

max pooling - the most common type of pooling operation that just slides a window over the input, and simply takes the max value in the window.

- *There are some other alternatives e.g. mean (average) pooling or L2-norm pooling. Similar to a filter size and sliding step in convolution, we specify the window size and stride for pooling operation.*
- *Pooling layers reduce the height and width, keeping the depth of convolution layer output intact. It down-sample each feature map independently, while keeping the important information.*
- *The intuition behind the pooling layer is that once there is a high activation value, there will be a specific feature in the original input volume and its exact location is not as important as its relative location to the other features.*



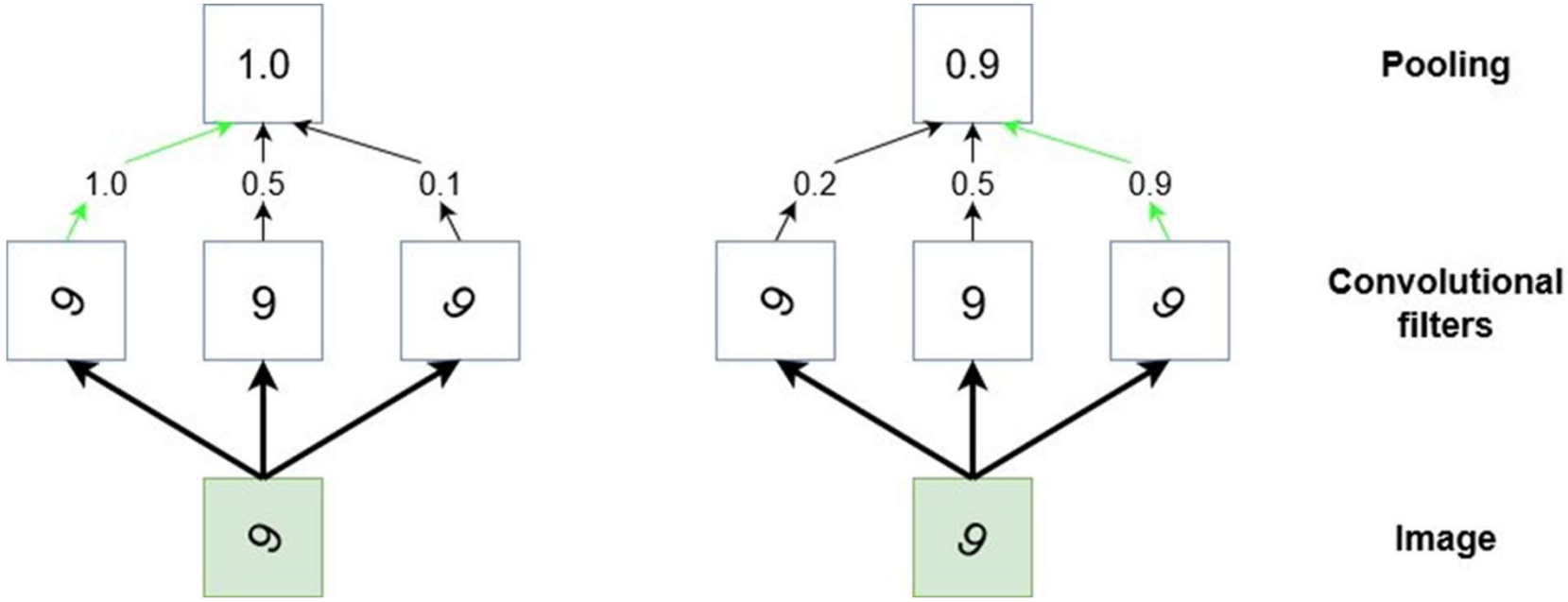


In CNN architectures, pooling is typically performed with 2x2 windows, stride 2 (stride [2,2]) and no padding. While convolution is done with 3x3 windows, stride 1 and with padding.

Pooling

Pooling in CNN:

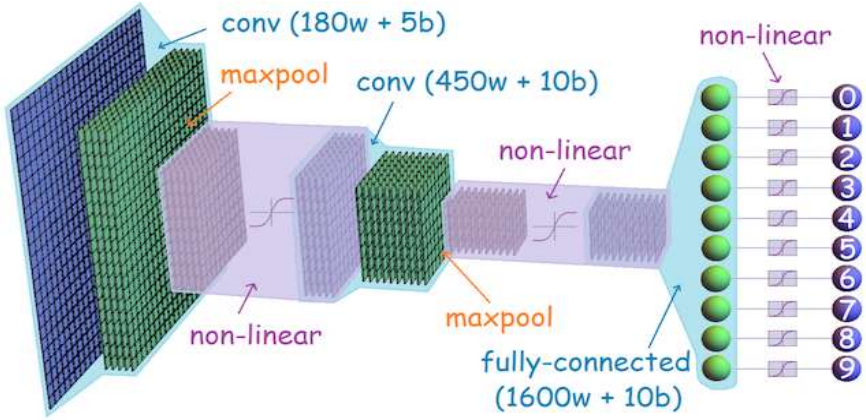
- *reduces the dimensionality of the output (called down-sampling), and reduces the number of parameters (or weights) in the model, thus lessening the computation cost.*
- *by controlling overfitting, makes the detection of certain features in the input invariant to scale and orientation changes.*



Pooling acts as a *generalizer* of the lower level information and so enables us to move *from high resolution data to lower resolution information*. In other words, pooling coupled with convolutional filters attempt to detect objects within an image.

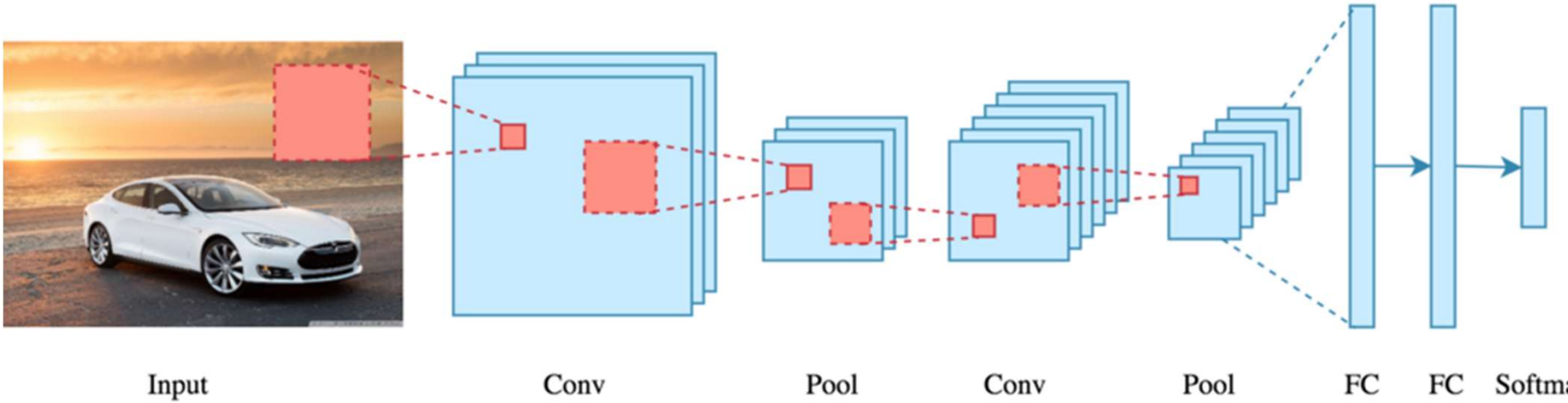
CNN

In CNN architecture, a chain of the *convolution* + *pooling* layers is wrapped up with a couple of *fully connected layers*.

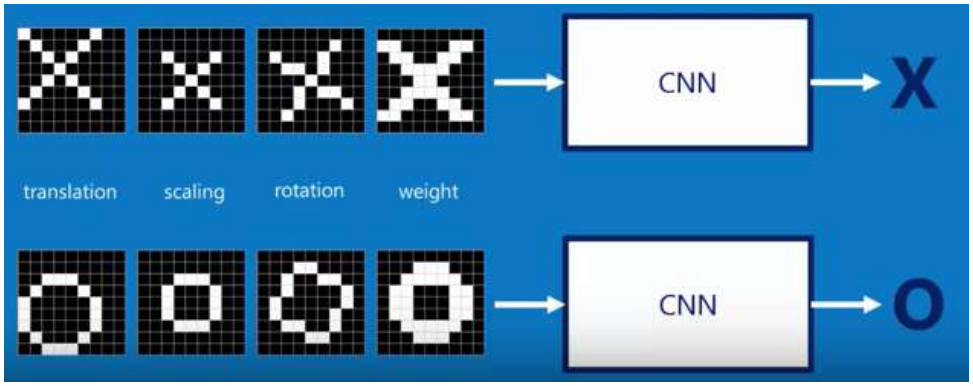


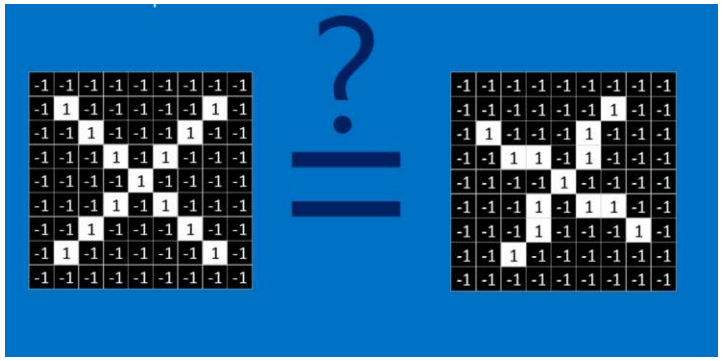
At the output of the convolutional-pooling layers we have moved *from high resolution low level data about the pixels to representations of objects within the image*. The purpose of these final, fully connected layers is to make classifications regarding these objects – so, we insert a standard neural network classifier onto the end of a trained object detector.

Since the output of both convolution and pooling layers are 3D volumes and a fully connected layer accepts input in a form of a 1D vector of numbers, the output of the final pooling layer should be *flatten* to a vector.

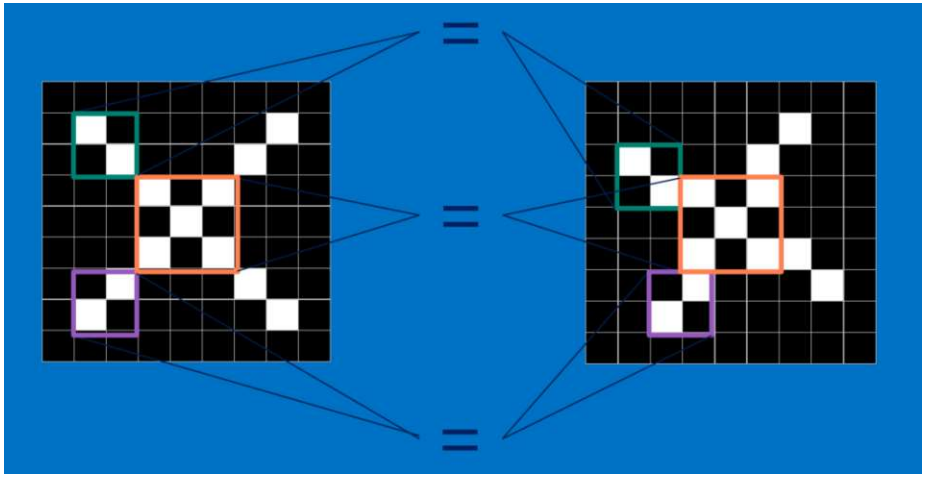


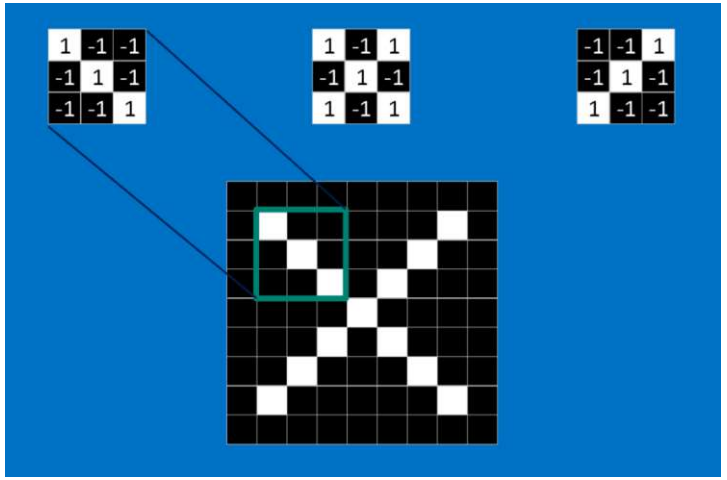
CNN simple example





*CNNs compare images based on generalized **features** rather than on pixel basis.*
Comparing images piece by piece, CNNs try to find rough feature matches in roughly the same positions in two images.





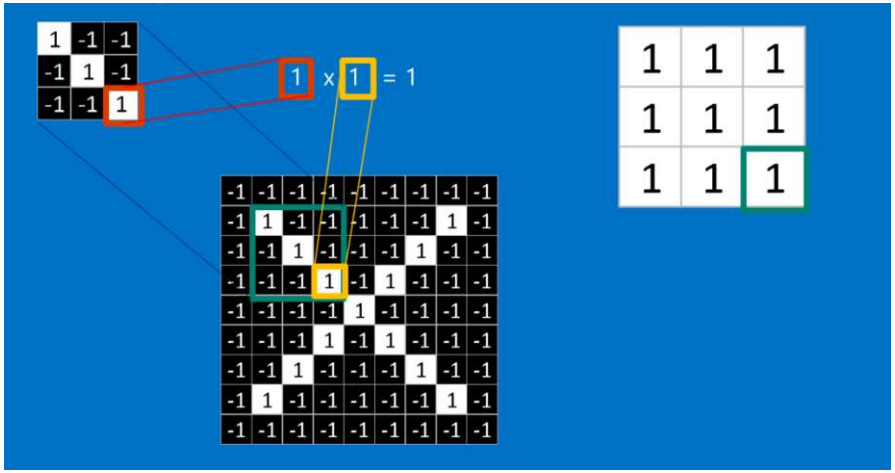
Relevant links:
https://brohrer.github.io/how_convolutional_neural_networks_work.html
https://www.edureka.co/blog/convolutional-neural-network/

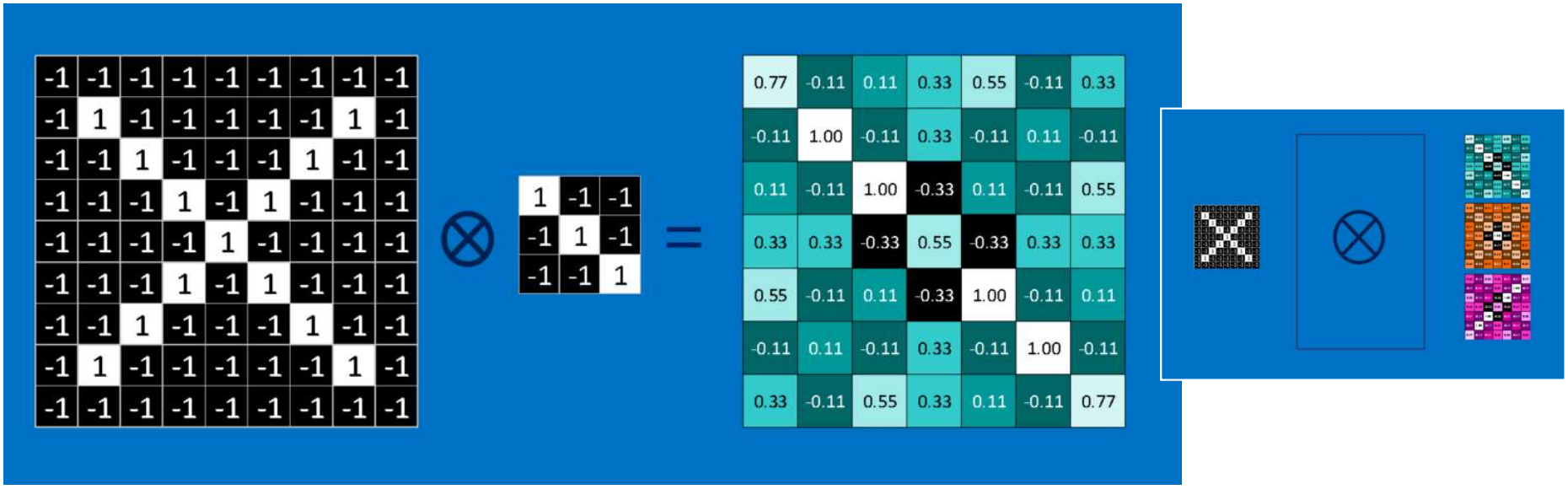
CNN simple example

Convolution *makes a filtering of the image by calculating the match to a feature across it.*

To calculate the match of a feature to a patch of the image, simply multiply each pixel in the feature by the value of the corresponding pixel in the image. Then add up the answers and divide by the total number of pixels in the feature.

Next repeat the convolution process in its entirety for each of the other features and get a set of filtered images, one for each of our filters.





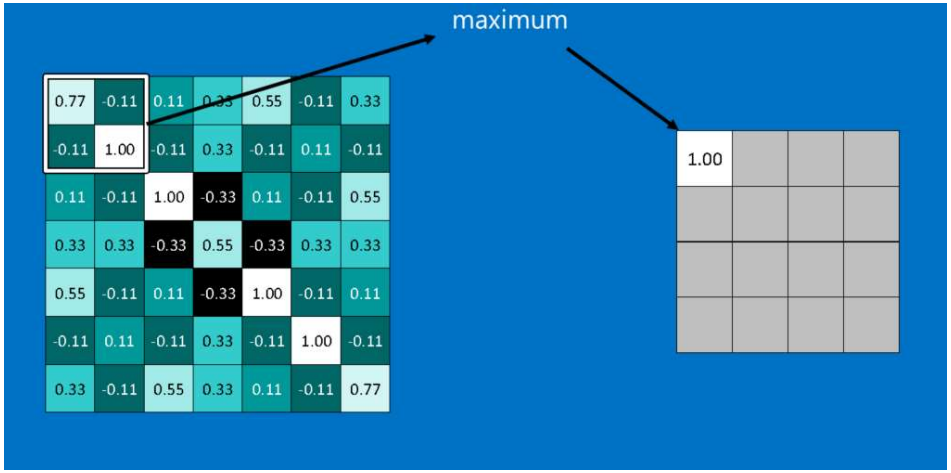
Relevant links:
https://brohrer.github.io/how_convolutional_neural_networks_work.html
https://www.edureka.co/blog/convolutional-neural-network/

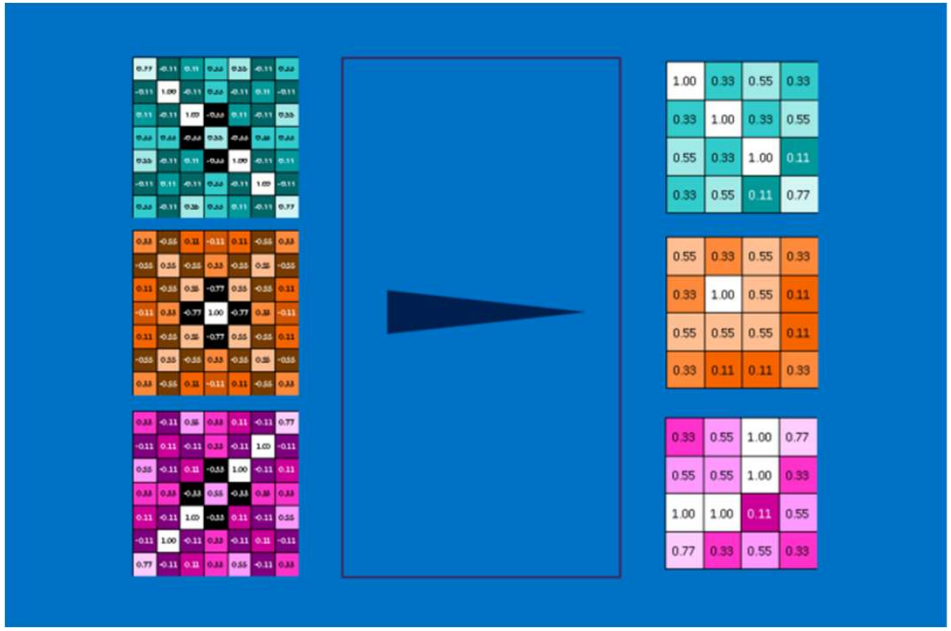
CNN simple example

Pooling *is a way to take large images and shrink them down while preserving the most important information in them.*

The math behind pooling consists of stepping a small window across an image and taking the maximum value (max pooling) from the window at each step.

After pooling, an image has about a quarter as many pixels as it started with. Because it keeps the maximum value from each window, it preserves the best fits of each feature within the window. This means that it doesn't care so much exactly where the feature fit as long as it fit somewhere within the window.



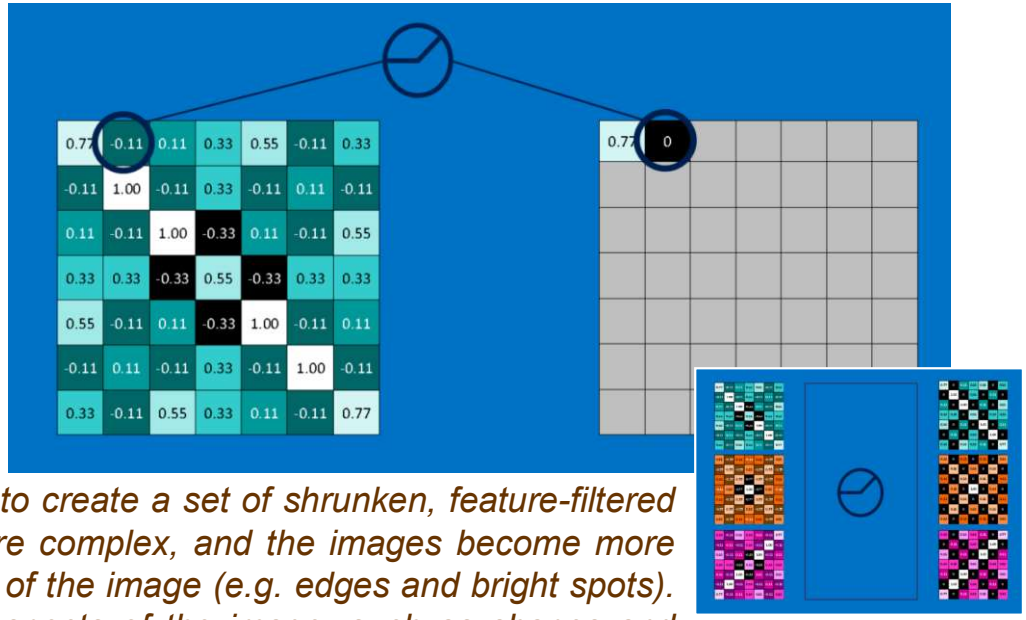


Relevant links:
https://brohrer.github.io/how_convolutional_neural_networks_work.html
https://www.edureka.co/blog/convolutional-neural-network/

CNN simple example

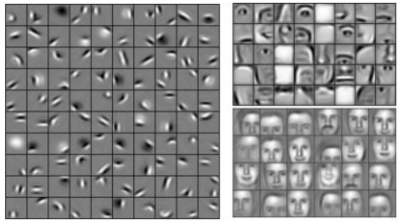
Rectified Linear Unit (ReLU) *helps the CNN stay mathematically healthy by keeping learned values from getting stuck near 0 or blowing up toward infinity.*

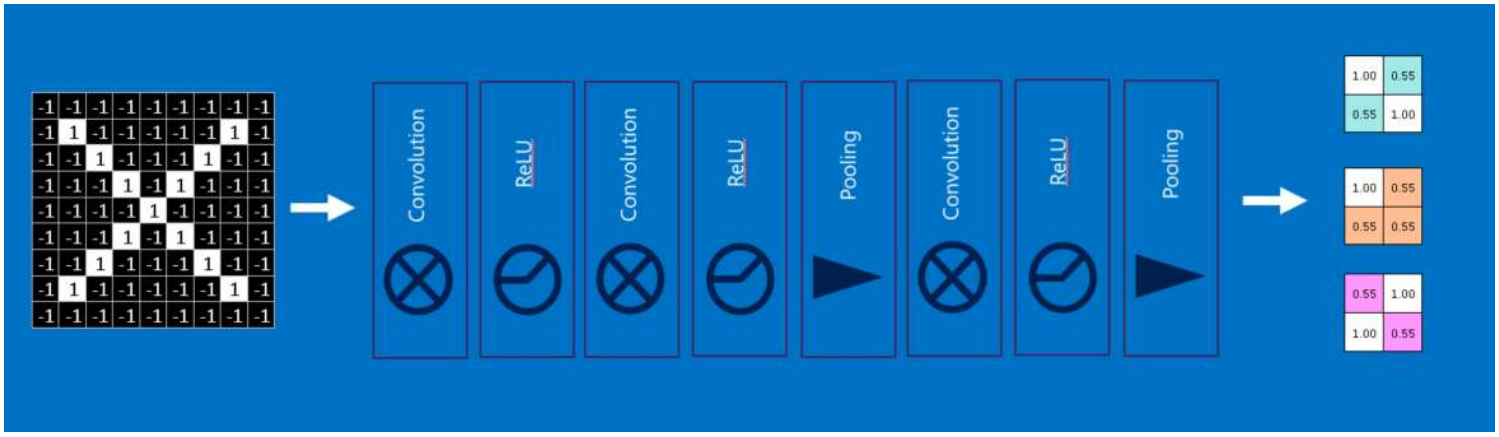
Wherever a negative number occurs, swap it out for a 0



Layers could be stacked like Lego bricks.

As a result, raw images get filtered, rectified and pooled to create a set of shrunken, feature-filtered images. Each time, the features become larger and more complex, and the images become more compact. This lets lower layers represent simple aspects of the image (e.g. edges and bright spots). Higher layers can represent increasingly sophisticated aspects of the image, such as shapes and patterns.



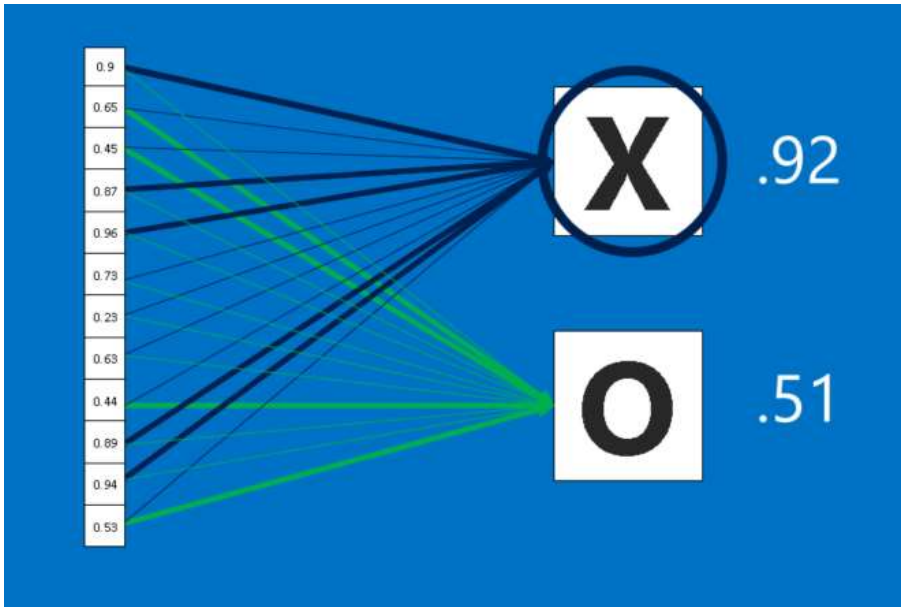


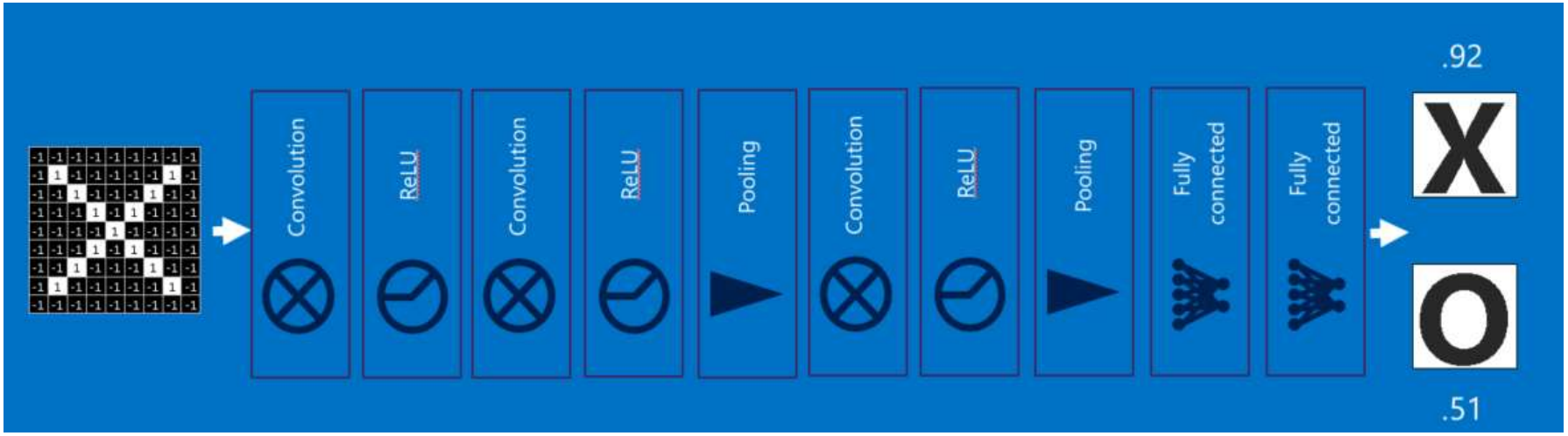
Relevant links:
https://brohrer.github.io/how_convolutional_neural_networks_work.html
https://www.edureka.co/blog/convolutional-neural-network/

CNN simple example

Fully connected layers *take the high-level filtered images and translate them into votes.*

Instead of treating inputs as a two-dimensional array, Fully connected layers are treated as a single list and all treated identically. Every value gets its own vote on whether the current image is an X or and O. Some values are much better than others at knowing when the image is an X, and some are particularly good at knowing when the image is an O. These get larger votes than the others. These votes are expressed as weights, or connection strengths, between each value and each category.





Relevant links:
https://brohrer.github.io/how_convolutional_neural_networks_work.html
https://www.edureka.co/blog/convolutional-neural-network/

CNN

Training…

- *What values filters in each layer should have?*
- *How do the filters in the initial conv layers know to what edges and curves they should look for?*
- *How filters on further layers know which edges and curves aggregate to construct higher level features?*
- *How does the fully connected layer know what activation maps to look at?*
- *etc.*

To address theses questions, CNN is trained the same way as ordinary ANN using Backpropagation with gradient descent to adjust its filter values (weights):

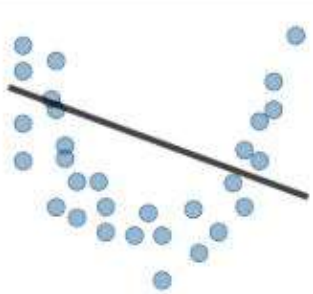
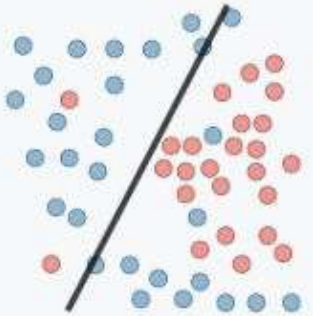
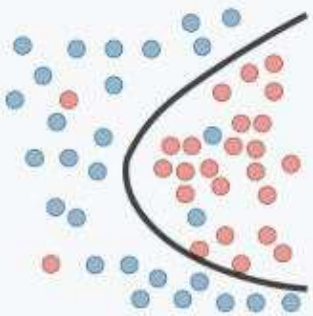
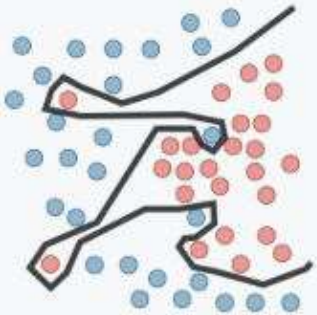
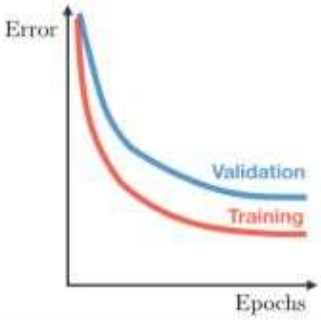
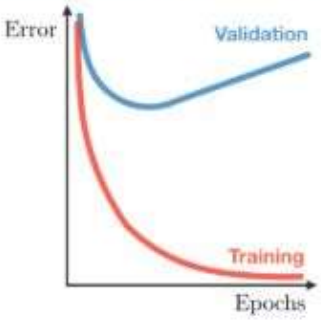
- **forward pass:** *on the first training example (W x H x 3 array of numbers that represents image) all of the weights/filter values were randomly initialized and the output will not give preference to any classification class in particular (e.g. [.1 .1 .1 .1 .1 .1 .1 .1 .1 .1] – probability distribution).*
- ***loss function:*** *having a training data with both an image and a label, we will use labels to compute a loss against the output of previous step (forward pass). One of the common ways to define a loss function we want to minimize is cross entropy between target (e.g. [0 0 0 0 0 0 0 1 0 0] that represents digit "7") and actual output:*
- ***backward pass:*** *solving an optimization problem, we find out which weights most directly contributed to the loss of the network. We have to calculate a derivative of the loss dE/dW (where W are the weights at a particular layer) to determining which weights contributed most to the loss and find ways to adjust them so that the loss decreases.*
- ***weight update:*** *update all the weights of the filters so that they change in the opposite direction of the gradient. Where the learning rate is a parameter chosen by the programmer to define a step in weight change.*

$$w = w_i - \eta \frac{dL}{dW}$$

w = Weight
w_i = Initial Weight
η = Learning Rate

Relevant links:
http://www.jefkine.com/general/2016/09/05/backpropagation-in-convolutional-neural-networks/
https://en.wikipedia.org/wiki/Backpropagation
http://neuralnetworksanddeeplearning.com/chap2.html
https://brilliant.org/wiki/backpropagation/
https://www.youtube.com/watch?v=Lakz2MoHy6o

Model fitting

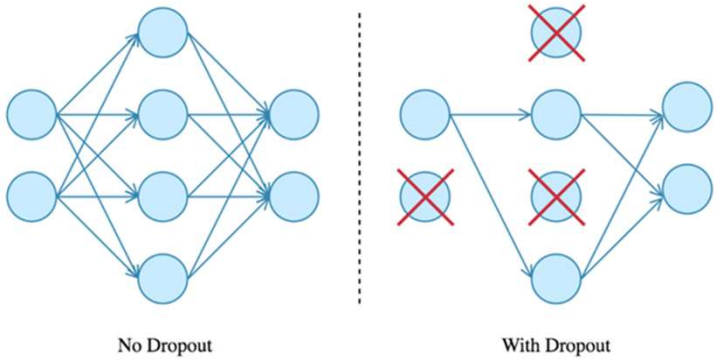
	Underfitting	Just right	Overfitting
Symptoms	• High training error • Training error close to test error • High bias	• Training error slightly lower than test error	• Very low training error • Training error much lower than test error • High variance
Regression illustration			
Classification illustration			
Deep learning illustration			
Possible remedies	• Complexify model • Add more features • Train longer		• Perform regularization • Get more data

CNN

We may face a case, when training loss keeps going down but the validation loss starts increasing after certain epoch. It is a sign of ***overfitting***. It tells us that our model is memorizing the training data, but it's failing to generalize to new instances.

The most popular regularization technique for deep neural networks is **Dropout**. It is used to prevent overfitting via temporarily "dropping"/disabling a neuron with probability *p* (a hyperparameter called the *dropout-rate* that is typically a number around 0.5) at each iteration during the training phase.

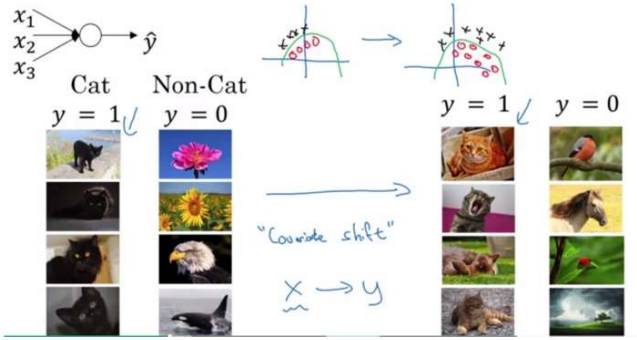
- The dropped-out neurons are resampled with probability *p* at every training step (a dropped out neuron at one step can be active at the next one). (Dropout is not applied during test time after the network is trained).
- Dropout can be applied to input or hidden layer nodes but not the output nodes.



Reason. Dropout forces every neuron to be able to operate independently and prevents the network to be too dependent on a small number of neurons.

Relevant links:
https://www.tensorflow.org/tutorials/images/classification
https://www.cs.toronto.edu/~hinton/absps/JMLRdropout.pdf
https://arxiv.org/abs/1502.03167
https://www.youtube.com/watch?v=EehRcPo1M-Q

CNN



Batch Normalization is a popular regularization technique…

Batch Normalization is a method to reduce internal covariate shift in neural networks, improving the performance and stability of neural networks. To speed up learning, it is reasonable to normalize not only the input layer, but similarly, to apply normalization for the values in the hidden layers as well, improving training speed and overall accuracy. Batch normalization allows each layer of a network to learn by itself a little bit more independently of other layers.

- **Speeds up training:** *it should converge much quicker, even though each training iteration will be slower because of the extra normalisation calculations during the forward pass and the additional hyperparameters to train during back propagation.*
- **Allows higher learning rates:** *as networks get deeper, initially small gradients get even smaller during back propagation, and so require even more iterations. Batch normalisation allows much higher learning rates, increasing the speed at which networks train.*
- **Simplifies weights initialization:** *batch normalisation helps reduce the sensitivity to the initial starting weights.*
- **Makes activation functions viable:** *as batch normalisation regulates the values going into each activation function, nonlinearities that don't work well in deep networks tend to become viable again.*
- **Reduces overfitting:** *it has a slight regularization effects and, similarly to dropout, it adds some noise to each hidden layer's activations. If we use batch normalization, we will use less dropout, which is a good thing because we are not going to lose a lot of information. However, we should not depend only on batch normalization for regularization; we should better use it together with dropout.*

Batch normalization adds two trainable parameters to each layer, so the normalized output is multiplied by a *"standard deviation"* parameter and add a *"mean"* parameter.

Being used before the activation function and dropout, Batch Normalization layer applies a transformation that maintains the mean activation close to 0 and the activation standard deviation close to 1.

tf.layers.batch_normalization(inputs, axis=-1, momentum=0.99, epsilon=0.001, center=True, scale=True, beta_initializer=tf.zeros_initializer(), gamma_initializer=tf.ones_initializer(), moving_mean_initializer=tf.zeros_initializer(), moving_variance_initializer=tf.ones_initializer(), beta_regularizer=None, gamma_regularizer=None, beta_constraint=None, gamma_constraint=None, training=False, trainable=True, name=None, reuse=None, renorm=False, renorm_clipping=None, renorm_momentum=0.99, fused=None)

tf.keras.layers.BatchNormalization(axis=-1, momentum=0.99, epsilon=0.001, center=True, scale=True, beta_initializer='zeros', gamma_initializer='ones', moving_mean_initializer='zeros', moving_variance_initializer='ones', beta_regularizer=None, gamma_regularizer=None, beta_constraint=None, gamma_constraint=None)

Relevant links:

https://www.coursera.org/learn/deep-neural-network/lecture/81oTm/why-does-batch-norm-work
https://towardsdatascience.com/batch-normalization-in-neural-networks-1ac91516821c
https://keras.io/layers/normalization/ , https://arxiv.org/abs/1502.03167 , https://www.youtube.com/watch?v=yXOMHOpbon8

CNN

Overfitting happens when we are training on very few examples (e.g. 1000 images per category), and even use of dropout does not help us much. To start think about Deep Learning, we have to operate with at least 100K training examples. On a small dataset we will overfit no matter which regularization technique is applied.

Fortunately, there is a ***data augmentation*** method which enables us to train deep models on small datasets. It allows us to artificially boost the size of the training set through enrichment or "augmentation" of the training data by generating new examples via random transformation of existing ones.

Data augmentation is done dynamically during training time. To generate realistic images, the common transformations are: rotation, shifting, resizing, exposure adjustment, contrast change etc.

Also, some data cleaning tricks on images can be applied (e.g. whitening and mean normalization).
http://ufldl.stanford.edu/tutorial/unsupervised/PCAWhitening/

Relevant links:
https://www.tensorflow.org/tutorials/images/classification
https://keras.io/preprocessing/image/
https://machinelearningmastery.com/image-augmentation-deep-learning-keras/
https://www.youtube.com/watch?v=EehRcPo1M-Q

TensorFlow

Convolution NN on MNIST dataset

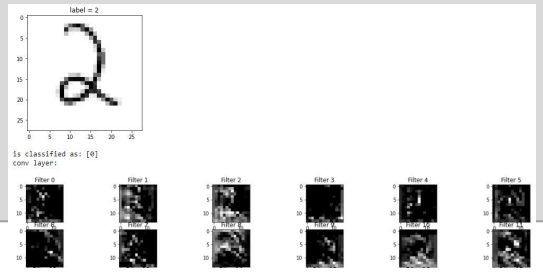
```
import tensorflow.compat.v1 as tf
tf.compat.v1.disable_eager_execution()
import matplotlib.pyplot as plt
import numpy as np
import math
# Import MNIST data
(train_images,train_labels),(test_images,test_labels) =
                                        tf.keras.datasets.mnist.load_data()
train_images = tf.reshape(train_images,[60000,784])
test_images = tf.reshape(test_images,[10000,784])
train_images /= 255
test_images /= 255
unique_category_count = 10
y_train = tf.one_hot(train_labels, unique_category_count)
y_test = tf.one_hot(test_labels, unique_category_count)
# Parameters
learning_rate = 0.001
training_epochs = 5
batch_size = 1000
def weight_variable(shape):
    initial = tf.truncated_normal(shape, stddev=0.1)
    return tf.Variable(initial)
def bias_variable(shape):
    initial = tf.constant(0.1, shape=shape)
    return tf.Variable(initial)
def conv2d(x, W):
    return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')
def max_pool_2x2(x):
    return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],strides=[1, 2, 2, 1],padding='SAME')
def getActivations(layer,stimuli):
    units =
sess.run(layer,feed_dict={x:np.reshape(stimuli,[1,784],order='F'),keep_prob:1.0})
    plotNNFilter(units)
def plotNNFilter(units):
    filters = units.shape[3]
    plt.figure(1, figsize=(20,20))
    n_columns = 6
    n_rows = math.ceil(filters / n_columns) + 1
    for i in range(filters):
        plt.subplot(n_rows, n_columns, i+1)
        plt.title('Filter ' + str(i))
        plt.imshow(units[0,:,:,i], interpolation="nearest",
cmap="gray")
# Create the model
x = tf.placeholder(tf.float32, [None, 784])
x_image = tf.reshape(x, [-1, 28, 28, 1])
W_conv1 = weight_variable([5, 5, 1, 32])
b_conv1 = bias_variable([32])
h_conv1 = tf.nn.relu(conv2d(x_image, W_conv1) + b_conv1)
h_pool1 = max_pool_2x2(h_conv1)
W_conv2 = weight_variable([5, 5, 32, 64])
b_conv2 = bias_variable([64])
h_conv2 = tf.nn.relu(conv2d(h_pool1, W_conv2) + b_conv2)
h_pool2 = max_pool_2x2(h_conv2)
W_fc1 = weight_variable([7 * 7 * 64, 1024])
b_fc1 = bias_variable([1024])
h_pool2_flat = tf.reshape(h_pool2, [-1, 7*7*64])
h_fc1 = tf.nn.relu(tf.matmul(h_pool2_flat, W_fc1) + b_fc1)
keep_prob = tf.placeholder(tf.float32)
h_fc1_drop = tf.nn.dropout(h_fc1, 1-keep_prob)
W_fc2 = weight_variable([1024, 10])
b_fc2 = bias_variable([10])
y_conv = tf.matmul(h_fc1_drop, W_fc2) + b_fc2
```

TensorFlow

Convolution NN on MNIST dataset

```
# Define loss and optimizer
y_ = tf.placeholder(tf.float32, [None, 10])
cross_entropy = tf.reduce_mean(
    tf.nn.softmax_cross_entropy_with_logits_v2(labels=y_,
    logits=y_conv))
train_step = tf.train.AdamOptimizer(1e-4).minimize(cross_entropy)
correct_prediction = tf.equal(tf.argmax(y_conv, 1), tf.argmax(y_, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))
# Add ops to save and restore all the variables.
saver = tf.train.Saver()
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    for ii in range(training_epochs):
        total_batch = int(train_images.shape[0]/batch_size)
        for i in range(total_batch):
            batch_xs = train_images[i * batch_size: (i+1) * batch_size]
            batch_ys = y_train[i * batch_size: (i+1) * batch_size]
            train_accuracy = accuracy.eval(feed_dict={x: sess.run(batch_xs),
                                    y_: sess.run(batch_ys), keep_prob: 1.0})
            print('step %d, training accuracy %g' % (ii, train_accuracy))
            train_step.run(feed_dict={x: sess.run(batch_xs),
                                    y_: sess.run(batch_ys), keep_prob: 0.5})
    print('test accuracy %g' % accuracy.eval(feed_dict={
            sess.run(test_images), y_: sess.run(y_test), keep_prob: 1.0}))

    save_path = saver.save(sess, "my_models_tmp/model.ckpt")
    print("Model saved in file: %s" % save_path)

    saver.restore(sess, "my_models_tmp/model.ckpt")
    print("Model restored.")
```

```
    print('----------------------')
    print("Test sample:")

    #Get 28x28 image
    img_to_use = test_images[47]
    sample_1 = sess.run(img_to_use).reshape(28,28)

    # Get corresponding integer label from one-hot encoded data
    sample_label_1 = np.where(sess.run(y_test)[47] == 1)[0][0]

    # Plot sample
    plt.imshow(sample_1, cmap='Greys')
    plt.title('label = {}'.format(sample_label_1))
    plt.show()

    predicted_value = tf.argmax(y_conv, 1)
    print("is classified as: {}".format(predicted_value.eval(
                session= sess,
feed_dict={x:isess.run(mg_to_use).reshape(1,784),
                keep_prob: 1.0})))

    print("conv layer:")
    getActivations(h_conv2, sess.run(img_to_use))
```



TensorFlow

The TensorFlow layers module provides a high-level API that makes it easy to construct a neural network.
https://www.tensorflow.org/api_docs/python/tf/layers

It provides methods that facilitate the creation of dense (fully connected) layers and convolutional layers, adding activation functions, and applying dropout regularization.

As an example… tf.layers.conv2d handles activation and bias automatically while you have to write additional codes for these if you use tf.nn.conv2d.

```
tf.nn.conv2d(input, filter, strides, padding, use_cudnn_on_gpu=None, data_format=None, name=None)
```

```
tf.layers.conv2d(inputs, filters, kernel_size, strides=(1, 1), padding='valid', data_format='channels_last', dilation_rate=(1, 1), activation=None,
use_bias=True, kernel_initializer=None, bias_initializer=tf.zeros_initializer(), kernel_regularizer=None, bias_regularizer=None,
activity_regularizer=None, trainable=True, name=None, reuse=None)
```

Check the tutorial that explains how to build a convolutional neural network model to recognize the handwritten digits in the MNIST data set using layers and creating corresponding Estimator to handle the model. *https://www.tensorflow.org/tutorials/layers*

TensorFlow 2.0

Keras

Convolution NN on MNIST dataset with Keras

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
get_ipython().magic(u'matplotlib inline')
from tensorflow.keras.datasets import mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Activation,
      Flatten, BatchNormalization, Conv2D, MaxPooling2D,
      ZeroPadding2D, GlobalAveragePooling2D
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import utils
from tensorflow.keras.preprocessing.image import
      ImageDataGenerator
# Import MNIST data
(X_train, Y_train), (X_test, Y_test) = mnist.load_data()
X_train = X_train.reshape(X_train.shape[0], 28, 28, 1)
X_test = X_test.reshape(X_test.shape[0], 28, 28, 1)
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train/=255
X_test/=255
# convert output if use 'categorical_crossentropy', or do not, if
# 'sparse_categorical_crossentropy'
#Y_train = utils.to_categorical(y_train, number_of_classes)
#Y_test = utils.to_categorical(y_test, number_of_classes)
number_of_classes = 10

# Three steps to create a CNN
# 1. Convolution
# 2. Activation
# 3. Pooling
```

```
# Repeat Steps 1,2,3 for adding more hidden layers
# 4. After that make a fully connected network
# This fully connected network gives ability to
# the CNN to classify the samples
model = Sequential()

model.add(Conv2D(32, (3, 3), input_shape=(28,28,1)))
model.add(BatchNormalization(axis=-1))
model.add(Activation('relu'))
model.add(Conv2D(32, (3, 3)))
model.add(BatchNormalization(axis=-1))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Conv2D(64,(3, 3)))
model.add(BatchNormalization(axis=-1))
model.add(Activation('relu'))
model.add(Conv2D(64, (3, 3)))
model.add(BatchNormalization(axis=-1))
model.add(Activation('relu'))
model.add(MaxPooling2D(pool_size=(2,2)))

model.add(Flatten())
# Fully connected layer
model.add(Dense(512))
model.add(BatchNormalization())
model.add(Activation('relu'))
model.add(Dropout(0.2))
model.add(Dense(number_of_classes))

model.add(Activation('softmax'))
```

TensorFlow 2.0

Keras

Convolution NN on MNIST dataset with Keras

```
#model.compile(loss=tf.keras.losses.categorical_crossentropy, optimizer=Adam(), metrics=['accuracy'])
model.compile(loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True), optimizer=Adam(), metrics=['accuracy'])

gen = ImageDataGenerator(rotation_range=8, width_shift_range=0.08, shear_range=0.3,
                         height_shift_range=0.08, zoom_range=0.08)

test_gen = ImageDataGenerator()

train_generator = gen.flow(X_train, Y_train, batch_size=64)
test_generator = test_gen.flow(X_test, Y_test, batch_size=64)

model.fit(train_generator, batch_size=64, epochs=5, validation_data=test_generator)
```

The CIFAR-10 and CIFAR-100 are labeled subsets of the 80 million tiny images dataset, collected by Alex Krizhevsky, Vinod Nair, and Geoffrey Hinton.
https://www.cs.toronto.edu/~kriz/cifar.html

CNN on CIFAR-10 tutorial: https://www.tensorflow.org/tutorials/images/cnn

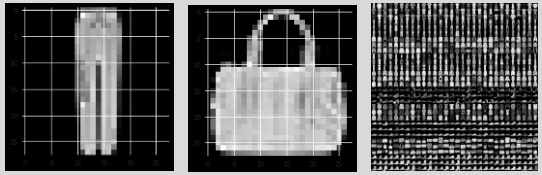
Some datasets: http://rodrigob.github.io/are_we_there_yet/build/classification_datasets_results.html
MNIST CNN based on csv data: https://github.com/tgjeon/kaggle-MNIST/blob/master/mnist.py
Visualizing convolutional neural networks (CNN with colored images): https://www.oreilly.com/ideas/visualizing-convolutional-neural-networks

Relevant links:
https://elitedatascience.com/keras-tutorial-deep-learning-in-python
http://cv-tricks.com/tensorflow-tutorial/keras/
http://adventuresinmachinelearning.com/keras-tutorial-cnn-11-lines/

TensorFlow 2.0 K Keras

CNN on Fashion-MNIST dataset…

```
from __future__ import print_function
import tensorflow as tf
from tensorflow.keras.datasets import fashion_mnist
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Conv2D,
        MaxPooling2D, Flatten
from tensorflow.keras.optimizers import RMSprop, SGD, Adam
import matplotlib.pyplot as plt
%matplotlib inline

batch_size = 128
num_classes = 10
epochs = 20
# Data Preparation
img_rows, img_cols = 28, 28
(x_train, y_train), (x_test, y_test) = fashion_mnist.load_data()
if tf.keras.backend.image_data_format() == 'channels_first':
    x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
    x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
    input_shape = (1, img_rows, img_cols)
else:
    x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
    x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
    input_shape = (img_rows, img_cols, 1)
x_train = x_train.astype('float32')
x_test = x_test.astype('float32')
x_train /= 255
x_test /= 255
print('x_train shape:', x_train.shape)
print(x_train.shape[0], 'train samples')
print(x_test.shape[0], 'test samples')
```



```
# convert class vectors to binary class matrices if use
# 'categorical_crossentropy' loss. Otherwise use
# 'spars_categorical_crossentropy' loss.
y_train = tf.keras.utils.to_categorical(y_train, num_classes)
y_test = tf.keras.utils.to_categorical(y_test, num_classes)
# Model Building
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
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(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=tf.keras.losses.categorical_crossentropy,
              optimizer=Adam(), metrics=['accuracy'])
model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Label Description

- *0 T-shirt*
- *1 Trouser*
- *2 Pullover*
- *3 Dress*
- *4 Coat*
- *5 Sandal*
- *6 Shirt*
- *7 Sneaker*
- *8 Bag*
- *9 Ankle boot*

```
…
Epoch 20/20
55040/60000 [==========================>...] - ETA: 0s - loss: 0.1247 - acc:
0.955060000/60000 [==============================] - 10s 165us/step - loss:
0.1239 - acc: 0.9553 - val_loss: 0.2282 - val_acc: 0.9299
Test loss: 0.22820208635628222
Test accuracy: 0.9299
```

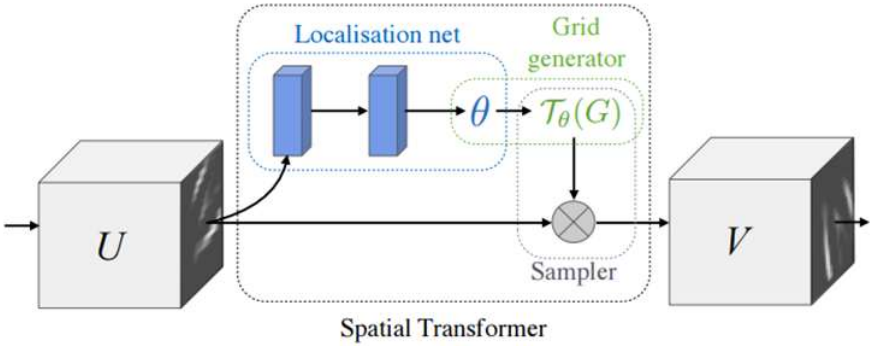
Spatial Transformation

Spatial Transformer Networks *(by a group at Google Deepmind)*

even though CNNs define an exceptionally powerful class of models, they are still limited by the lack of ability to be spatially invariant to the input data in a computationally and parameter efficient manner. To show good results, model should be trained on a huge variety of "transformed" samples…

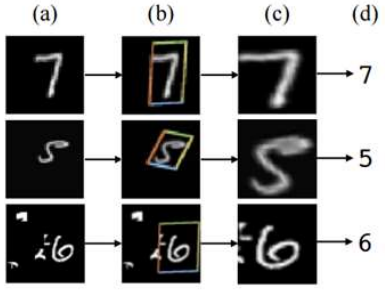
Spatial Transformer is a new learnable module, which explicitly allows the spatial manipulation of data within the network. This differentiable module can be inserted into existing convolutional architectures, giving neural networks the ability to actively spatially transform feature maps, conditional on the feature map itself, without any extra training supervision or modification to the optimization process. Authors has shown that the use of spatial transformers results in models which learn *invariance to translation, scale, rotation* and *more generic warping*, resulting in state-of-the-art performance on several benchmarks, and for a number of classes of transformations.

- *Instead of making changes to the main CNN architecture itself, the authors offer making changes to the image before it is fed into the specific conv layer.*
- *The module transforms the input image in a way so that the subsequent layers have an easier time making a classification...*
- *The module can be dropped into a CNN at any point and helps the network learn how to transform feature maps in a way that minimizes the cost function during training…*



Spatial Transformer

A Spatial Tranfomer module



Relevant links:
https://arxiv.org/pdf/1506.02025.pdf
Video from Deepmind: https://drive.google.com/file/d/0B1nQa_sA3W2iN3RQLXVFRkNXN0k/view
https://gist.github.com/kvn219/b42d382a06eff3254bf00e780e9b8e0f

Hinton: "The pooling operation used in convolutional neural networks is a big mistake and the fact that it works so well is a disaster."

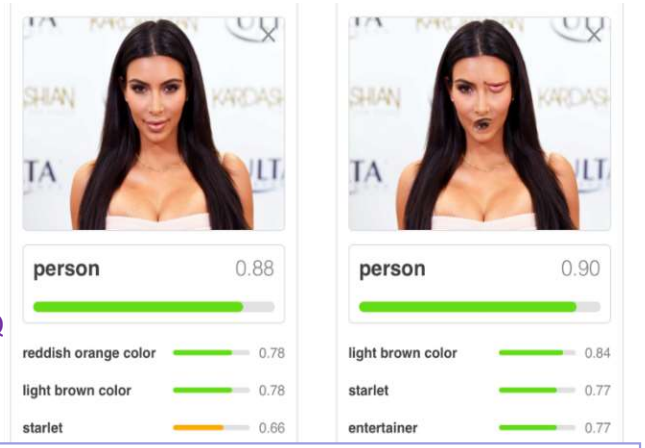
Capsule Net

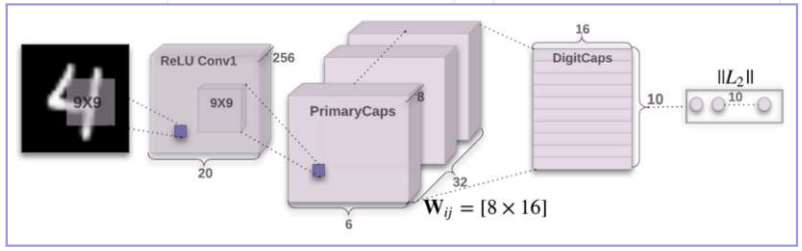
Capsule Net as an improvement of the CNN…

CNNs are awesome and can do amazing things. Nevertheless, they have their limits and they have fundamental drawbacks. Internal data representation of a convolutional neural network does not take into account important spatial hierarchies between simple and complex objects…

Geoffrey Hinton and his team introduced a completely new type of neural network based on so-called *capsules*. In addition to that, the team published an algorithm, called *dynamic routing between capsules* (October 2017), that allows to train such a network. Capsule is introduced as a group of neurons (subnet) that are nested inside the convolutional layer. Authors also introduced a corresponding new non-linearity function to be applied to the capsule…

- *High accuracy on MNIST (but not yet so good on CIFAR10). Is not tested yet on larger images (e.g. ImageNet)*
- *Requires less training data, but more training time (due to the inner loop)*
- *Position and pose information are preserved (equivariance), that is promising for image segmentation and object detection.*
- *Offers robustness to affine transformations (translation, scale, shear, rotation, etc.)*
- *A CapsNet cannot see two very close identical objects (it is called "crowding").*



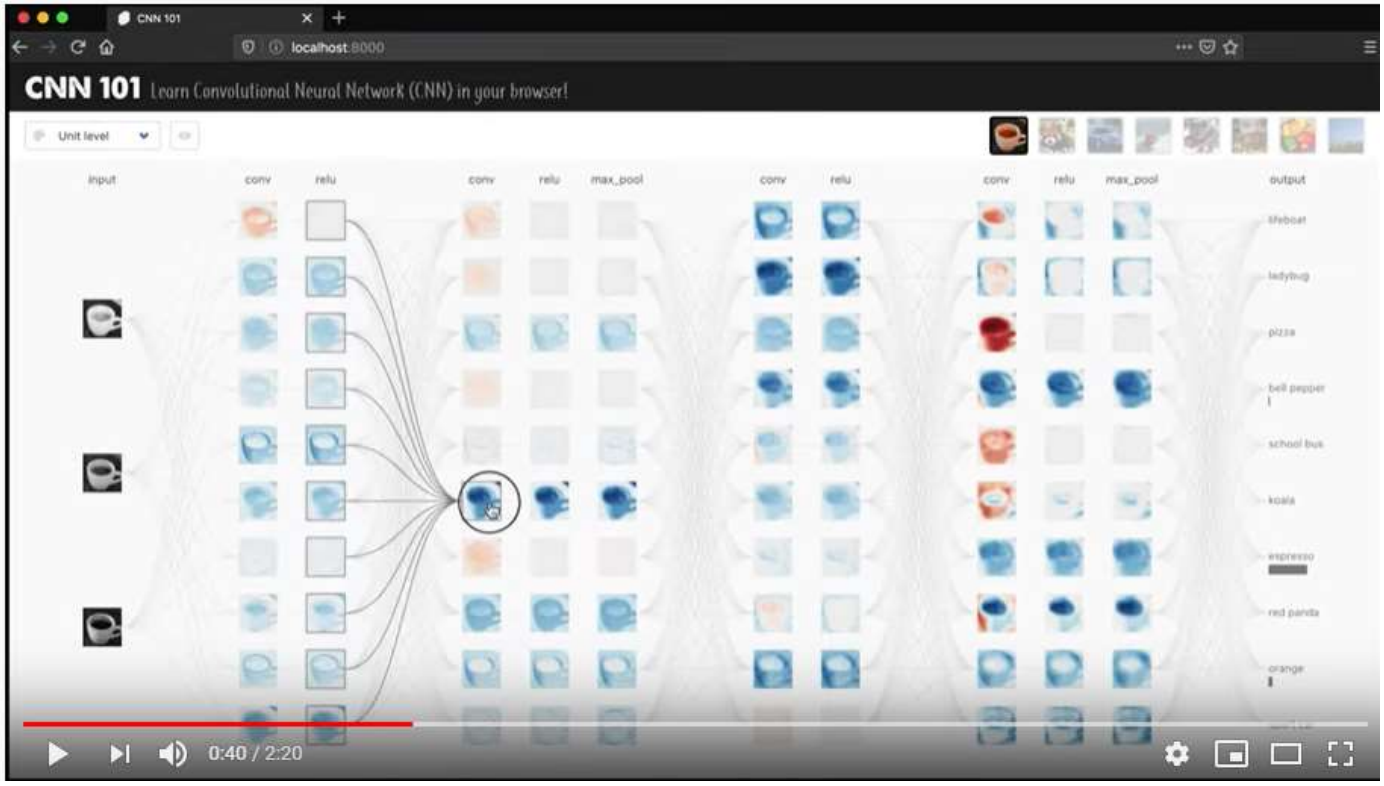


Relevant links:

https://arxiv.org/abs/1710.09829, https://blog.paperspace.com/capsule-networks/
https://www.sciencedirect.com/science/article/pii/S1319157819309322
https://www.youtube.com/watch?v=pPN8d0E3900, https://www.youtube.com/watch?v=6S1_WqE55UQ
https://paperswithcode.com/method/fixcaps
https://towardsdatascience.com/implementing-capsule-network-in-tensorflow-11e4cca5ecae
https://github.com/XifengGuo/CapsNet-Keras
https://www.nature.com/articles/s41598-021-93977-0
https://theailearner.com/2019/01/21/implementing-capsule-network-in-keras/
https://hackernoon.com/what-is-a-capsnet-or-capsule-network-2bfbe48769cc
https://medium.com/botsupply/running-capsulenet-on-tensorflow-1099f5c67189
https://www.youtube.com/watch?v=2Kawrd5szHE
https://www.youtube.com/watch?v=VKoLGnq15RM
https://github.com/jaesik817/adv_attack_capsnet
https://medium.com/ai³-theory-practice-business/understanding-hintons-capsule-networks-part-i-intuition-b4b559d1159b
https://github.com/naturomics/CapsNet-Tensorflow ; https://github.com/llSourcell/capsule_networks ; https://github.com/bourdakos1/capsule-networks
https://github.com/XifengGuo/CapsNet-Keras ; https://openreview.net/pdf?id=HJWLfGWRb
https://becominghuman.ai/understand-and-apply-capsnet-on-traffic-sign-classification-a592e2d4a4ea

CNN 101

Interactive Visual Learning for Convolutional Neural Networks an interactive visualization system for explaining and teaching convolutional neural networks. Through tightly integrated interactive views, CNN 101 offers both overview and detailed descriptions of how a model works. Built using modern web technologies, CNN 101 runs locally in users' web browsers without requiring specialized hardware, broadening the public's education access to modern deep learning techniques. https://arxiv.org/abs/2001.02004



Demo Video: https://www.youtube.com/watch?v=g082-zitM7s&feature=youtu.de