Deep Learning – The Big Picture

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Brief History of Deep Learning

Deep Learning Timeline - 1

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Ivakhnenko developed a learning algorithm using deep feedforward multilayer perceptrons. For that reason alone, many consider Ivakhnenko the father of modern deep learning.

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1970 - First AI Winter
AI was subject to critiques and financial setbacks. AI researchers had failed to appreciate the difficulty of the problems they faced.

AI was claimed to only be suitable for solving “toy” versions.

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1980

Kunihiko Fukushima creates Neocognitron, an artificial neural network that learned how to recognize visual patterns.

His work led to the development of the first convolutional neural networks, which are based on the visual cortex organization found in animals.

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Algorithms originally developed by AI researchers began to appear as parts of larger systems. AI had solved a lot of very difficult problems and their solutions proved to be useful throughout the technology industry, such as data mining, industrial robotics, logistics, speech recognition, banking software, medical diagnosis and Google's search engine.

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2011 - Deep Learning

Deep Learning appeared as Machine Learning method which uses deep graphs with many processing layers.

Today Deep Learning is everywhere and often wrongly equated with AI.

1980 → 1987 → 1993 → 1997 → 2011

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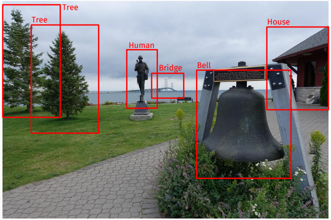
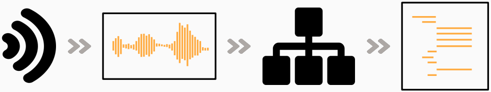
What is Possible With Deep Learning?

Deep Learning Applications

- Supervised learning tasks
- Object Recognition – Seeing:



- Speech Recognition and NLP – Hearing and understanding text:



Deep Learning Applications

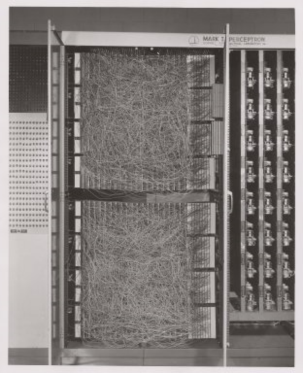
- And know we try to teach them creativity:
  - **Music and Text Generation**
    Example of generated text trained on Trump tweets:
    "The Fake News Media is a great people of the president was a great people of the many people who would be a great people of the president was a big crowd of the statement of the media is a great people of the people of the statement of the people ..."
    ... could be better.
  - **Neural Style Transfer**

  - ...

How Deep Learning Works

The Perceptron

- The perceptron was invented by Frank Rosenblatt 1957.

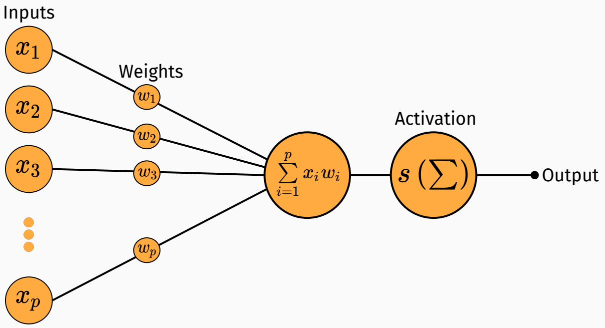


The Mark I Perceptron

- It is the basic computational unit for neural networks.

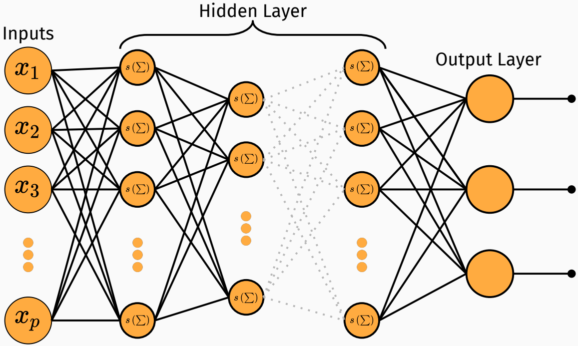
Singlelayer Perceptron

- Weighted sum of input values transformed by an activation function s
- If s is the sigmoid function $(1 + \exp \sum)^{-1}$, then the perceptron does exactly the same as the logistic regression

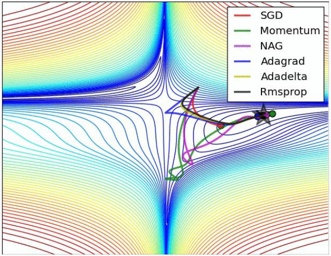


Multilayer Perceptron

- Stacking of multiple perceptrons
- Corresponds to stacking GLM models
- Number of parameter grows very fast
  $\rightarrow$ Optimization becomes more difficult



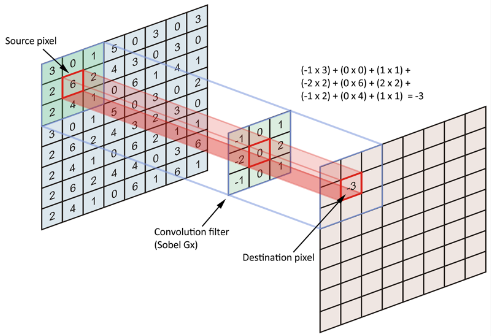
- Having that much parameter/weights to find, standard optimizer like Gradient Descent may fail
- Therefore, much effort was spend to get faster optimizer like adam, rmsprop, etc.:



Source: Ruder, S. (2016). An overview of gradient descent optimization algorithms. arXiv preprint arXiv:1609.04747.

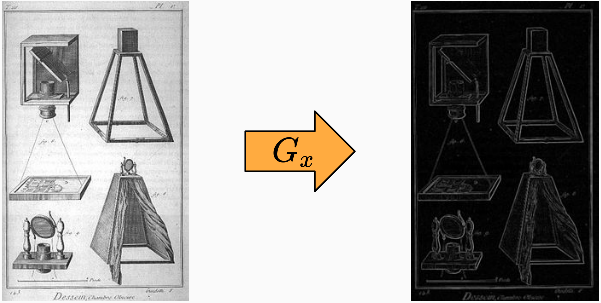
Convolution - As Operation

- Extraction of features of the input data:



Input Image

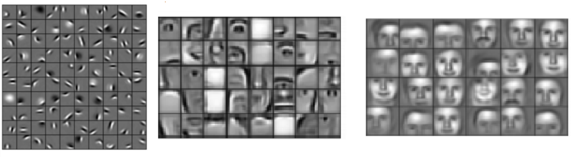
Generated Image/Feature



Note: The recognition of edges and corners requires a multiple application of the operator.

Convolution - In Neural Networks

- Filters, like the Sobel filter, are obtained by thinking long and hard about what should be obtained from a filter (like edges).
- In Deep Learning these filters are learned during the training and automatically generate new features:



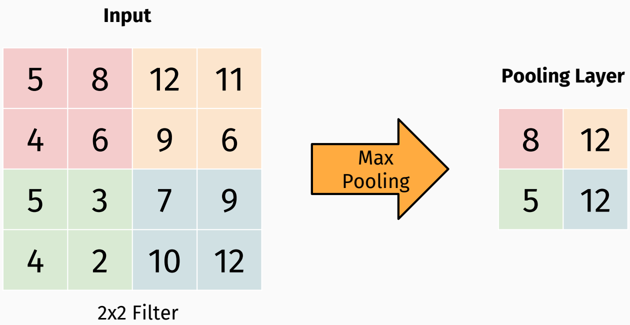
Source: Lee, H., Grosse, R., Ranganath, R., & Ng, A. Y. (2011). Unsupervised learning of hierarchical representations with convolutional deep belief networks. Communications of the ACM, 54(10), 95-103. *"Each feature can be thought of as a filter, which filters the input image for that feature (a nose). If the feature is found, the responsible unit or units generate large activations, which can be picked up by the later classifier stages as a good indicator that the class is present."*

Down-sampling of images:

→ Less weights to fit

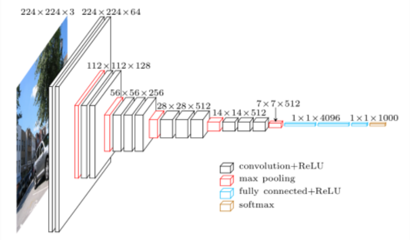
→ Smaller net size (less memory usage, faster fitting process)

→ Reduces overfitting



Lets Get Deep

- The power of Deep Neural Nets comes from chaining hidden layer such as convolution layers, pooling layers, and so on
- This deep structure allows the network to create powerful features and explore complex structures within the data
- VGG16 architecture:



Source: https://www.cs.toronto.edu/~frossard/post/vgg16/

Pre Trained Models

Model	Size	Parameters	Depth
Xception	88 MB	22,910,480	126
VGG16	528 MB	138,357,544	23
VGG19	549 MB	143,667,240	26
ResNet50	99 MB	25,636,712	168
InceptionV3	92 MB	23,851,784	159
InceptionResNetV2	215 MB	55,873,736	572
MobileNet	16 MB	4,253,864	88
MobileNetV2	14 MB	3,538,984	88
DenseNet121	33 MB	8,062,504	121
DenseNet169	57 MB	14,307,880	169
DenseNet201	80 MB	20,242,984	201
NASNetMobile	23 MB	5,326,716	-
NASNetLarge	343 MB	88,949,818	-

Source: Keras Documentation

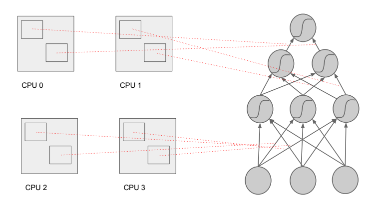
Challenges in Deep Learning

- **Finding a Good Architecture**
  Having that many possibilities of combining hidden layer, optimizer, and activation functions we run into the problem of finding a good architecture.
  - $\rightarrow$ Transfer learning, use already trained models, adjust them to your data situation, and train (a subset of) the weights.
  - $\rightarrow$ Architecture search
- **Expensive Training**
  Training of DNNs require billions of simple operations, hence training **one** DNN might take weeks.
  - $\rightarrow$ Use GPU server for serious applications. Why? See next slides.

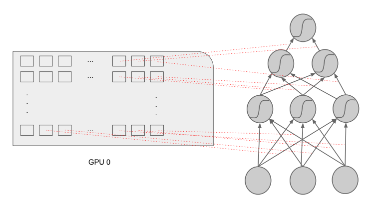
Tech Stack

Hardware

- Deep Neural Networks require special hardware to be trained efficiently.
- The training is done using **G**raphics **P**rocessing **U**nits and a special programming language called **CUDA**.
- Training on standard CPUs takes a very long long time and gets infeasible for anything but toy examples.



Each CPU can do 2 – 8 parallel computations.

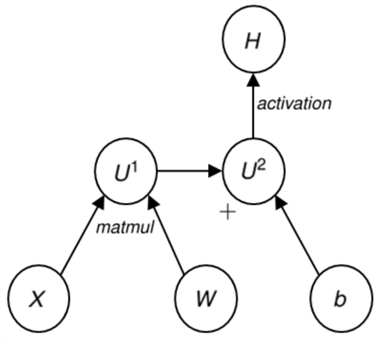


A single GPU can do thousands of simple parallel computations.

Software

CUDA is a very **low level** programming language and thus writing code for Deep Learning requires a lot of work. Software projects, like TensorFlow and abstract CUDA provide additional functionality.

The basic concept of calculations in deep neural networks is a *computational graph*, which describes the dependency structure of the network.



Computational graph for $f(XW + b)$.

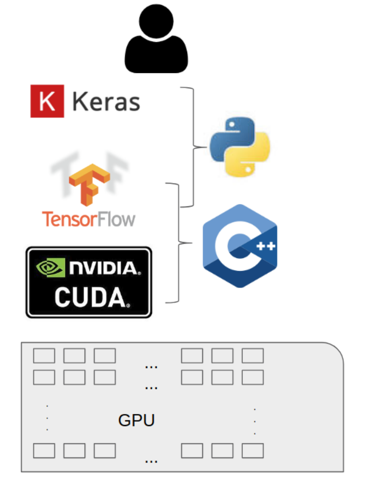
TensorFlow

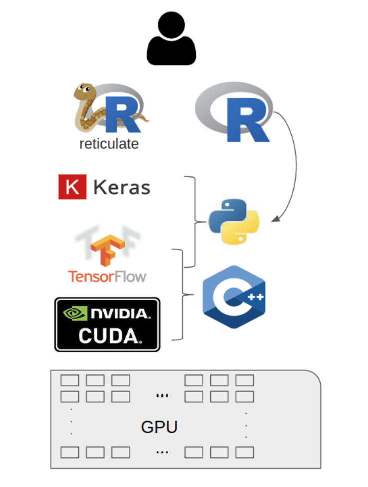
- Open-source framework developed by google.
- Rather low-level and aimed to directly work with computational graphs.
- Mainly support for Python (R support only via *reticulate*).
- Widely used and well documented.

Keras

- Open-source high-level API for Deep Learning.
- Can run on top of **TensorFlow**, CNTK or Theano.
- Mainly support for Python (R support only via **reticulate**).
- Widely used and well documented.

Keras in R





- Deep learning in R is the same as in Python.
- Communication from R to Python via **reticulate**.

Keras in R

- Syntax is (almost) identical.
- Same functionality.
- Same speed (slight overhead for communication between R and Python).
- More difficult to debug.

Useful resources:

https://keras.rstudio.com/

https://rstudio.github.io/reticulate/articles/introduction.html

PyTorch

- Open-source framework developed by facebook.
- Reimplementation of Torch.
- Only support for Python.
- Widely used and well documented.

Fast.ai

- Open-source high-level API build on top of PyTorch.
- Still in alpha version.
- Only support for Python.
- Initially developed for the *Practical Deep Learning for Coders* online course.

- Open-source framework in the Apache foundation.
- Scalable, allow easy training on multiple GPUs in parallel.
- Supports multiple languages (C++, Python, R, Julia, Matlab, JavaScript, Go, Scala, Pearl).
- Not as widely used as other frameworks.

Where to Start in the DL Jungle?

Getting Started with Keras - Installation

- Install keras using `pip` (or pip3 for python3) from the command line:

```
# python
pip install --upgrade tensorflow
pip install keras

# python3
pip3 install --upgrade tensorflow
pip3 install keras
```

- On linux you may need to run the commands as `sudo`.
- The GPU version requires `CUDA` and `cuDNN`. Installation is then done by

```
pip install --upgrade tensorflow-gpu
```

Getting Started with Keras - Overview

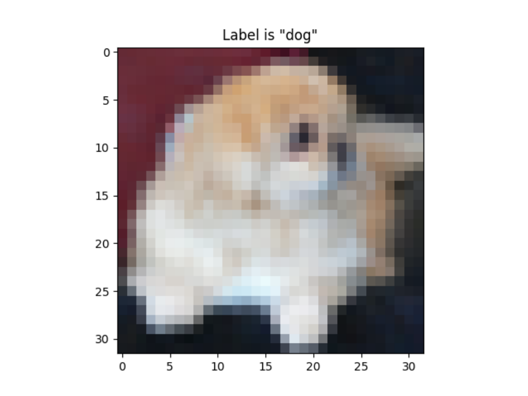
- Instead of introducing theory, we want to get into the topic by applying it.
- We using examples similar to the book **Deep Learning with Python** that are prepared as **notebooks**.
- **But**: When using something new, e.g. a convolution layer or optimizer, try to understand what it does and why it might be beneficial!
- First of all, we have to load keras and import models and layers:

```
import keras # equal to Rs library command
from keras import models
from keras import layers
```

Gettins Started with Keras - Example Data 1

```
import numpy as np
from keras.datasets import cifar10 # Our dataset
# See https://www.cs.toronto.edu/~kriz/cifar.html

(X_train, Y_train), (X_test, Y_test) = cifar10.load_data()
X_train.shape
## (50000, 32, 32, 3)

categories = ["airplane", "automobile", "bird", "cat",
              "deer", "dog", "frog", "horse", "ship",
              "truck"]

import matplotlib.pyplot as plt

category = categories[np.asscalar(Y_train[2305])]
plt.title('Label is \"{label}\"'.format(label=category))
plt.imshow(X_train[2305], cmap='gray')
plt.show()
```

Getting Started with Keras - Example Data 2



Getting Started with Keras - Example Data 3

The images are represented as rgb colors, each of the 32×32 pixels is represented as three numbers between 0 and 255. For the training we want to use values between 0 and 1:

```
train_images = X_train.astype('float32') / 255
test_images = X_test.astype('float32') / 255
```

Additionally, we have to convert the labels to a categorical data type:

```
from keras.utils import to_categorical

train_labels = to_categorical(Y_train)
test_labels = to_categorical(Y_test)
```

Getting Started with Keras - DNN 1

```
network = models.Sequential()

network.add(layers.Conv2D(64, (3, 3),
            input_shape=(32, 32, 3), padding='same'))
# now: model.output_shape == (None, 64, 32, 32)

network.add(layers.Flatten())

# Add fully connected hidden layer:
network.add(layers.Dense(units=128,
                         activation='relu'))

# Add output layer which maps each category to a neuron:
network.add(layers.Dense(10, activation='softmax'))

# Make the network ready for training:
network.compile(optimizer='rmsprop',
                loss='categorical_crossentropy',
                metrics=['accuracy'])
```

Getting Started with Keras - DNN 2

```
network.summary()
## ________________________________________________________________
## Layer (type)                 Output Shape              Param #
## ================================================================
## conv2d_2 (Conv2D)            (None, 32, 32, 64)        1792
## ________________________________________________________________
## flatten_2 (Flatten)          (None, 65536)             0
## ________________________________________________________________
## dense_3 (Dense)              (None, 128)               8388736
## ________________________________________________________________
## dense_4 (Dense)              (None, 10)                1290
## ================================================================
## Total params: 8,391,818
## Trainable params: 8,391,818
## Non-trainable params: 0
## ________________________________________________________________
##
```

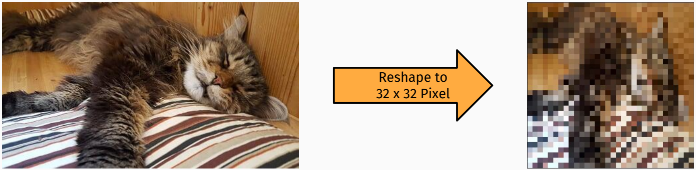
Getting Started with Keras - DNN 3

```
# Train network:
network.fit(train_images, train_labels, epochs=20, batch_size=128)

network.evaluate(test_images, test_labels)
## [3.5850785007747681, 0.4522]
```

Now we try to predict the class of a new image. Therefore, we have to rescale the original image to the same input shape of the training images:

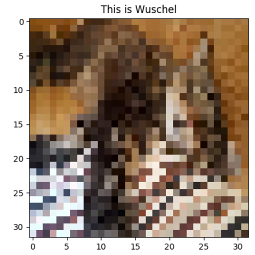
Original Image of Wuschel
(a cat)

Rescaled Image of Wuschel
(still a cat, but very blurred)



Getting Started with Keras - DNN 5

```
from keras.preprocessing.image import load_img, img_to_array
img = load_img('wuschel.jpg', target_size=(32, 32))
img = img_to_array(img).astype('float32') / 255

plt.title('This is Wuschel')
plt.imshow(img, cmap='gray')
plt.show()
```



Getting Started with Keras - DNN 6

```
wuschel_pred = network.predict(np.array([img]))
wuschel_pred
## array([[0.01510279, 0.03711035, 0.04978644, 0.25755176,
##         0.03696484, 0.23572417, 0.00041433, 0.3290789 ,
##         0.00335977, 0.03490658]], dtype=float32)

categories[wuschel_pred.argmax()]
## 'horse'
```

Getting Started with Keras - Transfer Learning 1

```
from keras.applications import VGG16

conv_base = VGG16(weights='imagenet',
                  include_top=False,
                  input_shape=(32, 32, 3))

from keras import optimizers

model = models.Sequential()
model.add(conv_base)
model.add(layers.Flatten())
model.add(layers.Dense(256, activation='relu'))
model.add(layers.Dense(10, activation='softmax'))

conv_base.trainable = False

model.compile(optimizer='rmsprop',
              loss='categorical_crossentropy',
              metrics=['accuracy'])
```

Getting Started with Keras - Transfer Learning 2

```
model.summary()
## _________________________________________________________________
## Layer (type)                 Output Shape              Param #
## =================================================================
## vgg16 (Model)                (None, 1, 1, 512)         14714688
## _________________________________________________________________
## flatten_3 (Flatten)          (None, 512)               0
## _________________________________________________________________
## dense_5 (Dense)              (None, 256)               131328
## _________________________________________________________________
## dense_6 (Dense)              (None, 10)                2570
## =================================================================
## Total params: 14,848,586
## Trainable params: 133,898
## Non-trainable params: 14,714,688
## _________________________________________________________________
##
```

Getting Started with Keras - Transfer Learning 3

```
# Train network:
model.fit(train_images, train_labels, epochs=20, batch_size=128)

model.evaluate(test_images, test_labels)
## [1.1461146575927734, 0.6175]
```

Getting Started with Keras - Transfer Learning 5

```
wuschel_pred = model.predict(np.array([img]))
wuschel_pred
## array([[1.4046730e-03, 1.0323318e-03, 1.2766185e-01,
##         4.6453097e-01, 5.1652599e-02, 5.0368346e-02,
##         2.9299492e-01, 1.0088098e-02, 2.4648944e-05,
##         2.4157017e-04]], dtype=float32)

categories[wuschel_pred.argmax()]
## 'cat'
```

What Next?

Improving Performance:

- Choosing the number of epochs using early stopping
- Data augmentation (increasing size of training data by rotating, scaling, flipping, . . .)

More Difficult Tasks:

- RNN, LSTM, GAN, Reinforcement Learning
- Natural Language Processing