TensorFlow: Federated Learning for Image Classification

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Kim Schmider

image source: https://commons.wikimedia.org/wiki/File:Tensorflow_logo.svg

Introduction

- Introduction to Machine Learning and Deep Learning
- Image Recognition
- CIFAR-10 dataset
- Practical example
- Why Federated Learning?
- `FederatedAveraging` Algorithm

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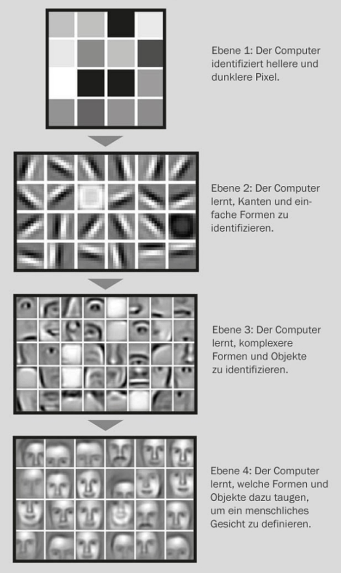
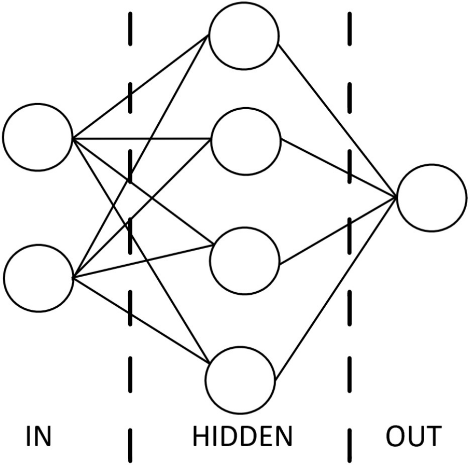
source: https://www.computerwoche.de/a/was-sie-ueber-maschinelles-lernen-wissen-muessen,3329560



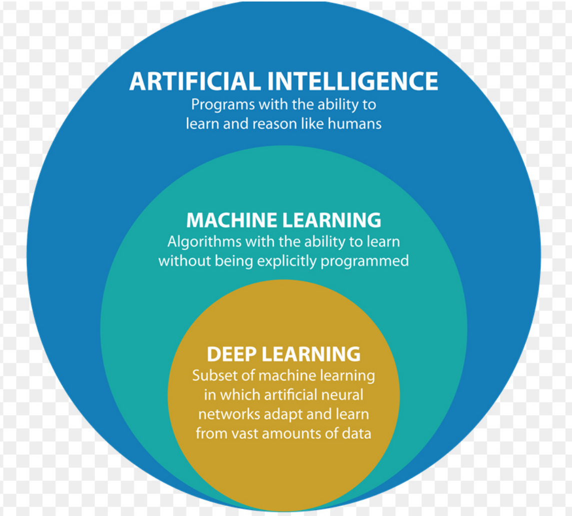
source:
`http://www.spektrum.de/news/maschinenlernen-deep-learning-macht-kuenstliche-intelligenz-praxistauglich/1220451`

Neural Network



source: own figure

Deep Learning



source: `https://de.cleanpng.com/png-vy5m68`

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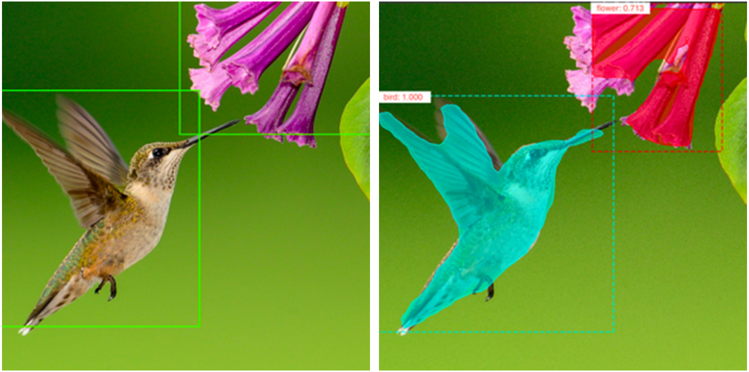
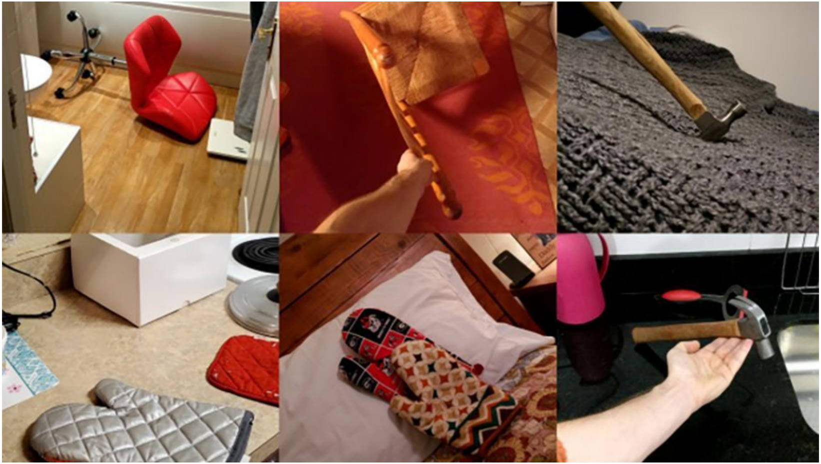
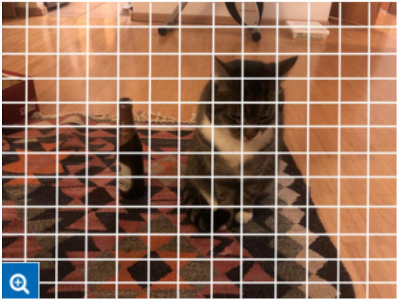
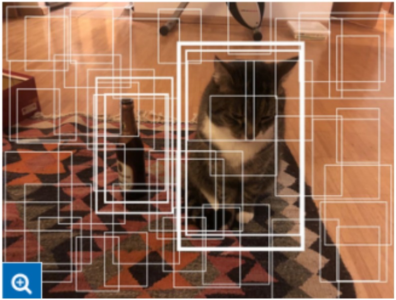


source: `https://www.burda.com/de/news/tech-einmaleins-bilderkennung-und-ki`



source:
https://www.spiegel.de/netzwelt/web/bilderkennung-an-diesen-fotos-scheitert-kuenstliche-intelligenz-a-1301234.html

YOLO Algorithm

source: https://www.sigs-datacom.de/trendletter/2018-10/4-wie-man-in-echtzeit-mehrere-objekte-mit-deep-learning-und-yolo-erkennen-und-klassifizieren-kann.html

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- Size 32 x 32

Image Classification

How does the image classification work?
`https://www.tensorflow.org/tutorials/images/cnn`
This tutorial demonstrates training a simple Convolutional Neural Network (CNN) to classify CIFAR images. (TensorFlow)

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- $w := w - \eta \nabla Q_i(w)$
- Algorithm sweeps through the training set and performs the above update for each training example. Several passes can be made over the training set until the algorithm converges. If this is done, the data can be shuffled for each pass to prevent cycles

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source: Bottou, Léon (1998). "Online Algorithms and Stochastic Approximations". Online Learning and Neural Networks. Cambridge University Press. ISBN 978-0-521-65263-6.

Why Federated Learning?

Federated Learning

- Calculations on end device

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- Results of calculations will be sent to global model

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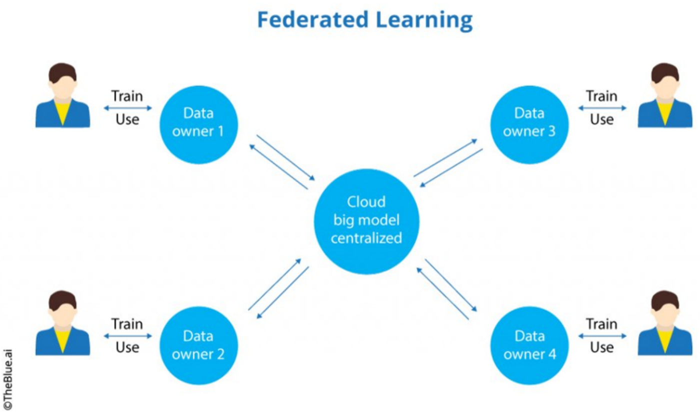

source: https://theblue.ai/blog-de/federated-learning-foederales-lernen

Federated Learning for image classification

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- this simulation example uses the NIST (National Institute of Standards and Technology) dataset

NIST Handprinted Forms and Characters Database

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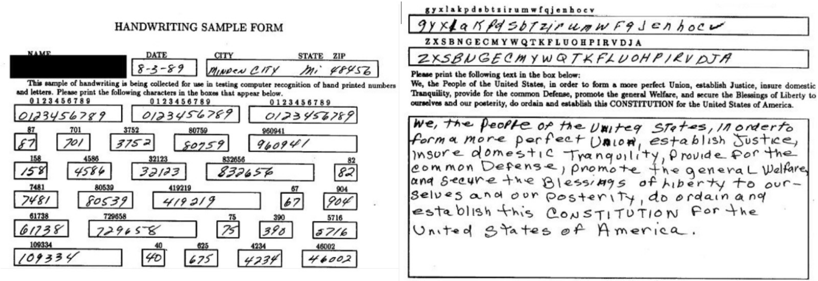

HANDWRITING SAMPLE FORM

NAME [redacted] DATE 8-3-89 CITY MINDEN CITY STATE MI ZIP 48456

This sample of handwriting is being collected for use in testing computer recognition of hand printed numbers and letters. Please print the following characters in the boxes that appear below.

0123456789 0123456789 0123456789

87 701 3752 80759 960941

158 4586 32123 832656 82

7481 80539 419219 67 904

61738 729658 75 390 5716

109334 40 625 4234 46002

gyxlakpdsbtzirumwfqjenhocv

ZXSBNGECMYWQTKFLUOHPIRVDJA

Please print the following text in the box below:

We, the People of the United States, in order to form a more perfect Union, establish Justice, insure domestic Tranquility, provide for the common Defense, promote the general Welfare, and secure the Blessings of Liberty to ourselves and our posterity, do ordain and establish this CONSTITUTION for the United States of America.

source: `https://www.nist.gov/srd/nist-special-database-19`

Short overview Simulation results

```
>>> state, metrics = iterative_process.next(state, federated_train_data)
>>> print('round  1, metrics={}'.format(metrics))
round  1, metrics=<sparse_categorical_accuracy=0.14228394627571106,loss=2.9735283851623535>
>>> for round_num in range(2, 11):
...   state, metrics = iterative_process.next(state, federated_train_data)
...   print('round {:2d}, metrics={}'.format(round_num, metrics))
...
round  2, metrics=<sparse_categorical_accuracy=0.18034979701042175,loss=2.6374611854553223>
round  3, metrics=<sparse_categorical_accuracy=0.21903292834758759,loss=2.547621965408325>
round  4, metrics=<sparse_categorical_accuracy=0.2531892955303192,loss=2.378369092941284>
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- The average metrics over all batches of data trained across all clients in the round

Example Uses of Federated Learning

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- With learning based on user interactions labels are directly available

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FederatedAveraging Algorithm

Server
Main() **do**
  initialize w_0
  for each round $t = 1, 2, \ldots$ **do**
    $S_t \leftarrow$ random fraction of clients
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source: H. Brendan McMahan, et. al. (2016). "Communication-Efficient Learning of Deep Networks from Decentralized Data". arXiv.org.

The End