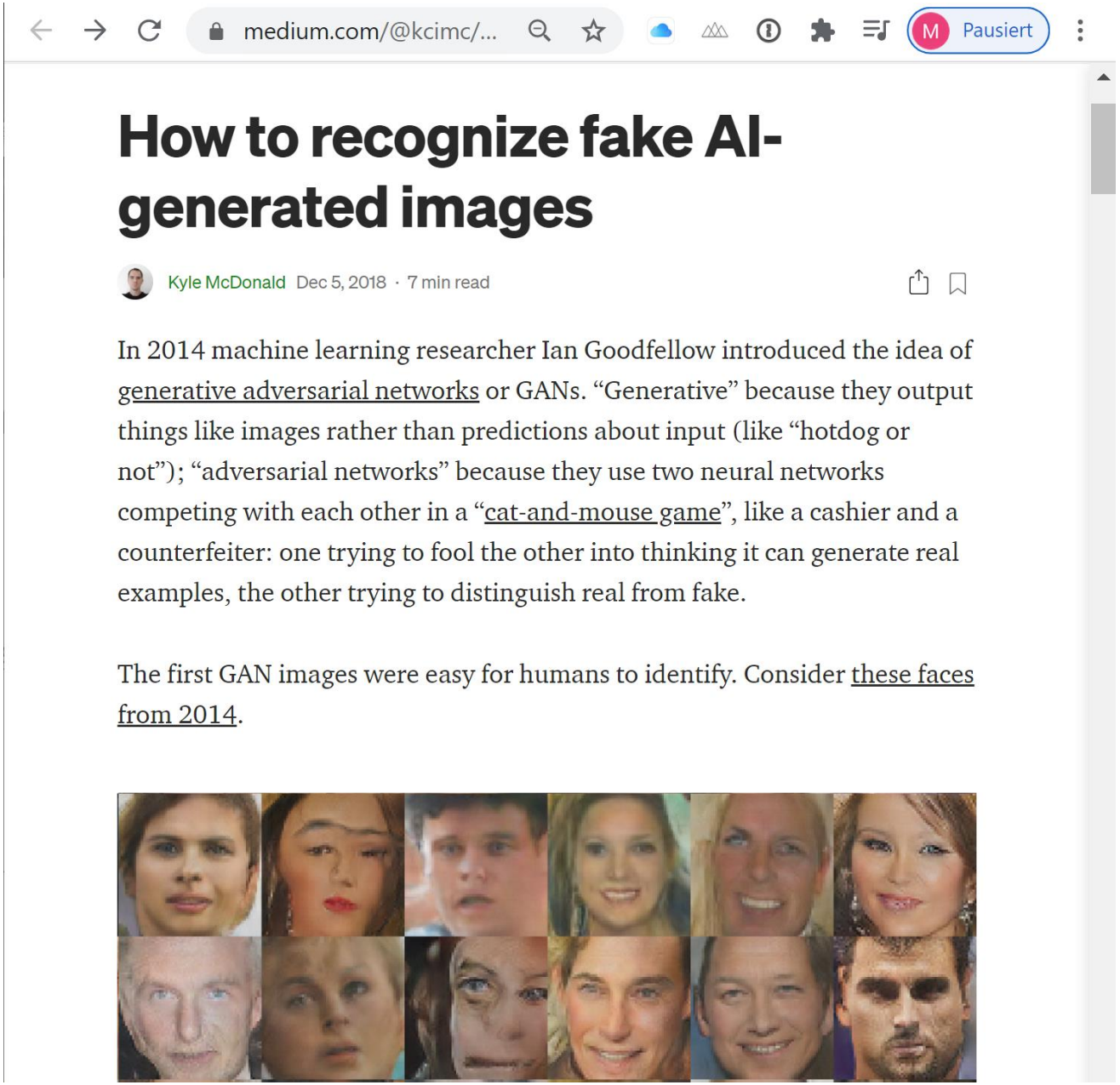
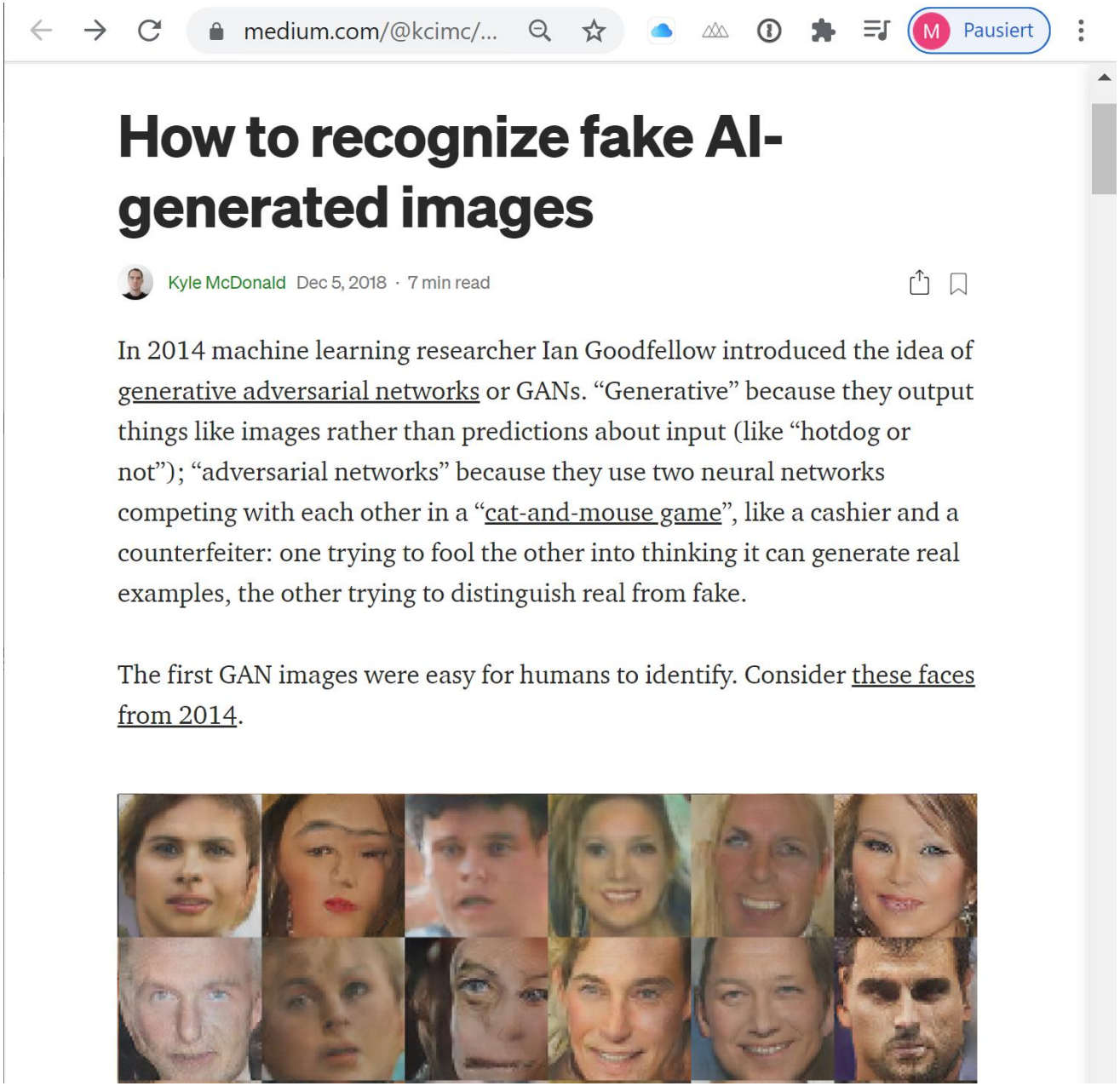


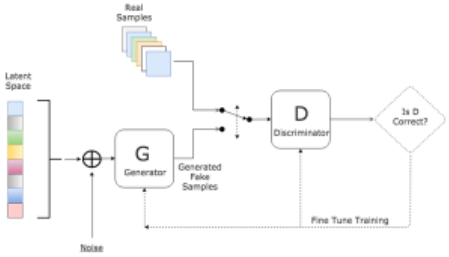
medium.com/@kcimc/how-to-recognize-fake-ai-generated-images-4d1f6f9a2842



medium.com/@kcimc/how-to-recognize-fake-ai-generated-images-4d1f6f9a2842

8 Machine Learning III
- Specialized Areas in Machine Learning
(4) Generative Adversarial Networks GAN

Generative Adversarial Networks (GAN)



A **Generative Adversarial Network (GAN)** is a class of **machine learning** frameworks designed by **Goodfellow** and his colleagues in **2014**.

Two neural networks contest with each other in a game. Given a **training set**, this technique learns to **generate new data** with the same statistics as the **training set**.

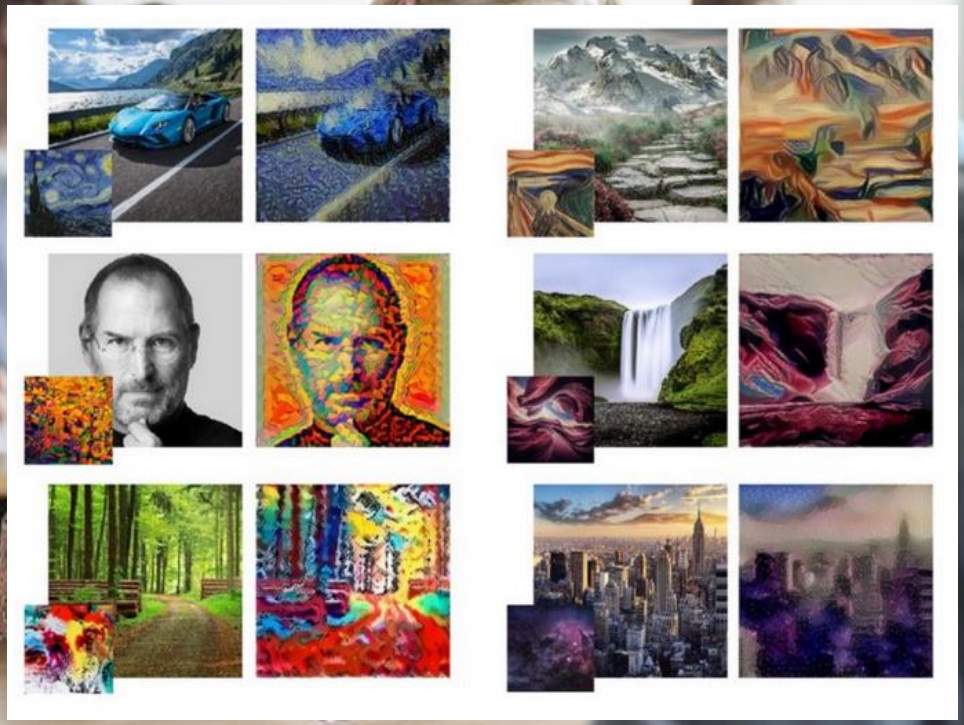
The **core idea** of a GAN is based on the **"indirect" training** through the **discriminator**, which itself is also being **updated dynamically**. This basically means that the **generator** is **not trained to minimize the distance to a specific image**, but rather to **fool the discriminator**. This enables the model to learn in an **unsupervised manner**. (**Wikipedia**)

StyleGAN: Motivation Style Transfer

Intuitive Guide to Neural Style Transfer, 2019
towardsdatascience.com/light-on-math-machine-learning-intuitive-guide-to-neural-style...

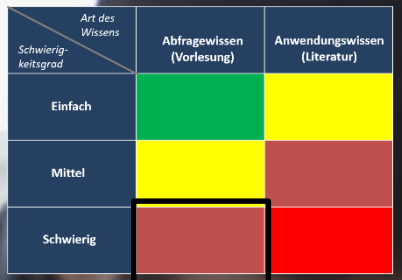
Which machine learning technique is used in this case (and in Deepfakes)?

Schwierigkeitsgrad \ Art des Wissens	Abfragewissen (Vorlesung)	Anwendungswissen (Literatur)
Einfach		
Mittel		
Schwierig		



a) Convolutional Neural Networks
b) Transfer Learning
c) Generative Adversarial Networks
d) Reinforcement Learning
e) Transformer

Which statement is TRUE about GANs?



a) The **generator** is **trained to minimize the distance** to a specific image.

b) GANs can be described by a **cooperative game** between two neural networks.

c) **Random noise** is **added in the discriminator** to better **create** the **fake images**.

d) GANs can **learn to mimic any distribution of data.**

e) GANs **use** a **supervised learning technique**.

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Your path to the right job

- Machine Learning Engineer
- Deep Learning Engineer
- Artificial Intelligence Specialist

Machine Learning Engineer

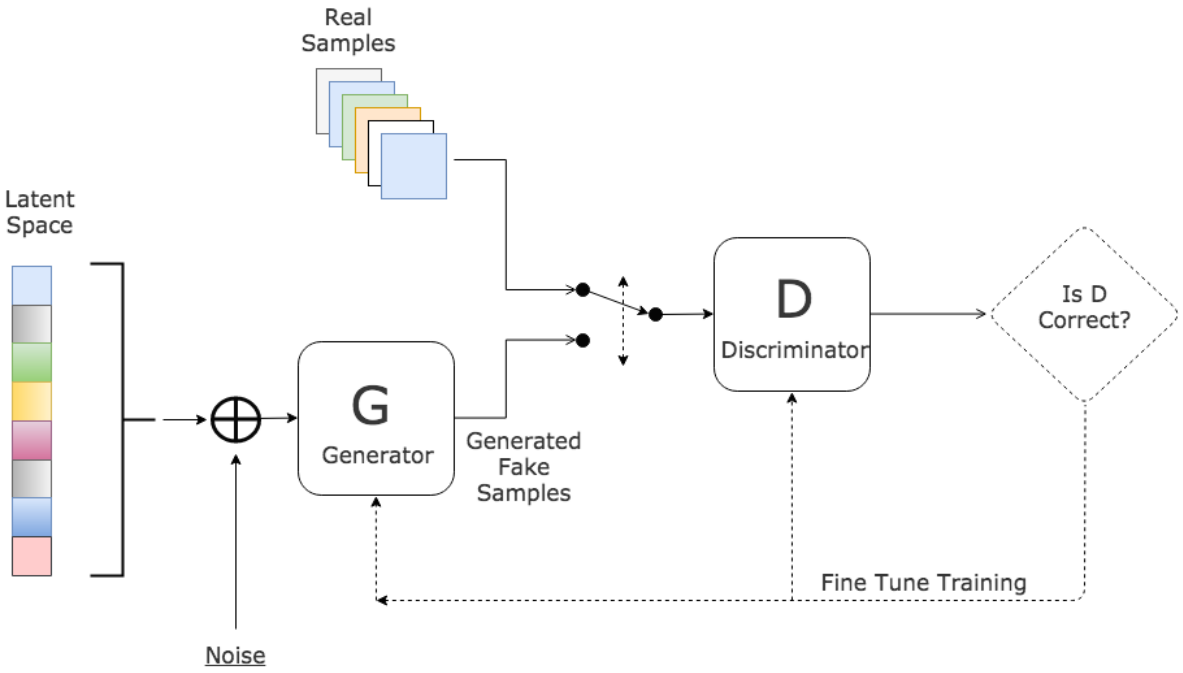
Machine learning is becoming a fundamental skill as software development is entering a new era. This path will enable you to start a career as a Machine Learning Engineer. First learn the fundamentals of programming in Python, linear algebra, and neural networks, and then move on to core Machine Learning concepts.

RECOMMENDED PROGRAMS

ALUMNI SUCCESS

Jeremy Jordan

Generative Adversarial Networks (GAN)



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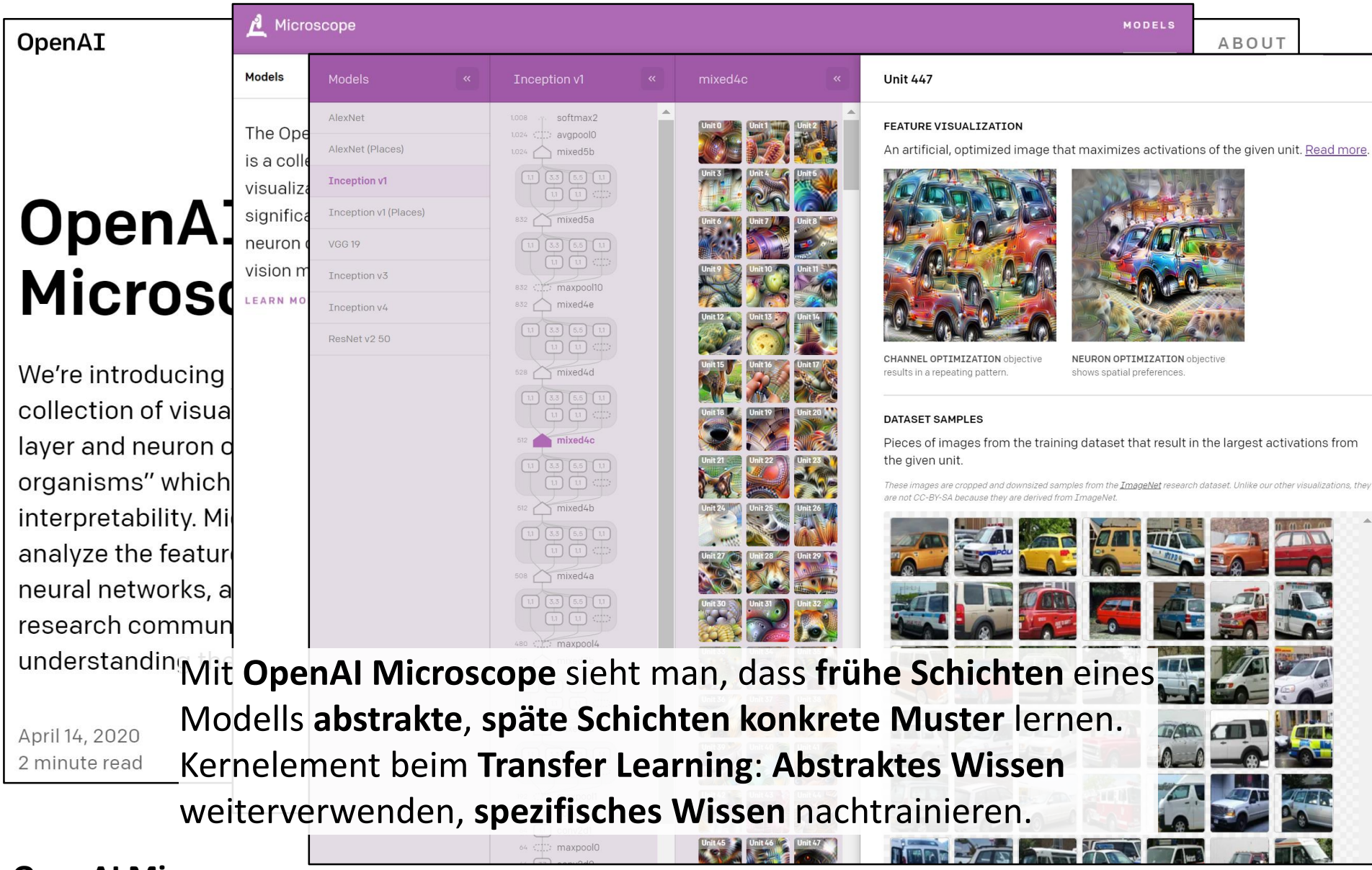
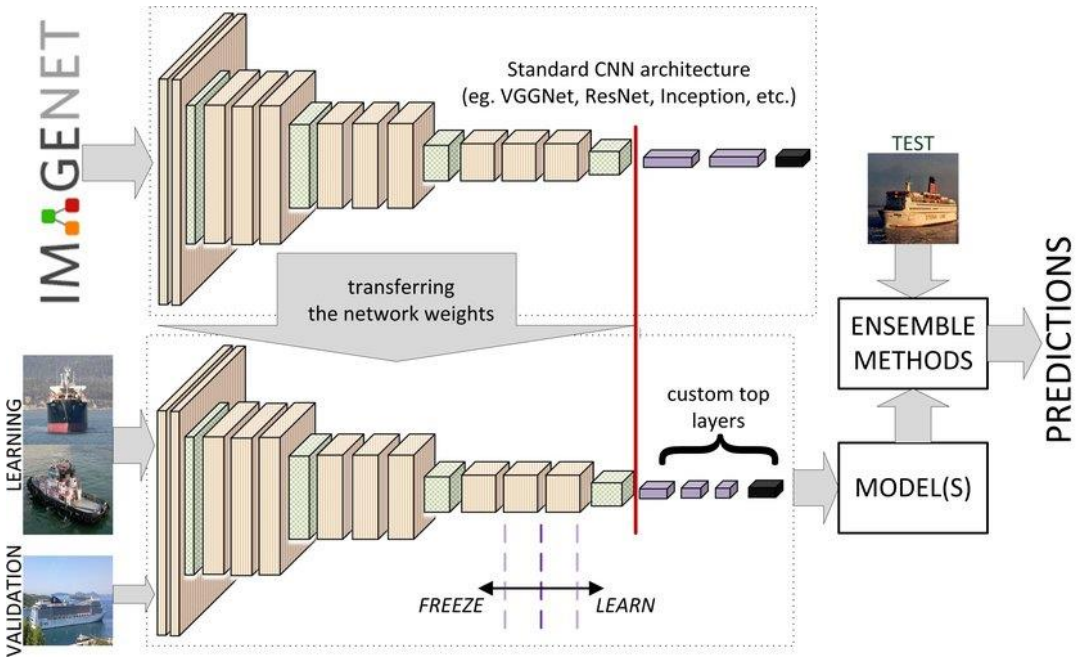
Transfer Learning with CNNs (Convolutional NN)



Mit **OpenAI Microscope** sieht man, dass **frühe Schichten** eines Modells **abstrakte**, **späte Schichten konkrete Muster** lernen. Kernelement beim **Transfer Learning**: **Abstraktes Wissen** weiterverwenden, **spezifisches Wissen** nachtrainieren.

OpenAI Microscope
microscope.openai.com/models

Transfer Learning: Options when applying



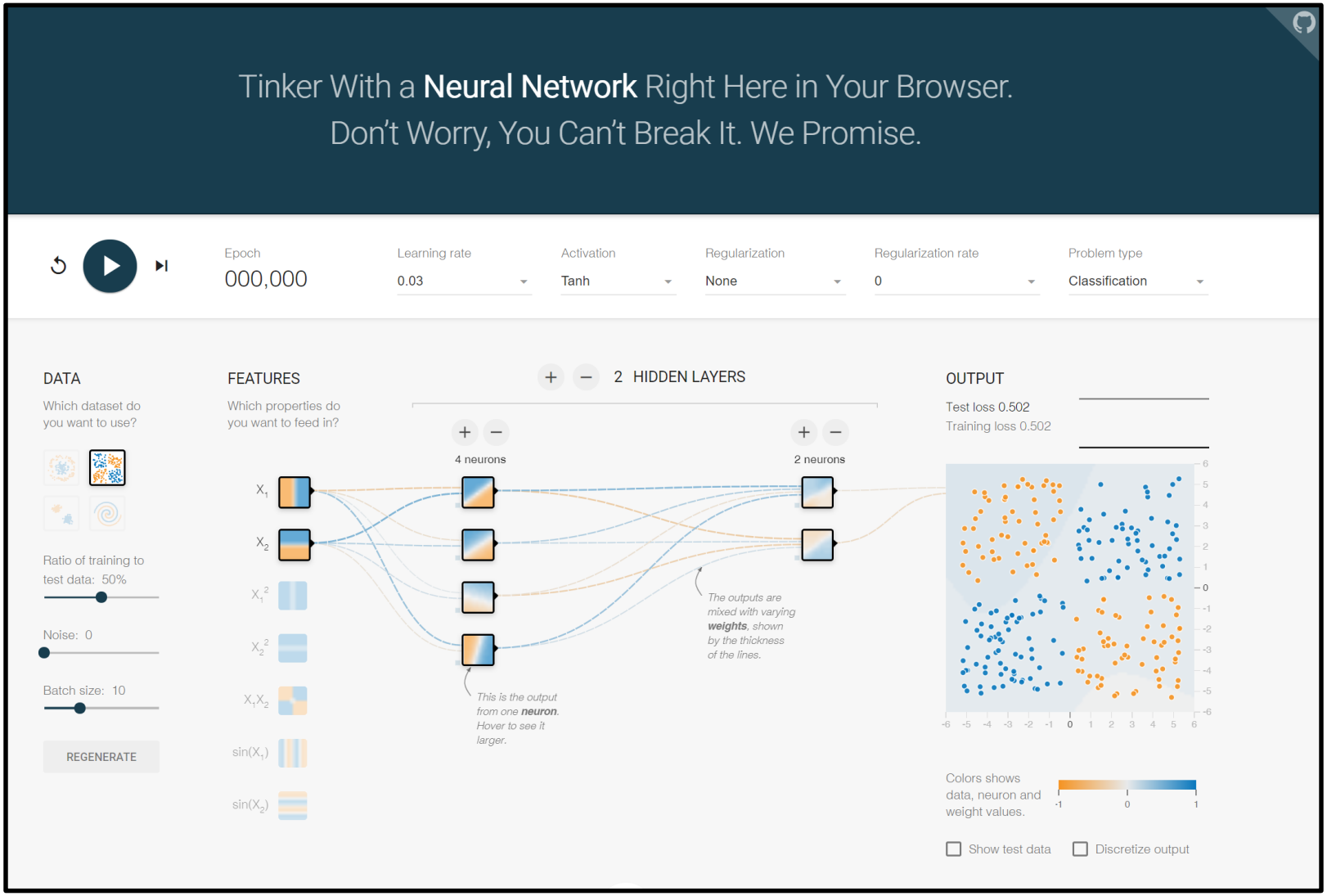
2 Options When applying **Transfer Learning in Neural Networks:**

- **Freeze the Weights and Bias** on **Initial Few Layers** and train only the **Last Few Layers** and **Fully Connected**.
  In this case you **don't** need to **re-train** the **whole Network Model** again.
- **Re-train the whole Network**, **initializing** from the **learned Weights** and **Bias**.
  Keep the Learning Rate very low so that the **original Weights** don't deviate **drastically**.

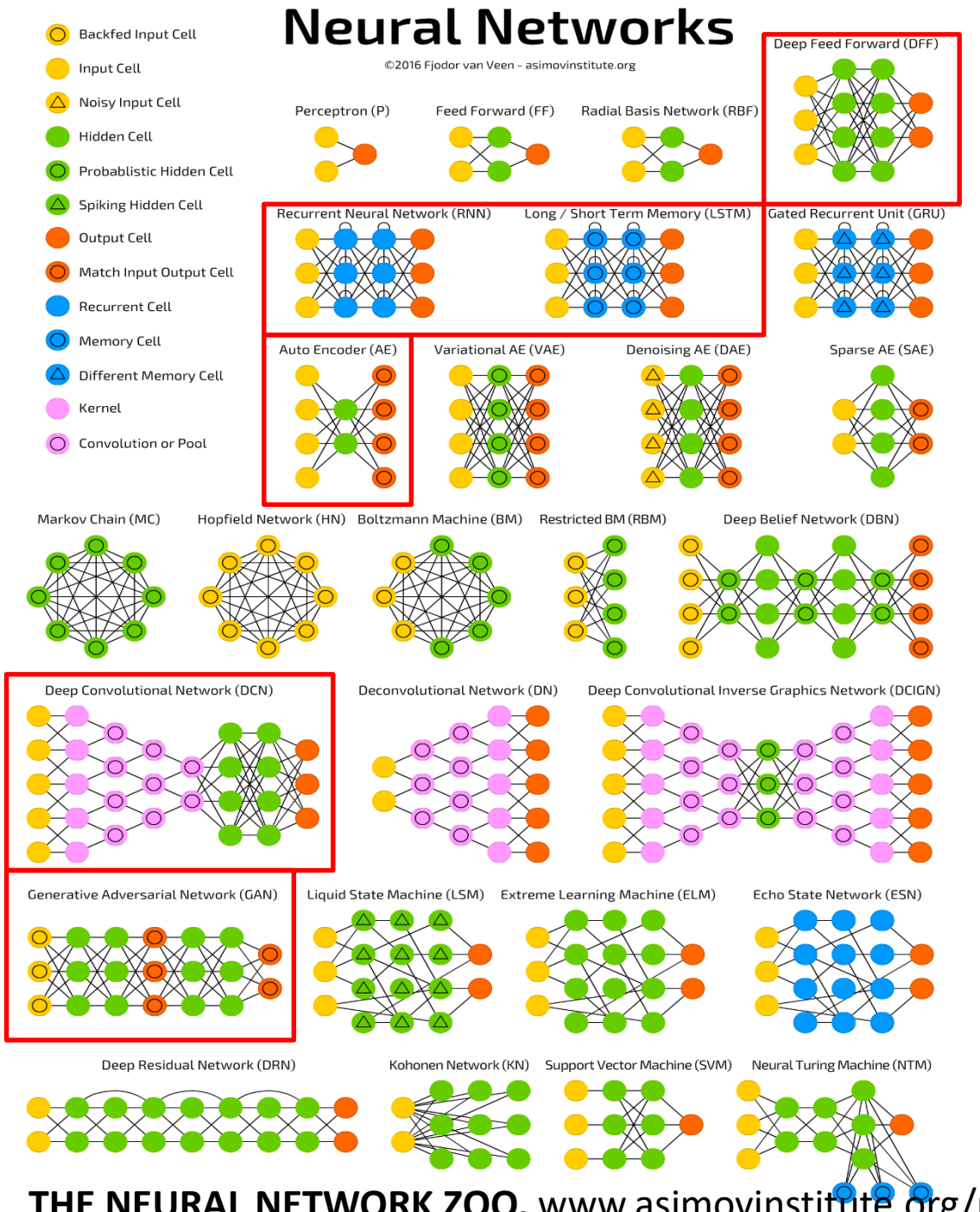
8 Machine Learning I

- Neural Networks & Deep Learning

(3) **TensorFlow Playground**



playground.tensorflow.org



Neuronale Netze stellen einen zentralen **Baustein** für **Deep Learning** dar.

Im Laufe der Jahre wurden zahlreiche **Architekturen** für Neuronale Netze entwickelt.

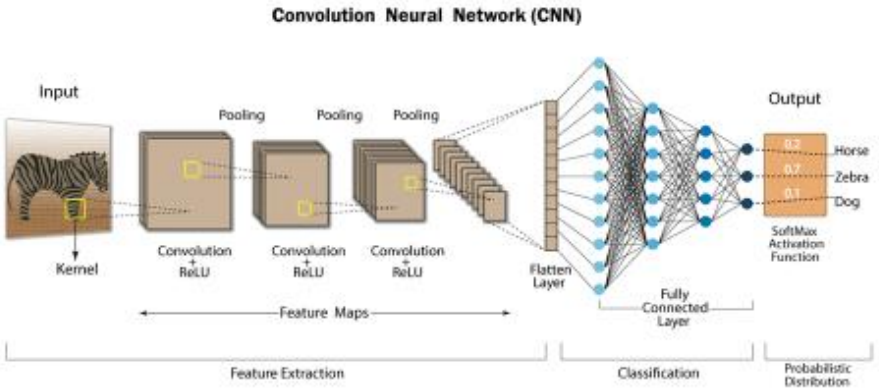
Die Wahl der **Architektur** hängt von der **Datenstruktur**, den **Dateninhalten** und der **Aufgabenstellung** ab.

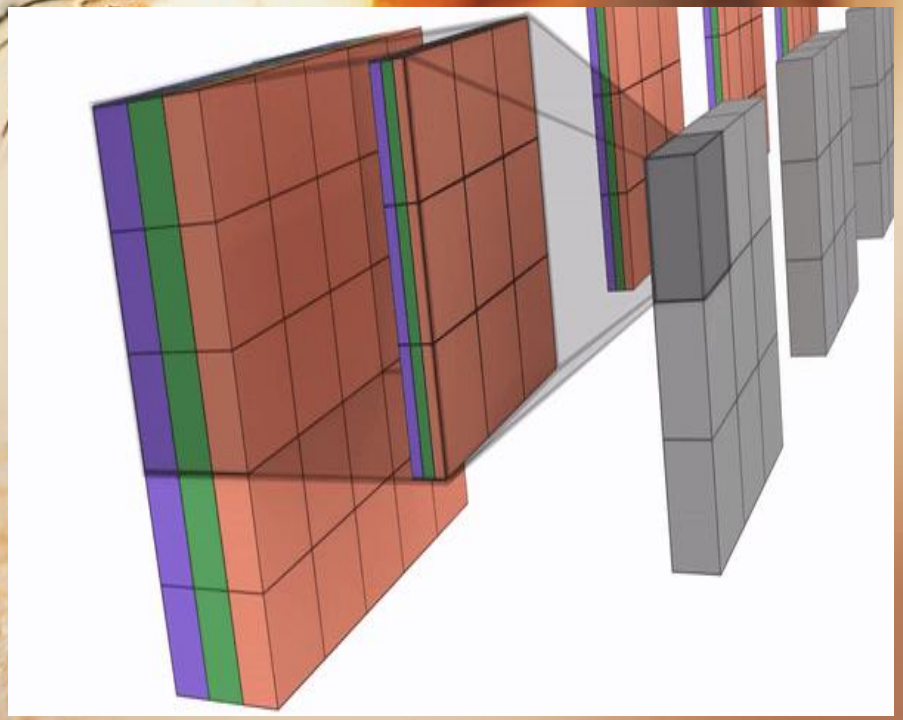
Aktuell wichtige Klassen sind u.a. **Convolutional Neural Networks (CNN)**, **Recurrent Neural Networks (RNN)**, **Autoencoder**, **Generative Adverserial Networks (GAN)**.

THE NEURAL NETWORK ZOO, www.asimovinstitute.org/neural-network-zoo/

8 Machine Learning I
- Neural Networks & Deep Learning
(4) Basics of **Convolutional Neural Networks (CNN)**

CNN: Grundstruktur am Beispiel





JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2020MS002301

Potential and Limitations of Machine Learning for Modeling Warm-Rain Cloud Microphysical Processes

Axel Seifert[1] **and Stephan Rasp**[2]

[1]Deutscher Wetterdienst, Offenbach, Germany, [2]TU München, Munich, Germany

Key Points:

- Machine learning is successfully applied to the warm-rain parameterization problem
- Training and testing data for the warm-rain kinetic collection equation are provided using the superdroplet method
- Standard training methods show some limitations for the resulting ODE system

Supporting Information:

- Supporting Information S1

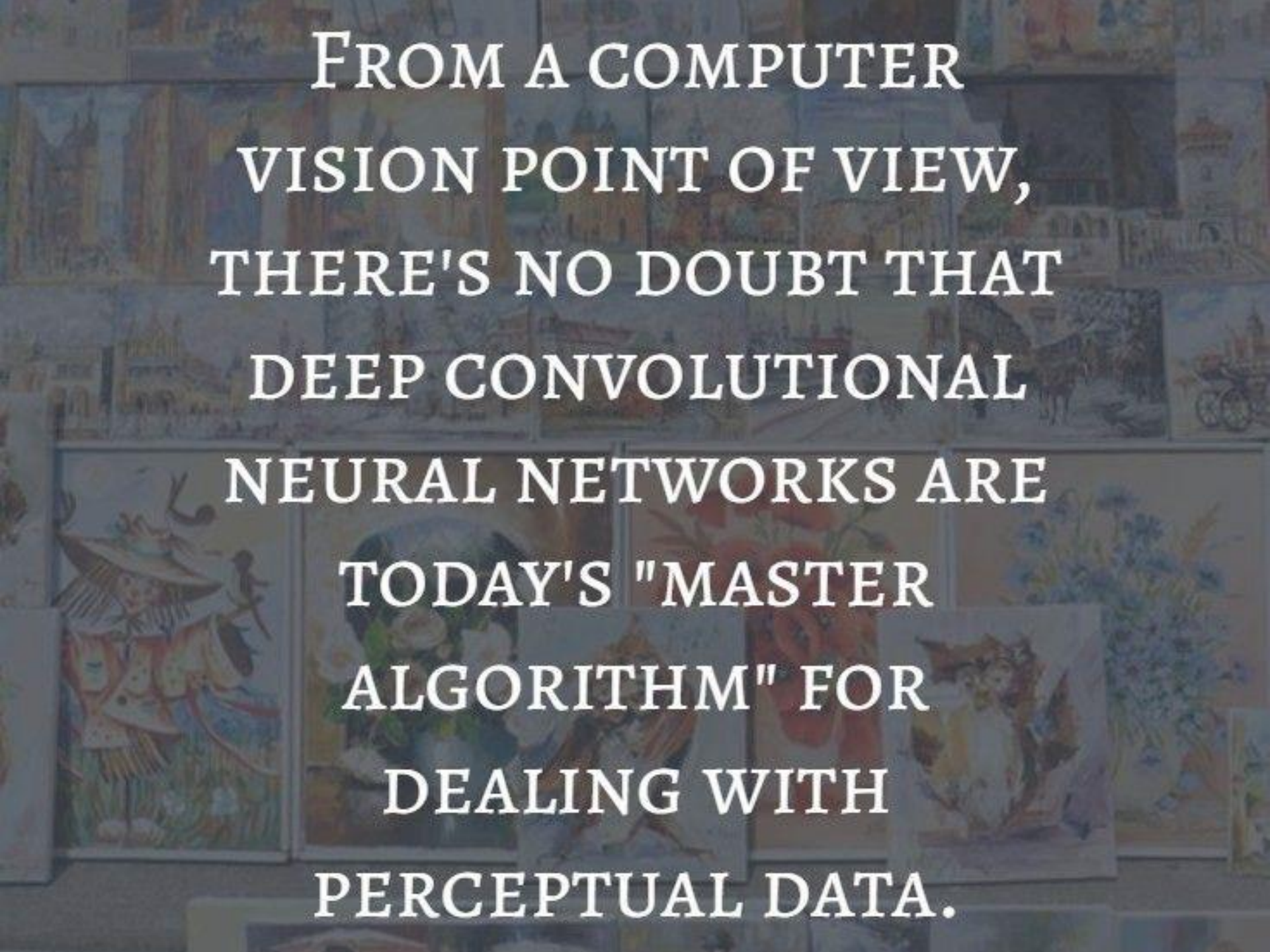
Correspondence to:
A. Seifert,
axel.seifert@dwd.de

Citation:
Seifert, A., & Rasp, S. (2020). Potential and limitations of machine learning for modeling warm-rain cloud microph
Advances
12, e202
10.1029/

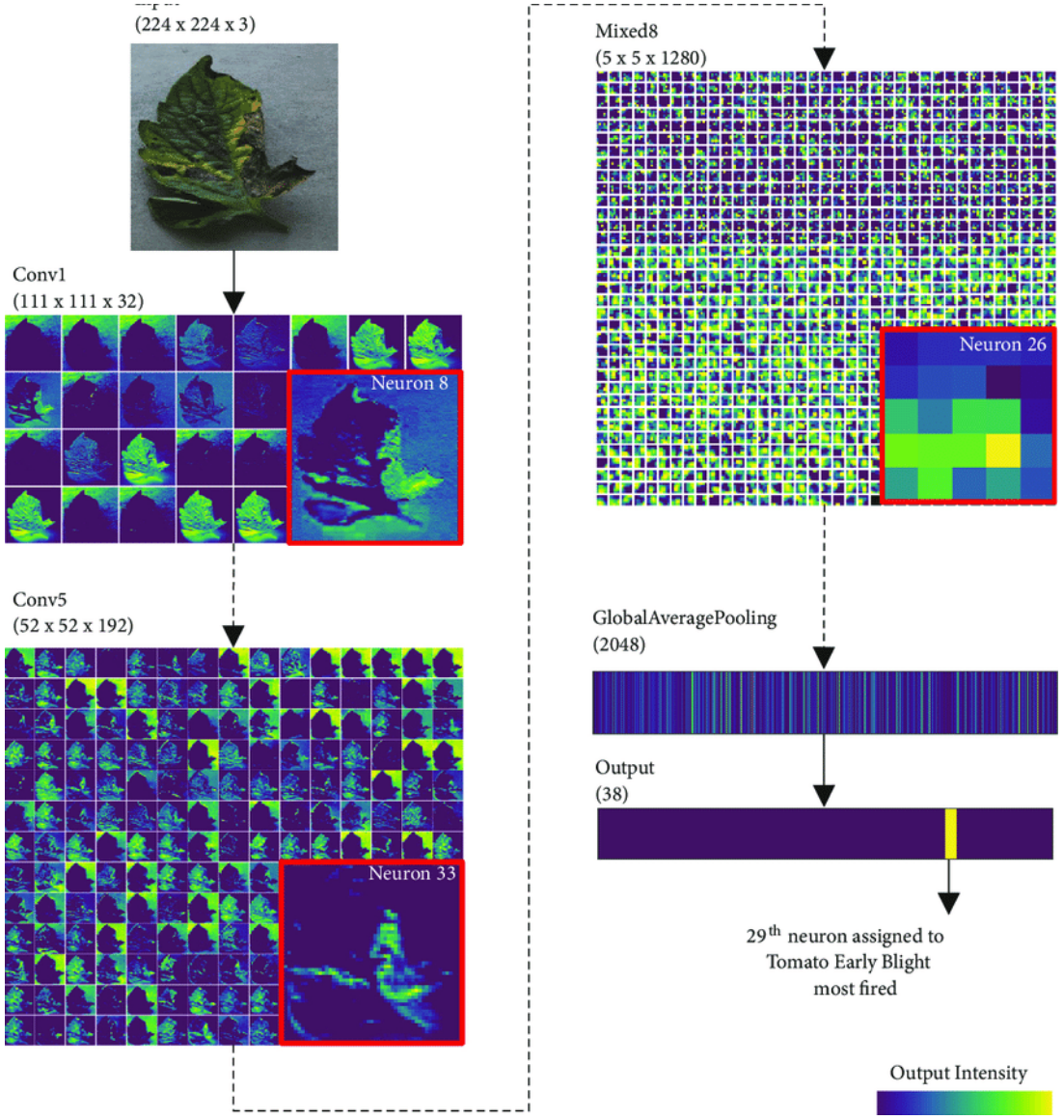
Received
Accepted
Accepted

Abstract The use of machine learning based on neural networks for cloud microphysical parameterizations is investigated. As an example, we use the warm-rain formation by collision-coalescence, that is, the parameterization of autoconversion, accretion, and self-collection of droplets in a two-moment framework. Benchmark solutions of the kinetic collection equations are performed using a Monte Carlo superdroplet algorithm. The superdroplet method provides reliable but noisy estimates of the warm-rain process rates. For each process rate, a neural network is trained using standard machine learning techniques. The resulting models make skillful predictions for the process rates when compared to the testing data. However, when solving the ordinary differential equations, the solutions are not as good as those of an established warm-rain parameterization. This deficiency can be seen as a limitation of the machine learning methods that are applied, but at the same time, it points toward a fundamental ill-posedness of the commonly used two-moment warm-rain schemes. More advanced machine learning methods that include a notion of time derivatives, therefore, have the potential to overcome these problems.

Plain Language Summary In our work, we are trying to teach a computer how rain forms in clouds. We show that computer hundreds of cases in the form of data. To be honest, the data are not real data but only results of simulations with a more complicated computer model. This complicated model can track the collisions of 10,000 of droplets, and we save all that data about the growth of the droplets into larger raindrops. This is what we then give to the simpler computer model to teach it something about clouds and rain. Afterward, it can make pretty good predictions about which clouds will rain and how long it will take them to produce the first rain. Unfortunately, the current machine learning methods are still a bit stupid because they only learn from the data but do not understand the mathematics and the physics behind the data. Therefore, the new computer model is still not as good at predicting rain as some clever mathematical formulas that were developed 20 years ago. Maybe we first have to teach the computer model more about calculus before it can learn to predict rain.


From a computer vision point of view, there's no doubt that deep convolutional neural networks are today's "master algorithm" for dealing with perceptual data.

CNN: Eine Beispielanwendung



Toda Y., Okura F.: **How Convolutional Neural Networks Diagnose Plant Disease**, 2019

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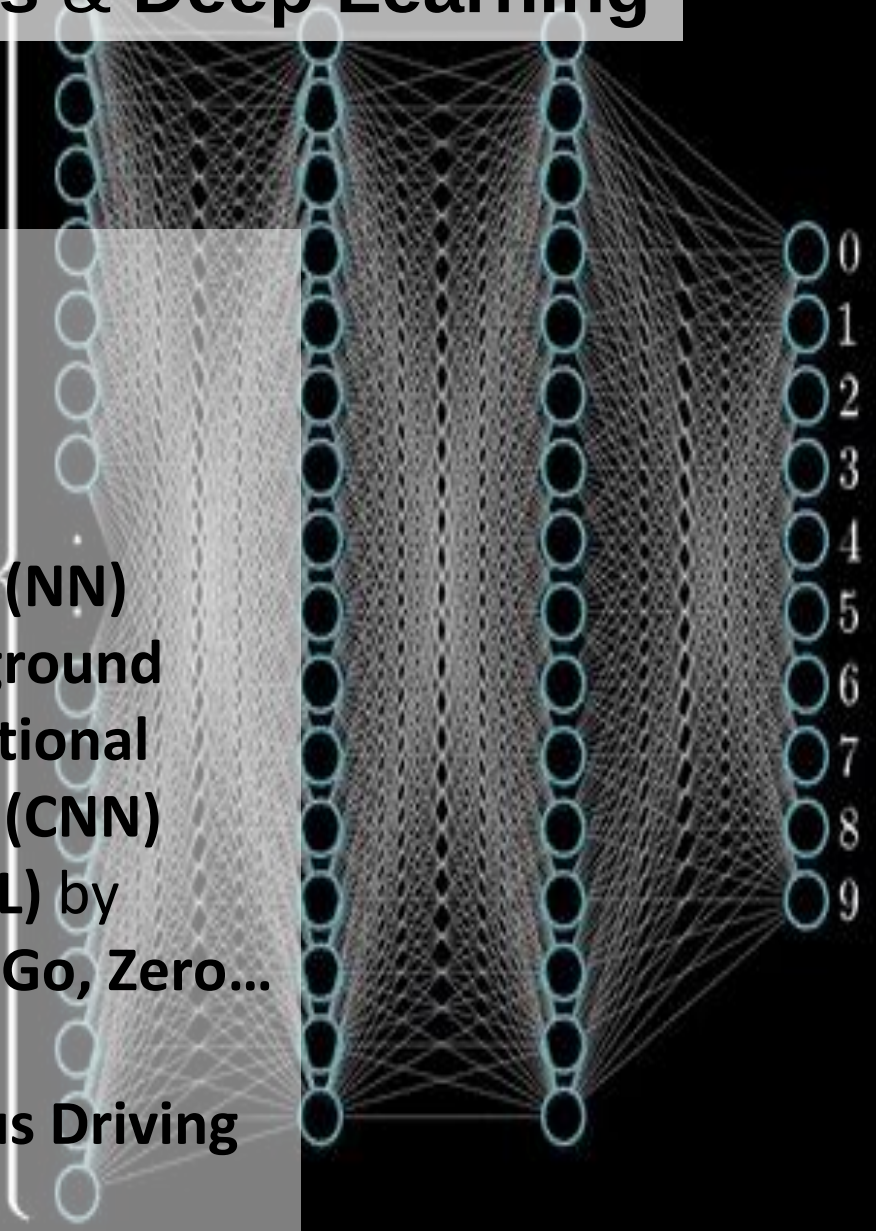
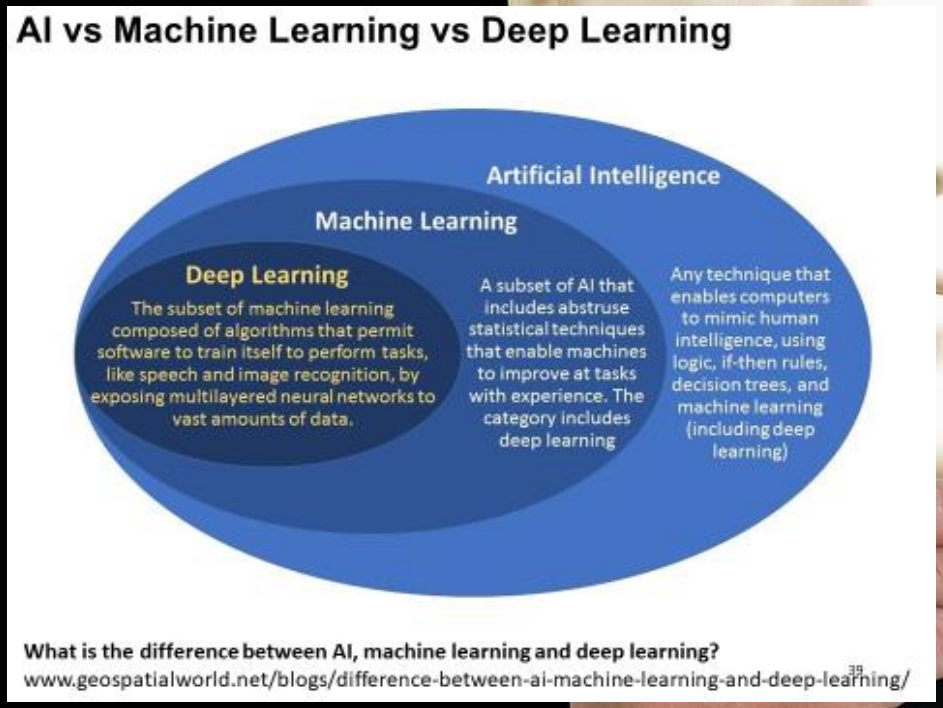
- Neural Networks & Deep Learning



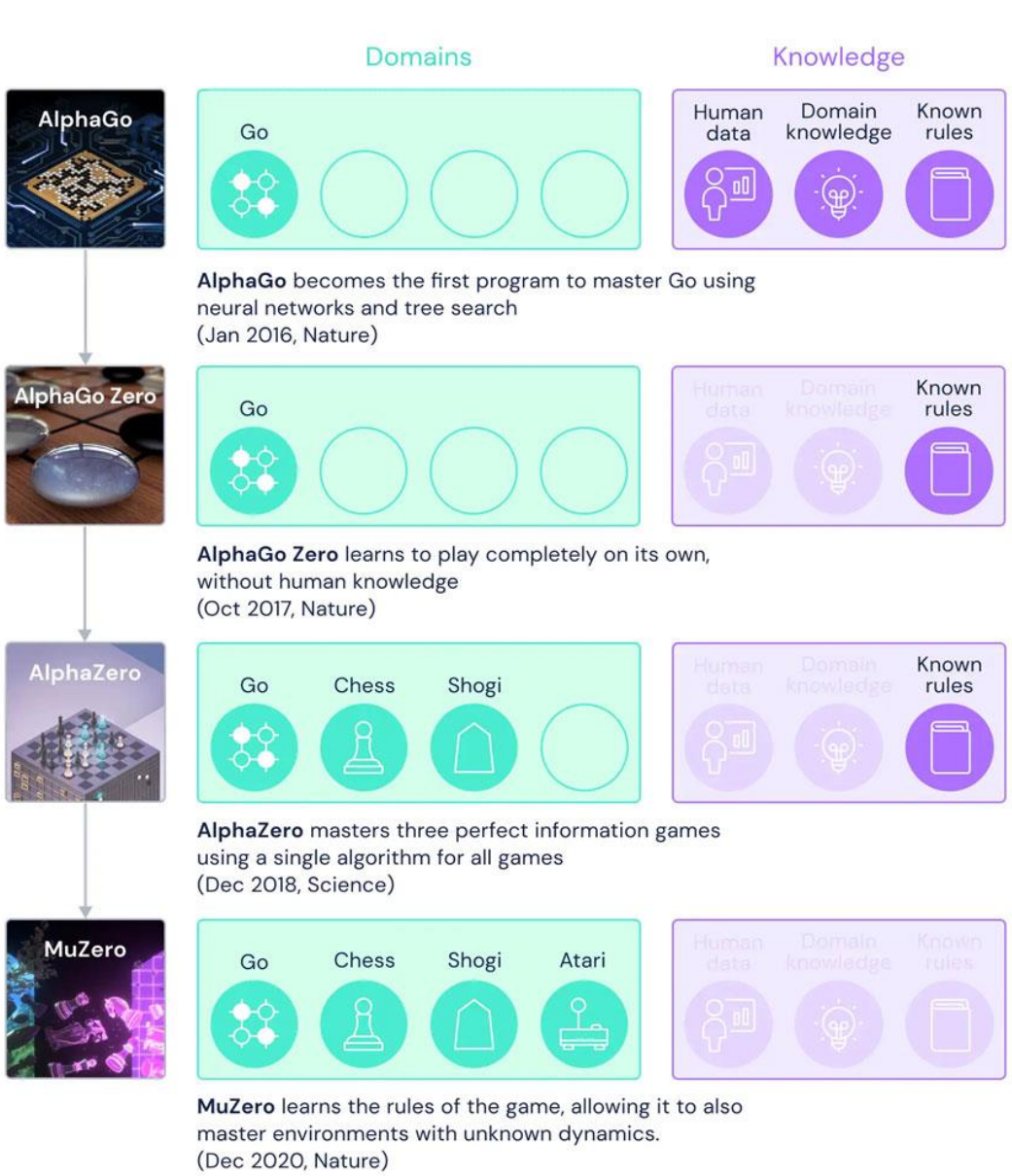
Content:

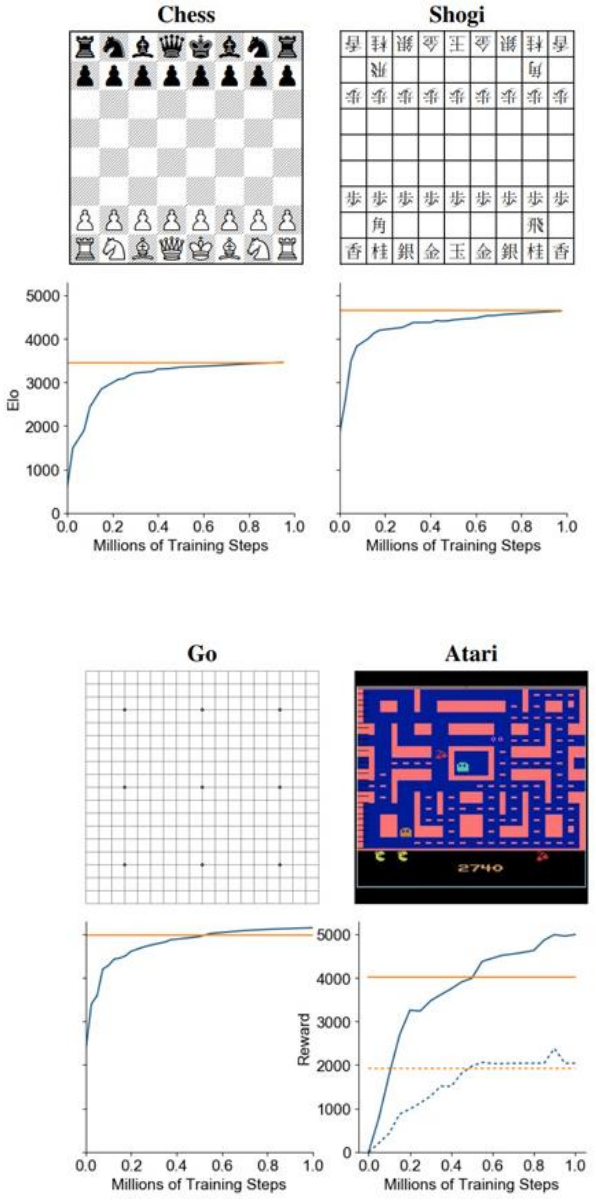
1. **Motivation**
2. Basics of **Neural Networks (NN)**
3. **TensorFlow Playground**
4. Basics of **Convolutional Neural Networks (CNN)**
5. **Deep Learning (DL)** by **Deepmind: AlphaGo, Zero…**
6. **Deep NN** in **Tesla Autonomous Driving**
7. **Summary**

8 Machine Learning I
- Neural Networks & Deep Learning
(1) **Motivation** & Intro **Machine Learning**

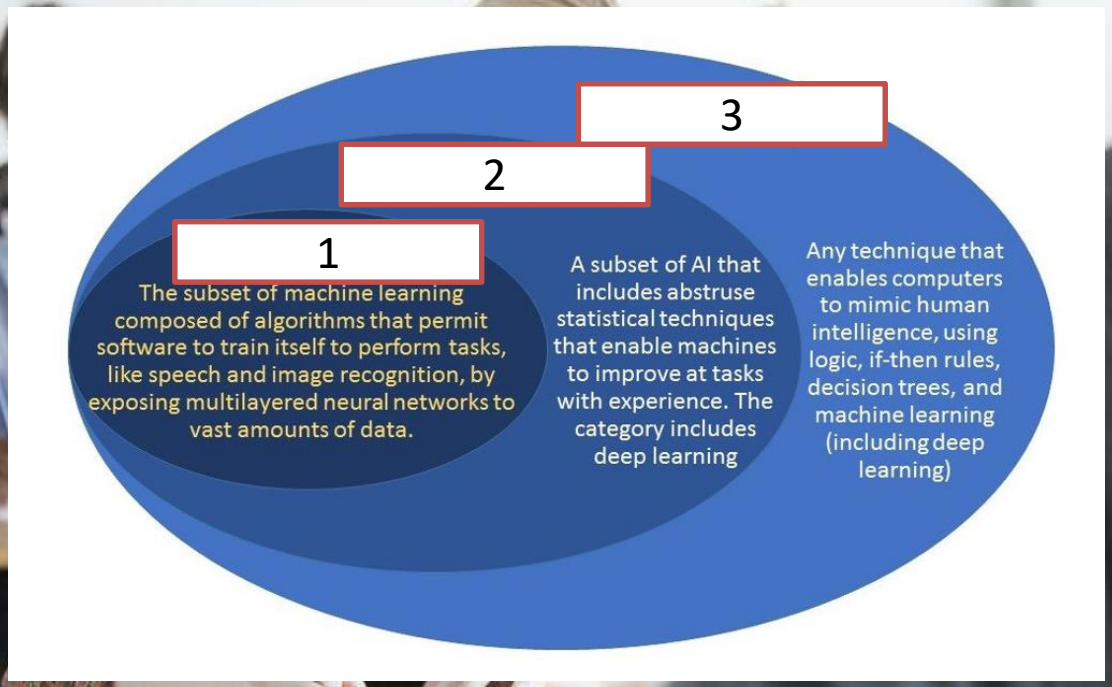


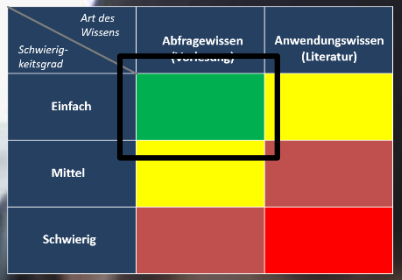
Deepmind: Von AlphaGo über AlphaZero zu MuZero





Fill in the blank





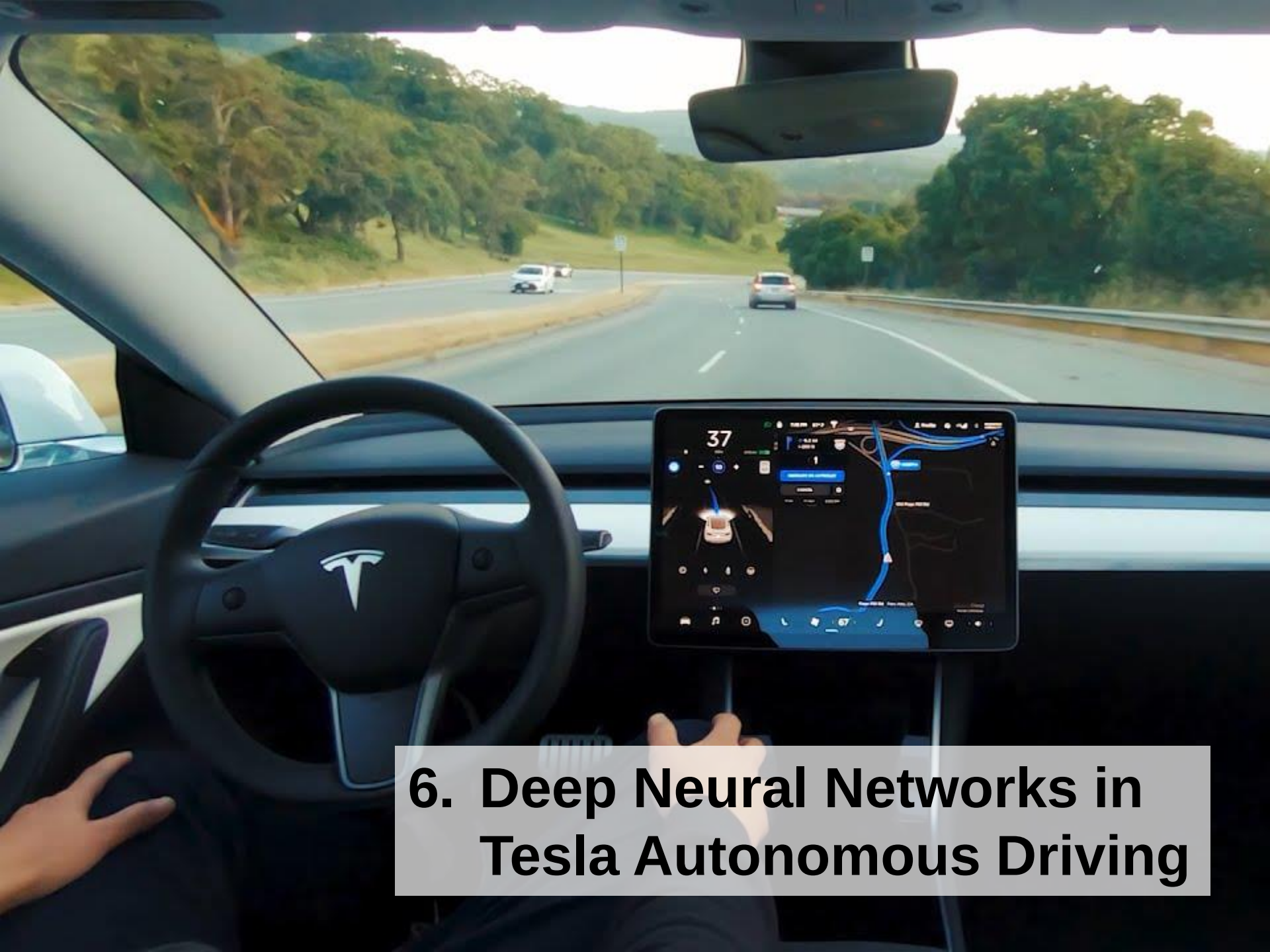
a) **Artificial Intelligence |Machine Learning|Deep Learning**

b) **Artificial Intelligence|Deep Learning|Machine Learning**

c) **Machine Learning| Deep Learning|Artificial Intelligence**

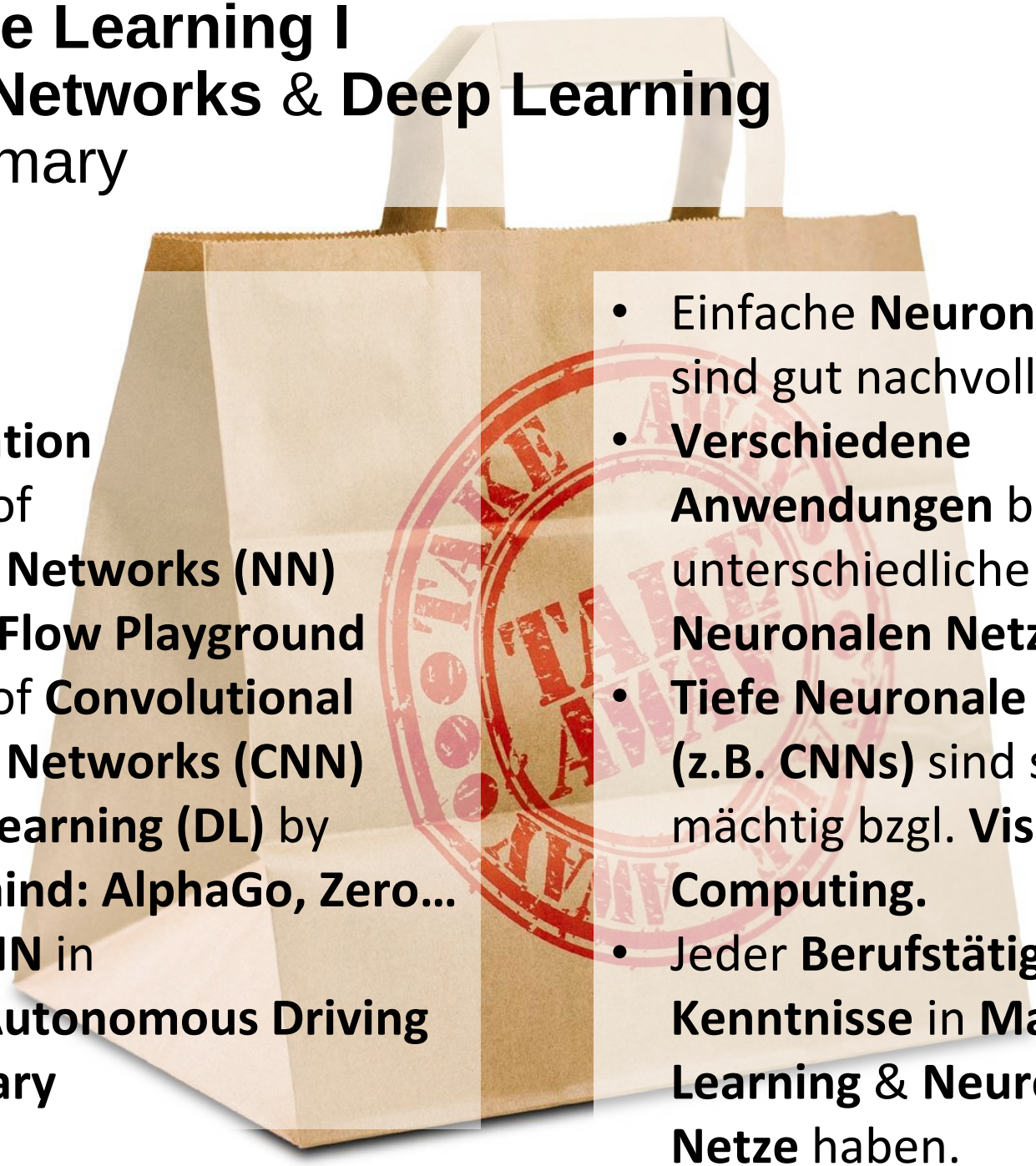
d) **Deep Learning|Machine Learning|Artificial Intelligence**

e) **Machine Learning|Artificial Intelligence |Deep Learning**



6. Deep Neural Networks in Tesla Autonomous Driving

8 Machine Learning I
- Neural Networks & Deep Learning
(7) Summary



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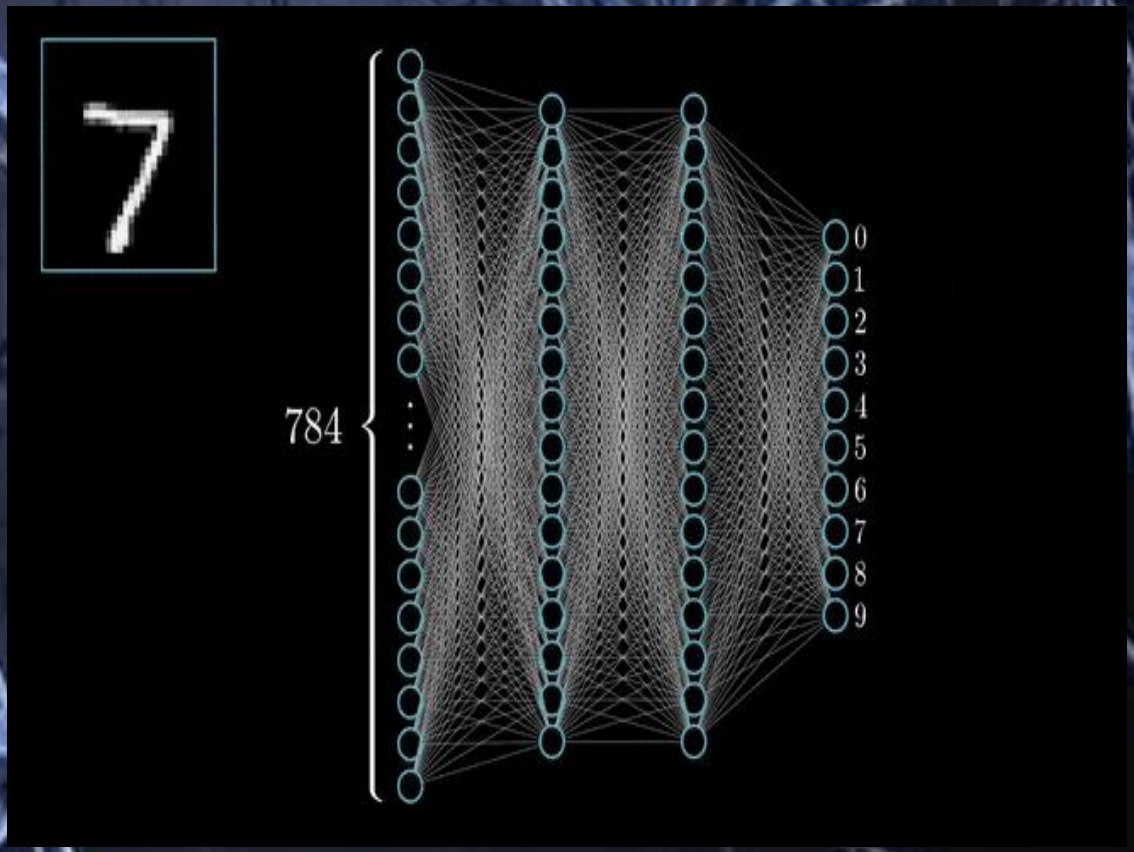
7. **Summary**

- Einfache **Neuronale Netze** sind gut nachvollziehbar.
- **Verschiedene Anwendungen** benötigen unterschiedliche **Neuronalen Netze**.
- **Tiefe Neuronale Netze (z.B. CNNs)** sind sehr mächtig bzgl. **Visual Computing.**
- Jeder **Berufstätige** sollte **Kenntnisse** in **Machine Learning** & **Neuronale Netze** haben.

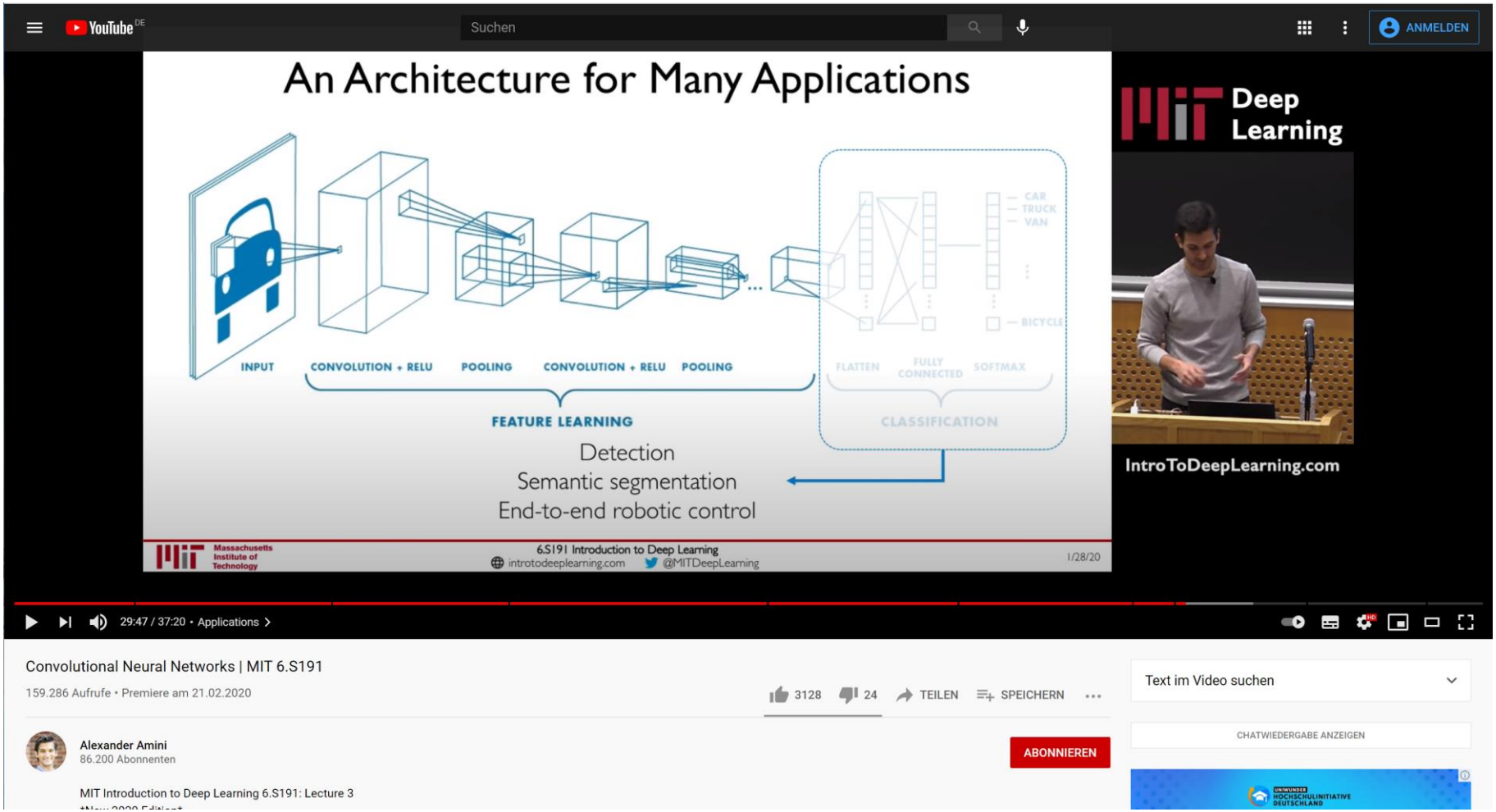
8 Machine Learning I

- Neural Networks & Deep Learning

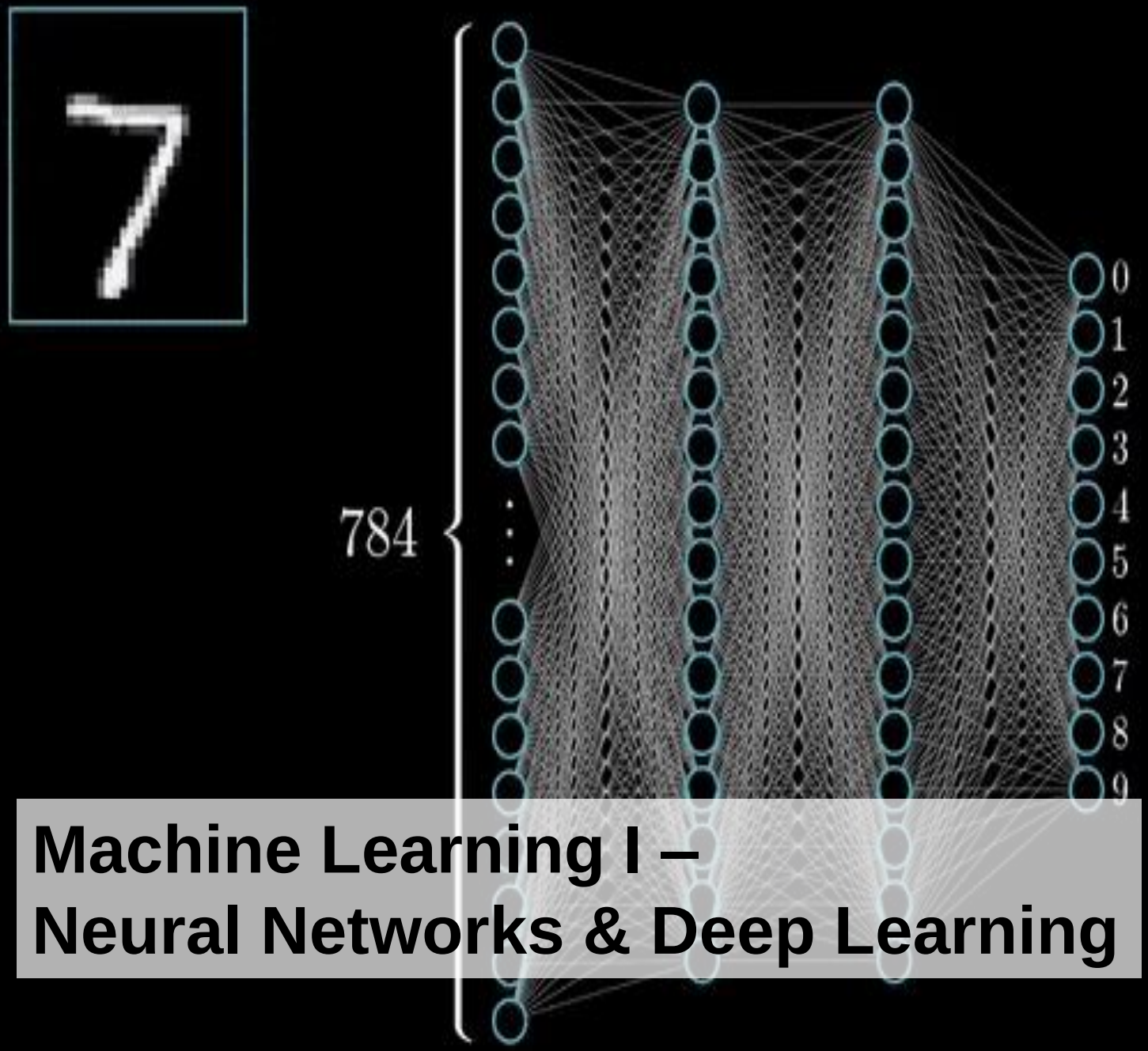
(2) **Basics of Neural Networks (NN)**



MIT Introduction to Deep Learning 6.S191



MIT 6.S191 Convolutional Neural Networks, 2020
www.youtube.com/watch?v=iaSUYvmCekI



Machine Learning I – Neural Networks & Deep Learning

Michael Amberg

Todays Content:

1. **Motivation**
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6. **Deep NN** in **Tesla Autonomous Driving**
7. **Summary**

Artificial Intelligence (AI)
The **theory** and **development** of **computer systems able** to **perform tasks normally requiring human intelligence**, such as visual perception, speech recognition, decision-making, and translation between languages.

Machine Learning (ML)
The **use** and **development** of **computer systems** that can **learn** and **adapt without following explicit instructions**, by **using algorithms** and **statistical models** to **analyze** and **draw inferences from patterns in data**.

Neural Networks (NN)
Use a **network of functions** to **understand** and **translate** a **data input** of **one form into** a **desired output.** Neural Networks are one **approach to machine learning** that **learn a representation by themselves** and can **vary in depth**.

Deep Learning (DL)
A **subset of machine learning based on neural networks** in which **multiple layers** of processing are used to **extract progressively higher-level features** from **data**. Without neural networks, there would be no deep learning. But deep learning may comprise other techniques from machine learning.

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Artificial intelligence

From Wikipedia, the free encyclopedia

"AI" redirects here. For other uses, see AI (disambiguation) and Artificial intelligence (disambiguation).

Artificial intelligence (**AI**), is intelligence demonstrated by machines, unlike the **natural intelligence** displayed by humans and animals, which involves consciousness and emotionality. The distinction between the former and the latter categories is often revealed by the acronym chosen. 'Strong' AI is usually labelled as AGI (Artificial General Intelligence) while attempts to emulate 'natural' intelligence have been called ABI (Artificial Biological Intelligence). Leading AI textbooks define the field as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals.[3] Colloquially, the term "artificial intelligence" is often used to describe machines (or computers) that mimic "cognitive" functions that humans associate with the human mind, such as "learning" and "problem solving".[4]

Part of a series on
Artificial intelligence
Major goals [show]
Approaches [show]
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History [show]
Technology [show]
Glossary [show]
V · T · E

As machines become increasingly capable, tasks considered to require "intelligence" are often removed from the definition of AI, a phenomenon known as the AI effect.[5] A quip in Tesler's Theorem says "AI is whatever hasn't been done yet."[6] For instance, optical character recognition is frequently excluded from things considered to be AI,[7] having become a routine technology.[8] Modern machine capabilities generally classified as AI include successfully understanding human speech,[9] competing at the highest level in strategic game systems (such as chess and Go),[10] autonomously operating cars, intelligent routing in content delivery networks, and military simulations.[11]

Artificial intelligence was founded as an academic discipline in 1955, and in the years since has experienced several waves of optimism,[12][13] followed by disappointment and the loss of funding (known as an "AI winter"),[14][15] followed by new approaches, success and renewed funding.[13][16] After AlphaGo successfully defeated a professional Go player in 2015, artificial intelligence once again attracted widespread global attention.[17] For most of its history, AI research has been divided into sub-fields that often fail to communicate with each other.[18] These sub-fields are based on technical considerations, such as particular goals (e.g. "robotics" or "machine learning"),[19] the use of particular tools ("logic" or artificial neural networks), or deep philosophical differences.[22][23][24] Sub-fields have also been based on social factors (particular institutions or the work of particular researchers).[18]

The traditional problems (or goals) of AI research include reasoning, knowledge representation, planning, learning, natural language processing, perception and the ability to move and manipulate objects.[19] General intelligence is among the field's long-term goals.[25] Approaches include statistical methods, computational intelligence, and traditional symbolic AI. Many tools are used in AI, including versions of search and mathematical optimization, artificial neural networks, and methods based on statistics, probability and economics. The AI field draws upon computer science, information engineering, mathematics, psychology, linguistics, philosophy, and many other fields.

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Deep learning

From Wikipedia, the free encyclopedia

Deep learning (also known as **deep structured learning**) is part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised.[1][2][3]

Deep-learning architectures such as deep neural networks, deep belief networks, recurrent neural networks and convolutional neural networks have been applied to fields including computer vision, machine vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation, bioinformatics, drug design, medical image analysis, material inspection and board game programs, where they have produced results comparable to and in some cases surpassing human expert performance.[4][5][6]

Artificial neural networks (ANNs) were inspired by information processing and distributed communication nodes in biological systems. ANNs have various differences from biological brains. Specifically, neural networks tend to be static and symbolic, while the biological brain of most living organisms is dynamic (plastic) and analog.[7][8][9]

The adjective "deep" in deep learning comes from the use of multiple layers in the network. Early work showed that a linear perceptron cannot be a universal classifier, and then that a network with a nonpolynomial activation function with one hidden layer of unbounded width can on the other hand so be. Deep learning is a modern variation which is concerned with an unbounded number of layers of bounded size, which permits practical application and optimized implementation, while retaining theoretical universality under mild conditions. In deep learning the layers are also permitted to be heterogeneous and to deviate widely from biologically informed connectionist models, for the sake of efficiency, trainability and understandability, whence the "structured" part.

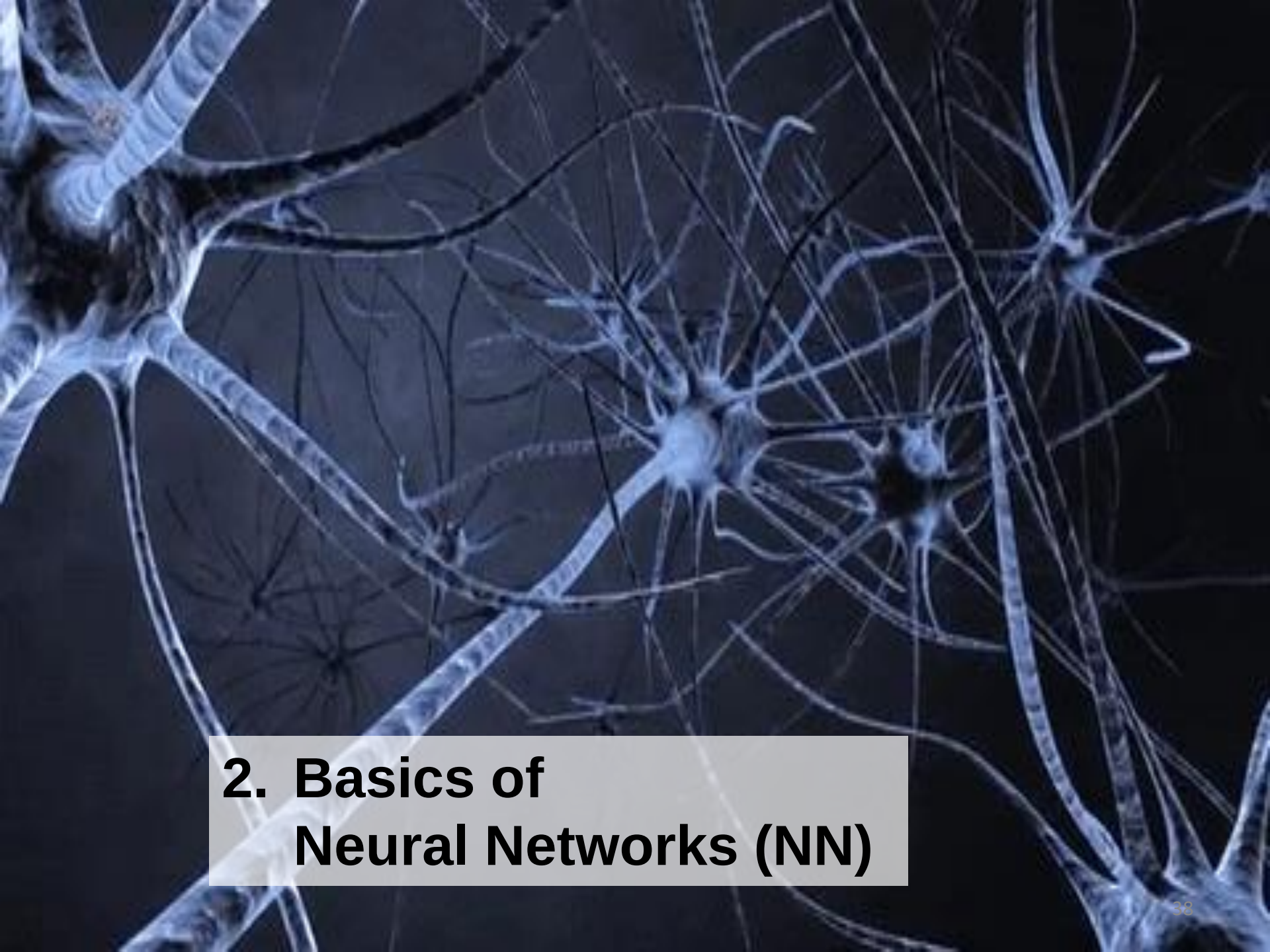
Part of a series on
Machine learning and data mining

Problems	[show]
Supervised learning (classification • regression)	[show]
Clustering	[show]
Dimensionality reduction	[show]
Structured prediction	[show]
Anomaly detection	[show]
Artificial neural network	[show]
Reinforcement learning	[show]
Theory	[show]
Machine-learning venues	[show]
Glossary of artificial intelligence	[show]
Related articles	[show]

V • T • E

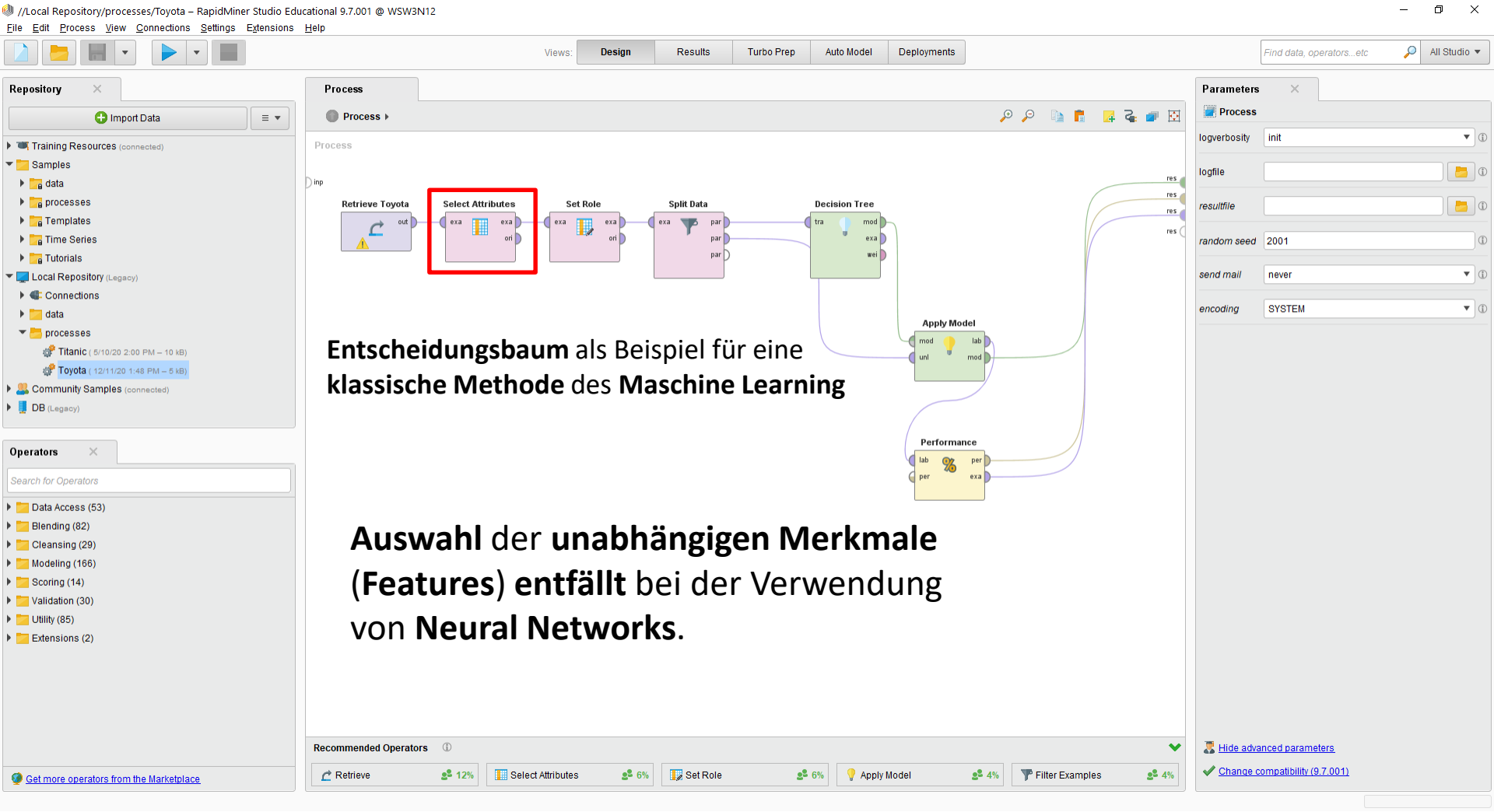
Part of a series on
Artificial intelligence

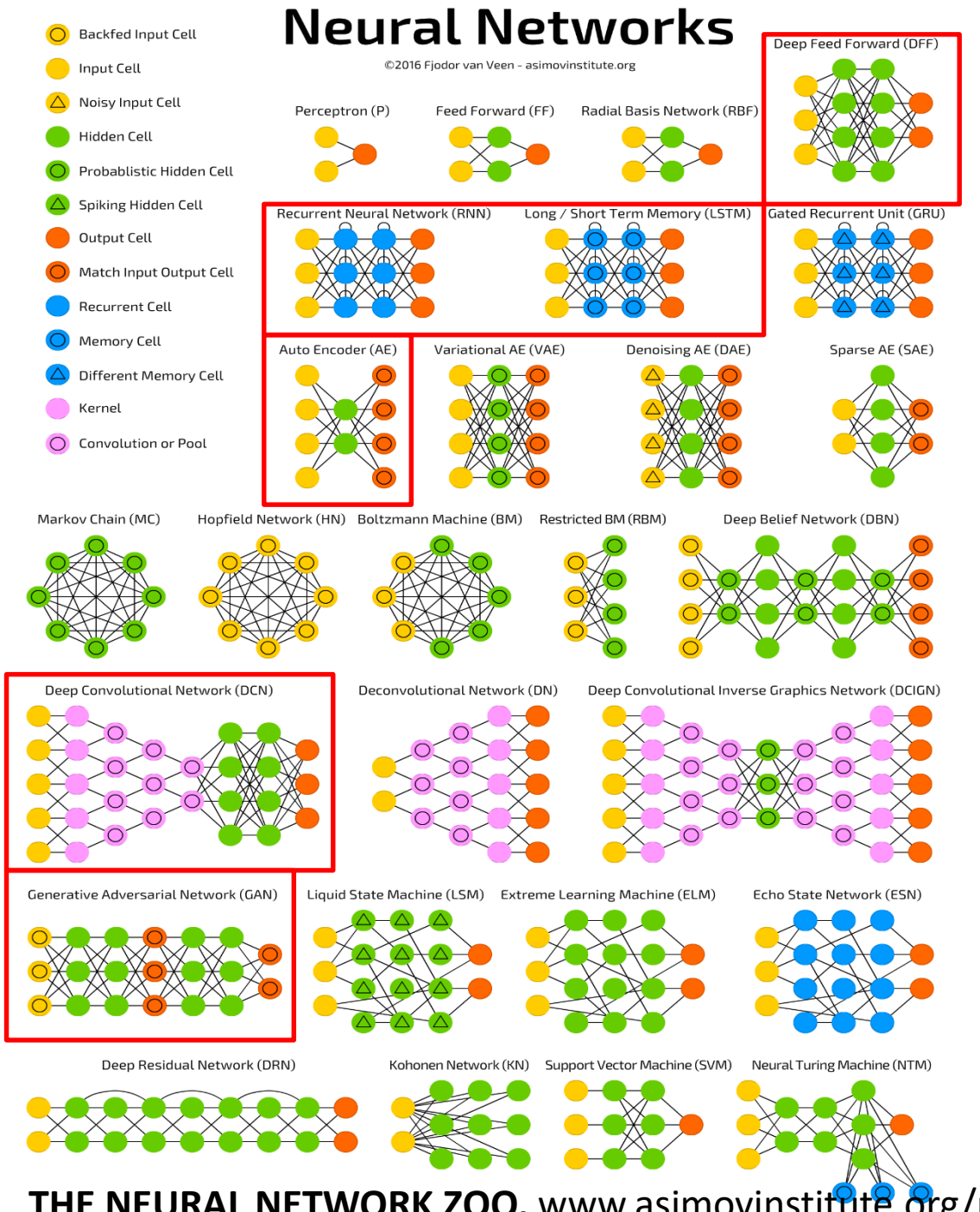
Major goals	[show]



2. Basics of Neural Networks (NN)

Extraktion und **Selektion** von **Merkmalen** in *RapidMiner Studio*





Neuronale Netze stellen einen zentralen **Baustein** für **Deep Learning** dar.

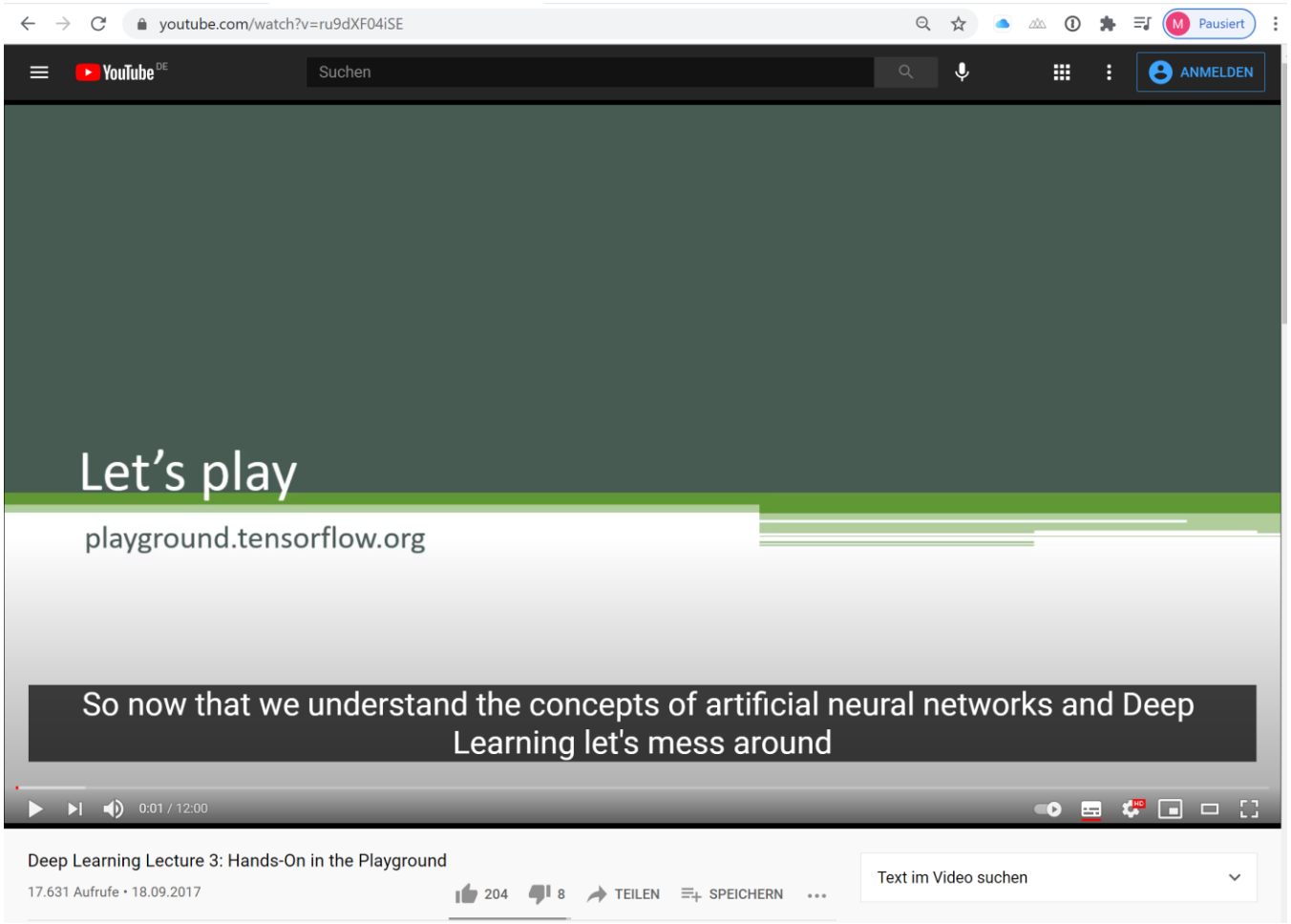
Im Laufe der Jahre wurden zahlreiche **Architekturen** für Neuronale Netze entwickelt.

Die Wahl der **Architektur** hängt von der **Datenstruktur**, den **Dateninhalten** und der **Aufgabenstellung** ab.

Aktuell wichtige Klassen sind u.a. **Convolutional Neural Networks (CNN)**, **Recurrent Neural Networks (RNN)**, **Autoencoder**, **Generative Adverserial Networks (GAN)**.

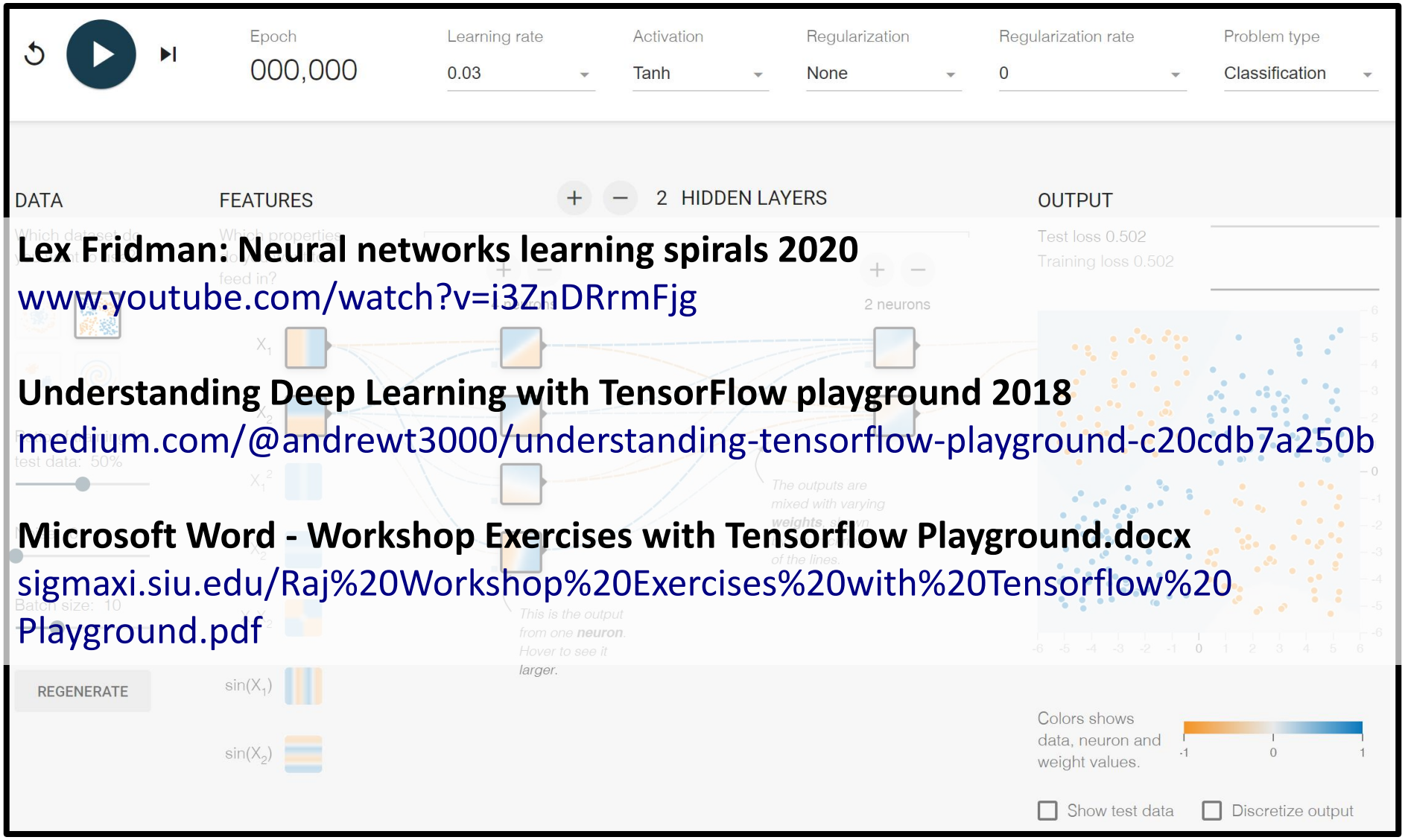
THE NEURAL NETWORK ZOO, www.asimovinstitute.org/neural-network-zoo/

TensorFlow Playground Tutorial



Deep Learning Lecture 3: Hands-On in the Playground 2017 (12min)
https://www.youtube.com/watch?v=ru9dXF04iSE

TensorFlow Playground Help



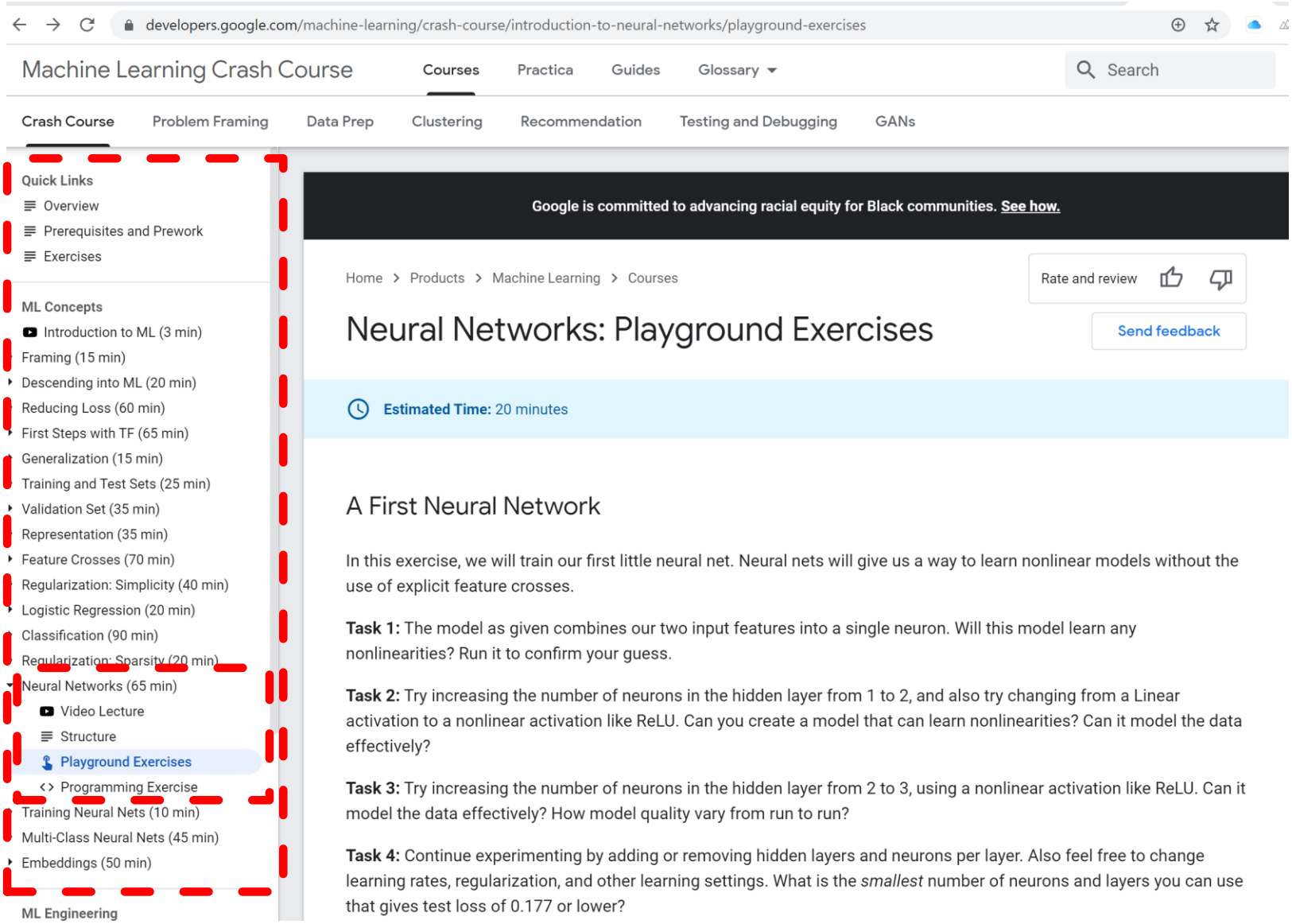
Lex Fridman: Neural networks learning spirals 2020
www.youtube.com/watch?v=i3ZnDRrmFjg

Understanding Deep Learning with TensorFlow playground 2018
medium.com/@andrewt3000/understanding-tensorflow-playground-c20cdb7a250b

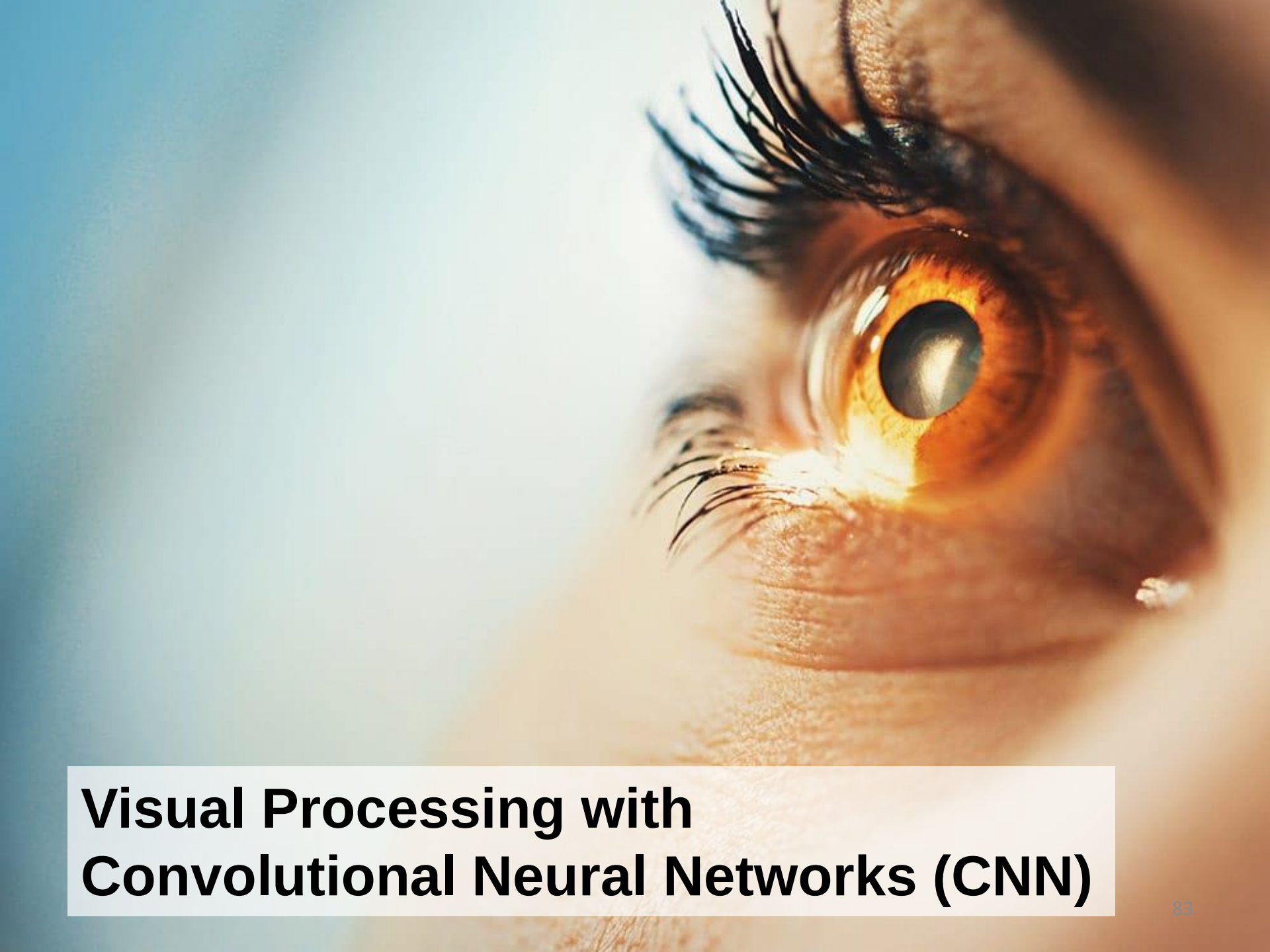
Microsoft Word - Workshop Exercises with Tensorflow Playground.docx
sigmaxi.siu.edu/Raj%20Workshop%20Exercises%20with%20Tensorflow%20Playground.pdf

playground.tensorflow.org

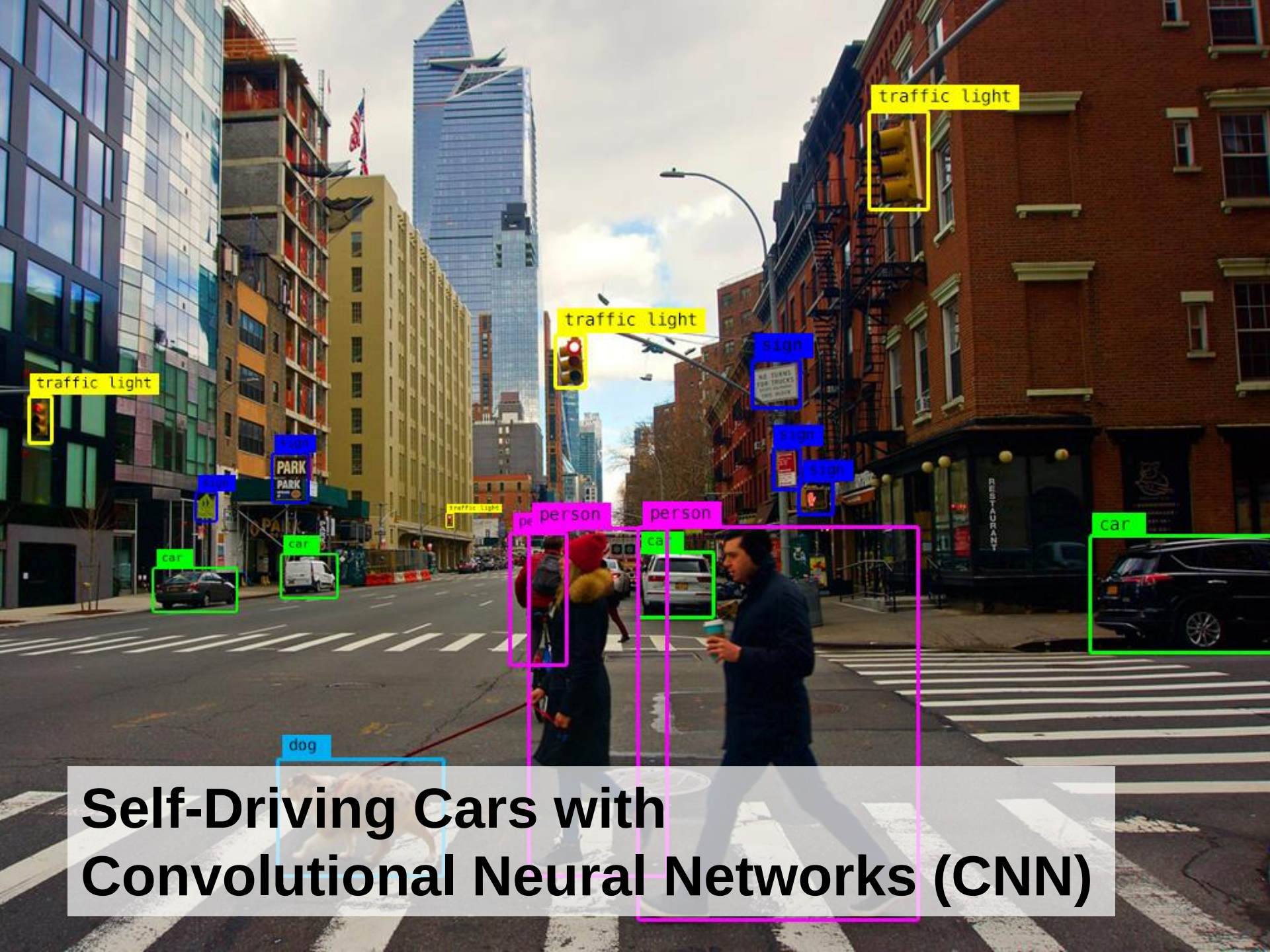
Machine Learning Crash Course – A self-study Guide



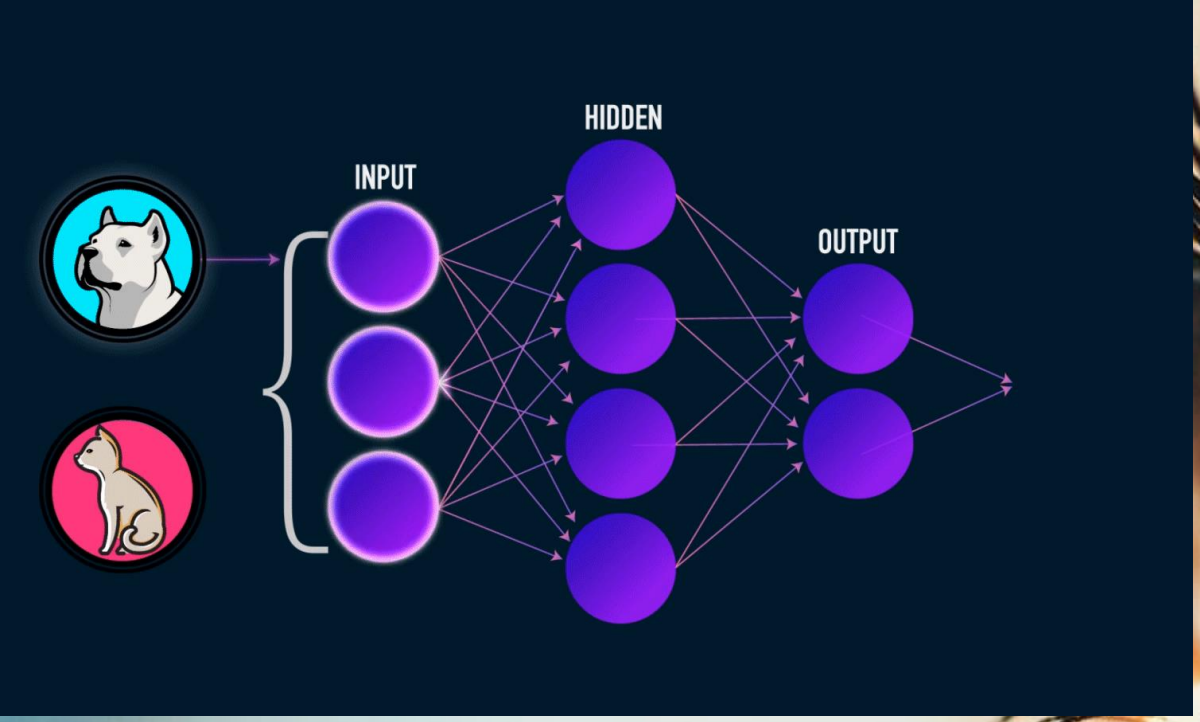
developers.google.com/machine-learning/crash-course/introduction-to-neural-networks



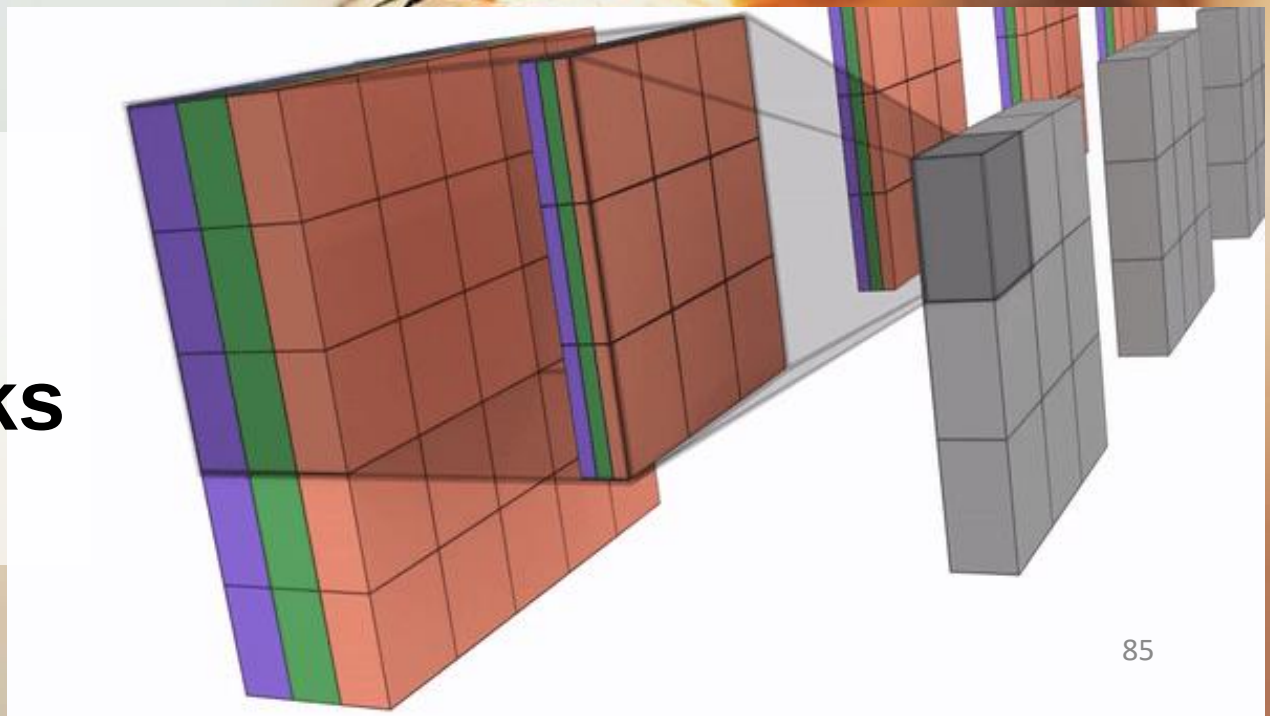
Visual Processing with Convolutional Neural Networks (CNN)



Self-Driving Cars with Convolutional Neural Networks (CNN)

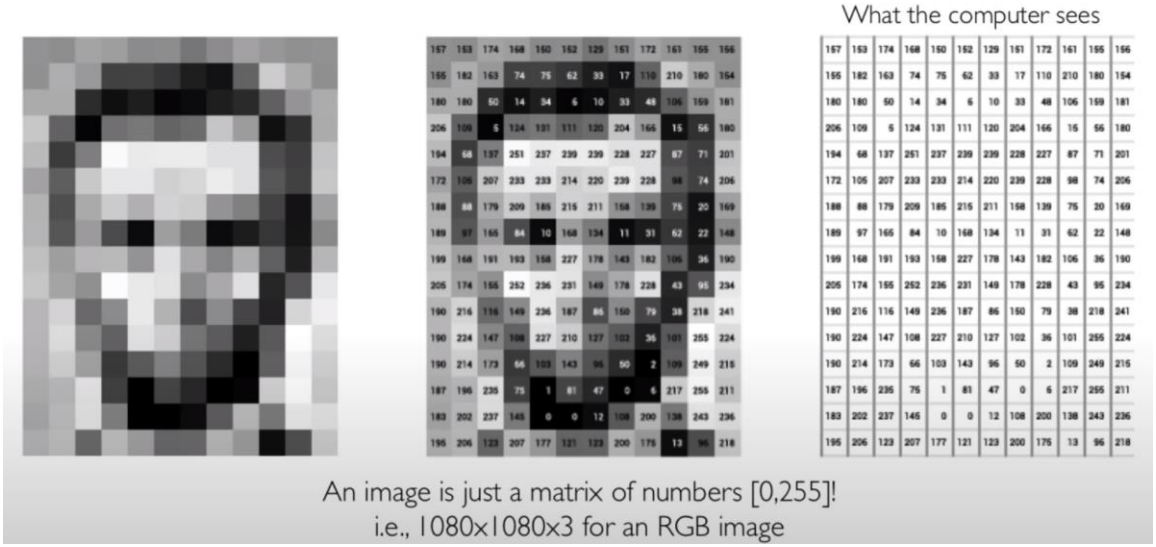


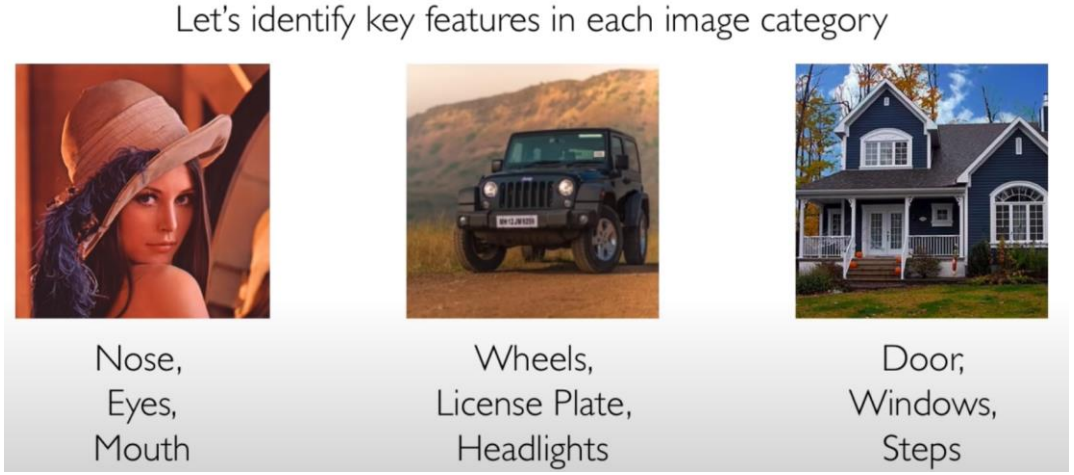
Basics of Convolutional Neural Networks (CNN)



CNN: Grundlegende Problemstellung (1/3)

Was **Computer sehen:** Ein **Bild** ist eine **Folge von Bildpunkten** (Pixel).





MIT 6.S191 Convolutional Neural Networks, 2020
www.youtube.com/watch?v=iaSUYvmCekI

CNN: Grundlegende Problemstellung (2/3)

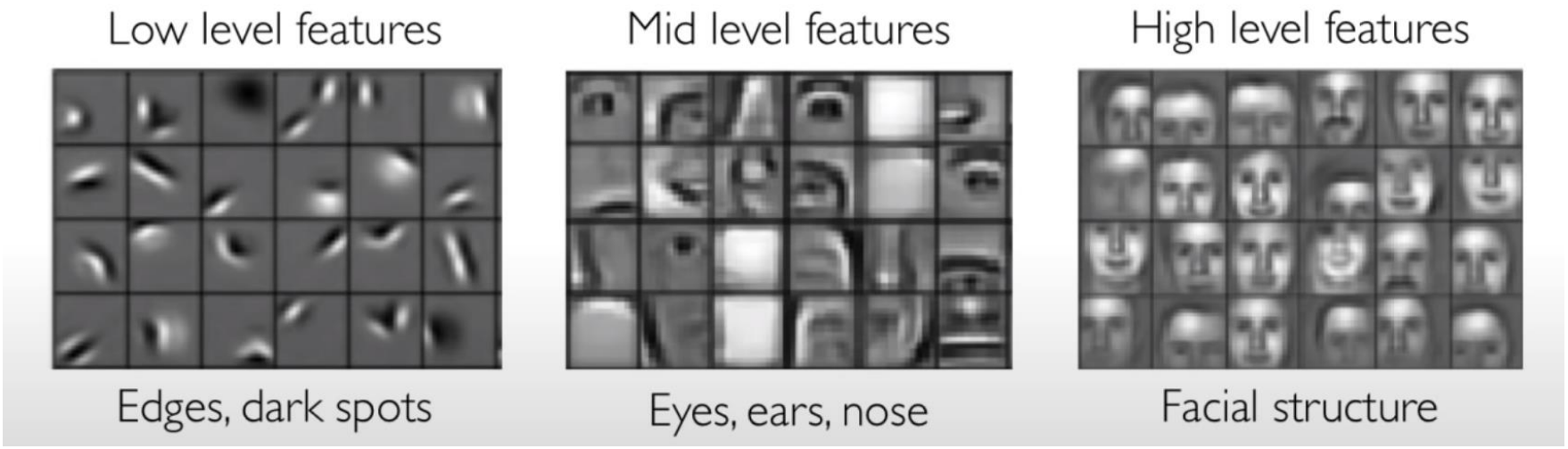
Eine **Objekterkennung** in **Bildern** ist **nicht einfach,**
da das **Umfeld** und **weitere Rahmenbedingungen** dies **erschweren.**

MIT 6.S191 Convolutional Neural Networks, 2020
www.youtube.com/watch?v=iaSUYvmCekI

CNN: Grundlegende Problemstellung (3/3)

Kann ein **Computer** die **relevanten Aspekte (Features)** zur **Objekterkennung** aus **Daten selbständig erlernen,** ohne sich von den Rahmenbedingungen „**ablenken**“ zu lassen?

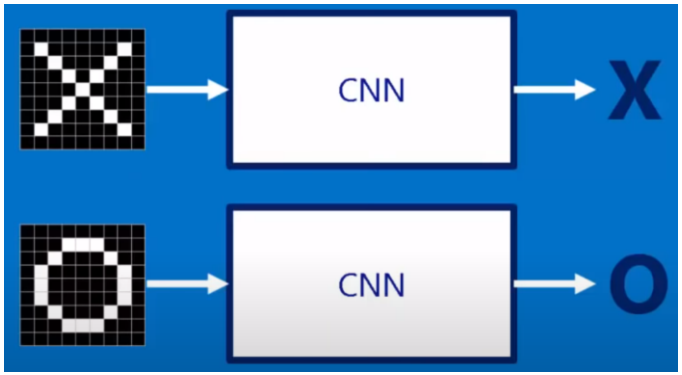
Can we learn a **hierarchy of features** directly from the data instead of hand engineering?



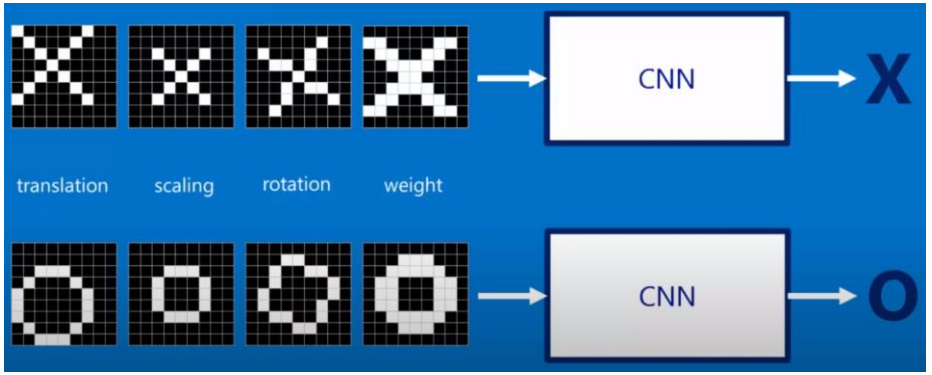
MIT 6.S191 Convolutional Neural Networks, 2020
www.youtube.com/watch?v=iaSUYvmCekI

CNN: Kernidee am Beispiel Objekterkennung (1/5)

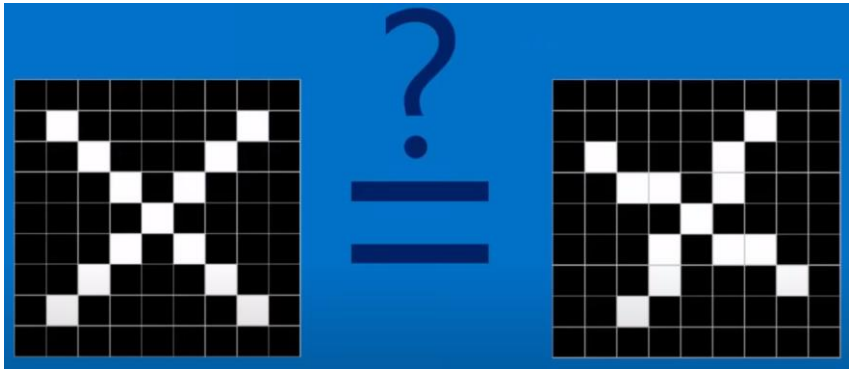
Problemstellung



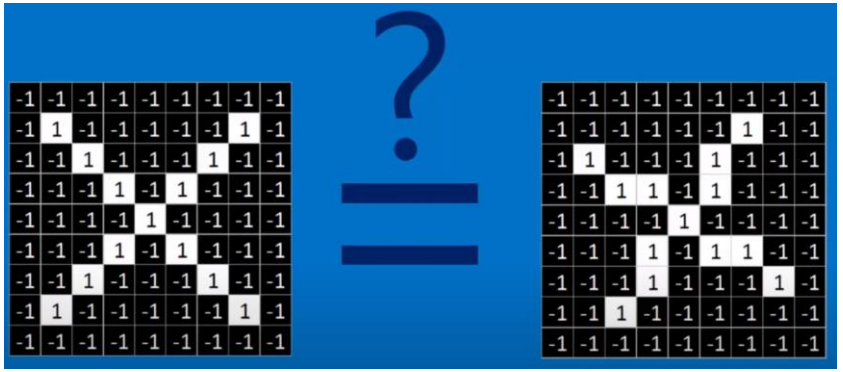
Herausforderung



Problem



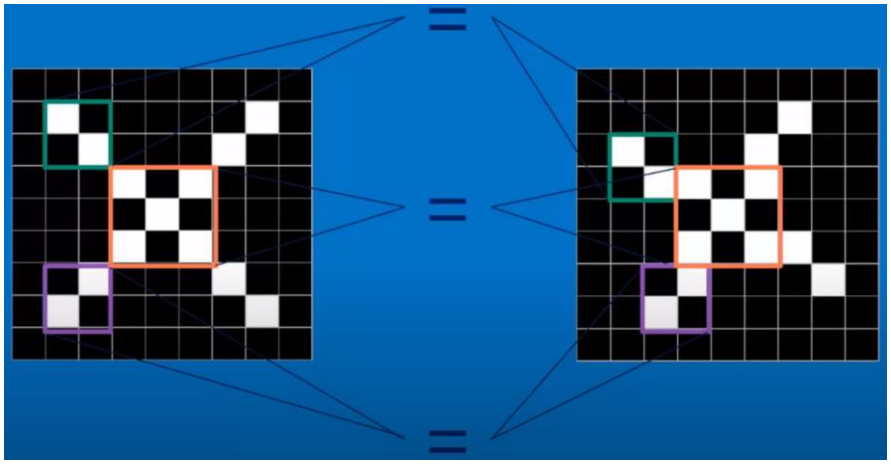
Problem (Computerdarstellung)



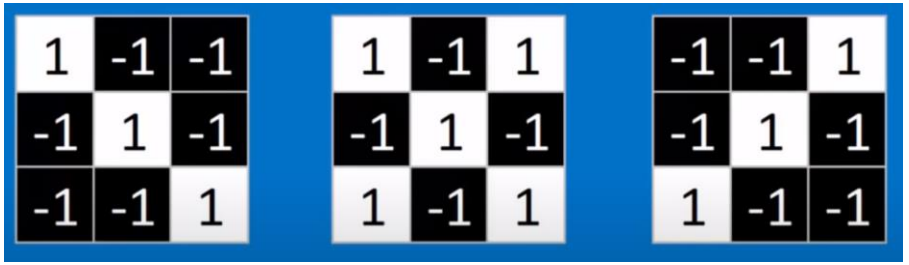
How Convolutional Neural Networks work, 2016
www.youtube.com/watch?v=FmpDIaiMIeA

CNN: Kernidee am Beispiel Objekterkennung (2/5)

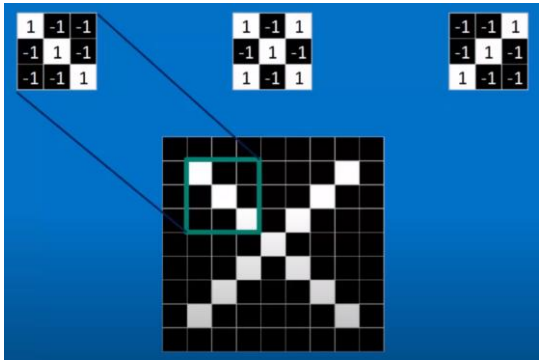
Idee: Features (Filter) helfen

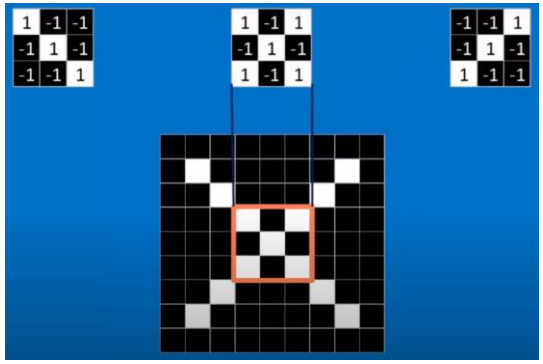


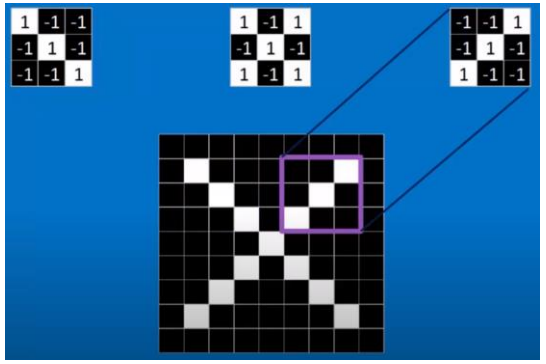
Relevante Features (Filter) identifizieren



Features (Filter) anwenden: Suche nach Features im Bild







How Convolutional Neural Networks work, 2016
www.youtube.com/watch?v=FmpDIaiMIeA

CNN: Kernidee am Beispiel Objekterkennung (3/5)

Stapel von mehreren Features (Filtern)

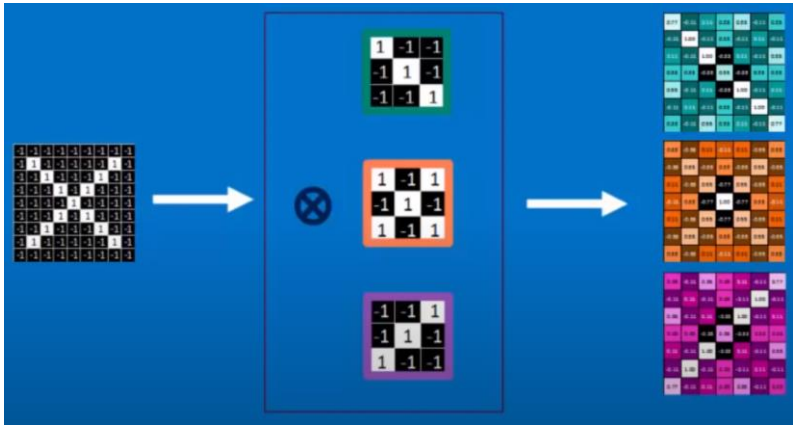
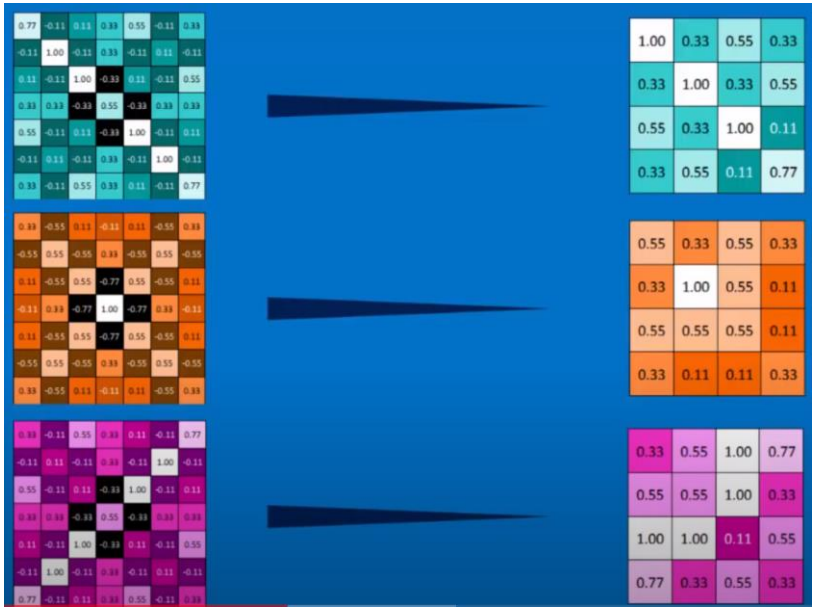
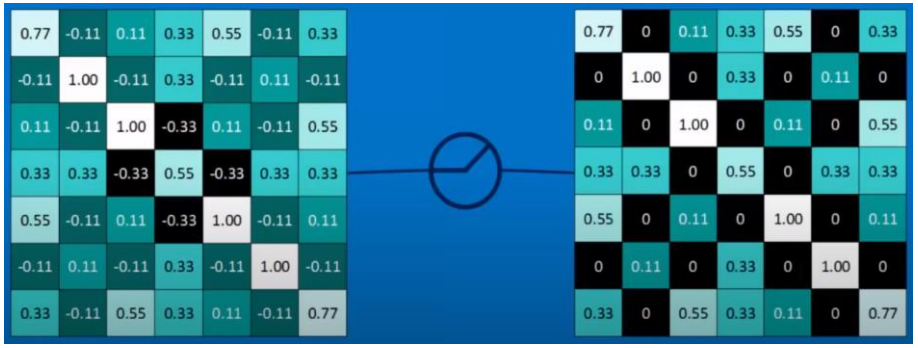


Bild Filter Feature

Pooling (Komplexität reduzieren & ungenauer werden)



ReLU (Unwichtiges entfernen)

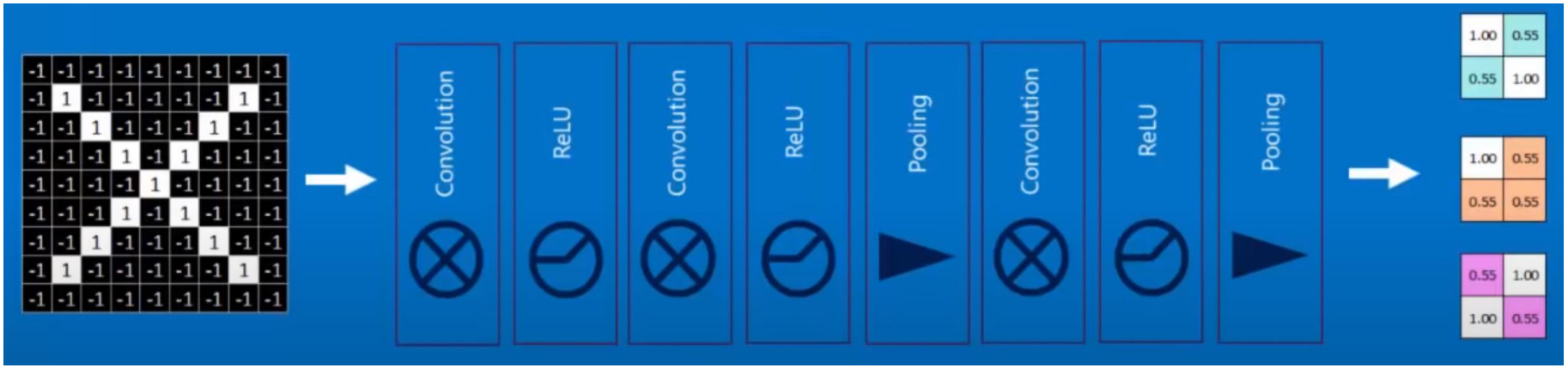


How Convolutional Neural Networks work, 2016

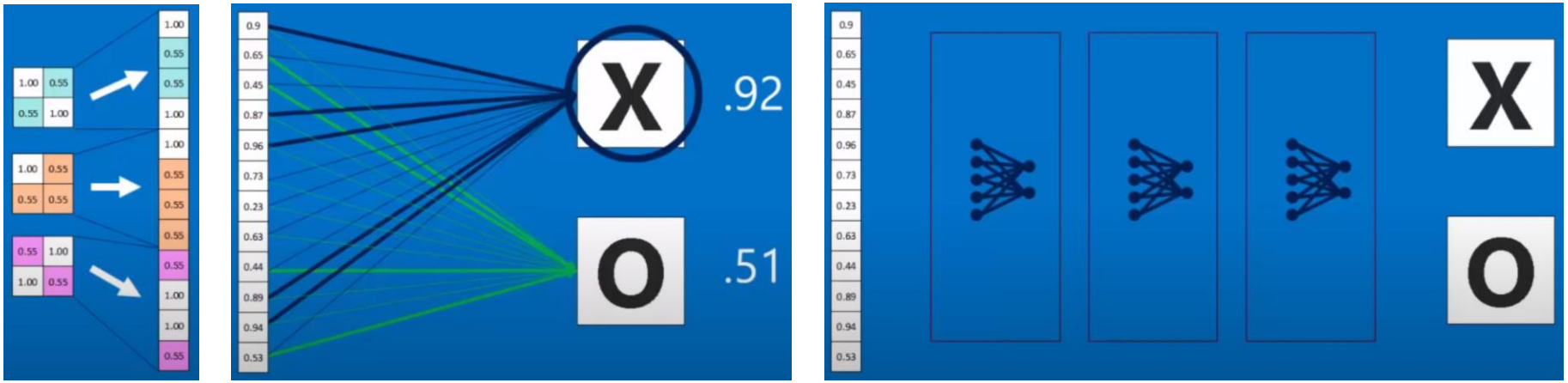
www.youtube.com/watch?v=FmpDIaiMIeA

CNN: Kernidee am Beispiel Objekterkennung (4/5)

Diese Operationen können mehrfach wiederholt werden:
Features suchen (Conv./Falten), Ergebnis bereinigen (ReLU) und komprimieren (Pooling).



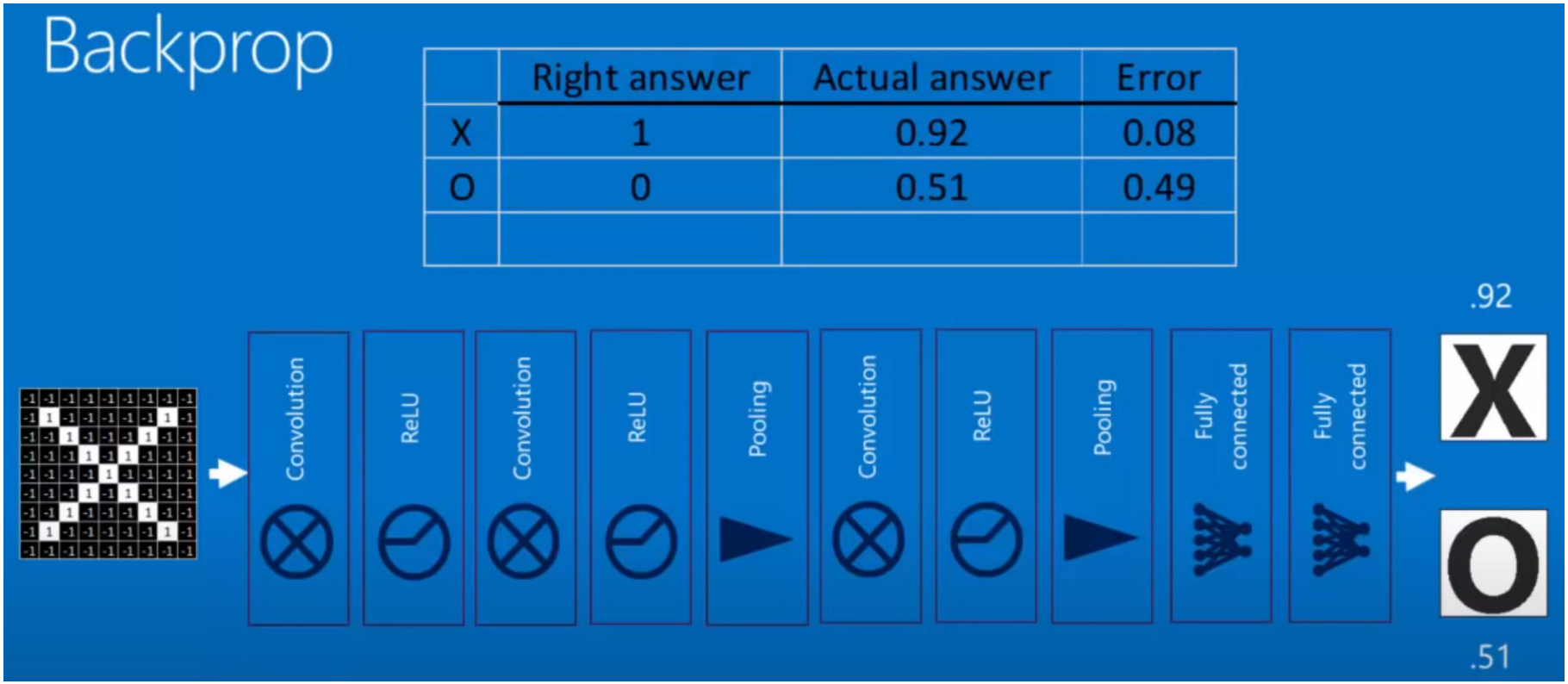
Ergebnis (die finalen Features) ebnen (engl. flatten) und bewerten (evtl. mehrstufig)



How Convolutional Neural Networks work, 2016
www.youtube.com/watch?v=FmpDIaiMIeA

CNN: Kernidee am Beispiel Objekterkennung (5/5)

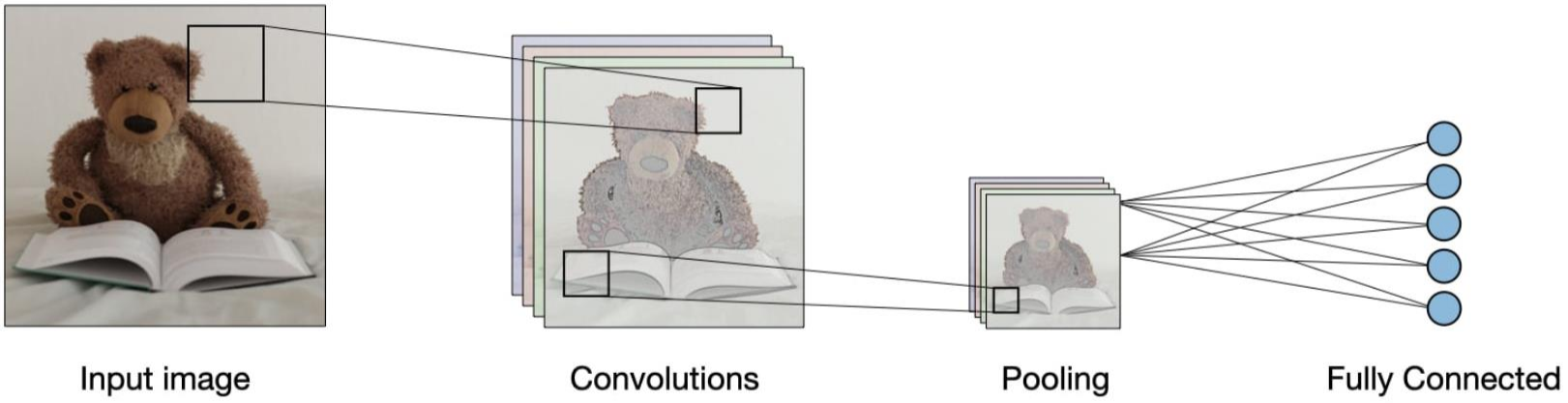
Backpropagation (Trainieren)



How Convolutional Neural Networks work, 2016
www.youtube.com/watch?v=FmpDIaiMIeA

Zentrale Bausteine klassischer CNN am Beispiel

❒ **Architecture of a traditional CNN** — Convolutional neural networks, also known as CNNs, are a specific type of neural networks that are generally composed of the following layers:

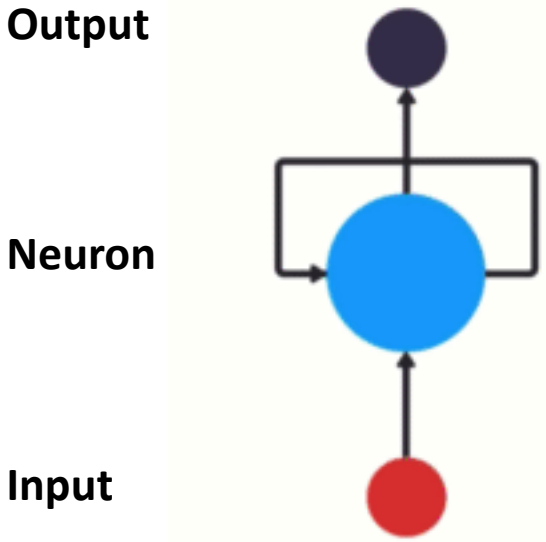


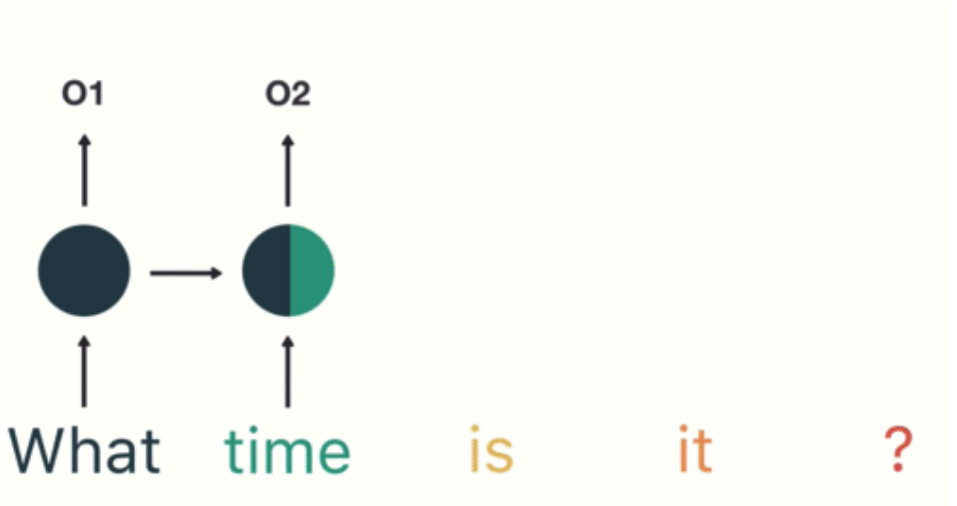
The convolution layer and the pooling layer can be fine-tuned with respect to hyperparameters that are described in the next sections.

stanford.edu/~shervine/teaching/cs-230/cheatsheet-convolutional-neural-networks

Recurrent Neural Networks (RNN)

Textanalyse mit einem **RNN** (Beispiel)



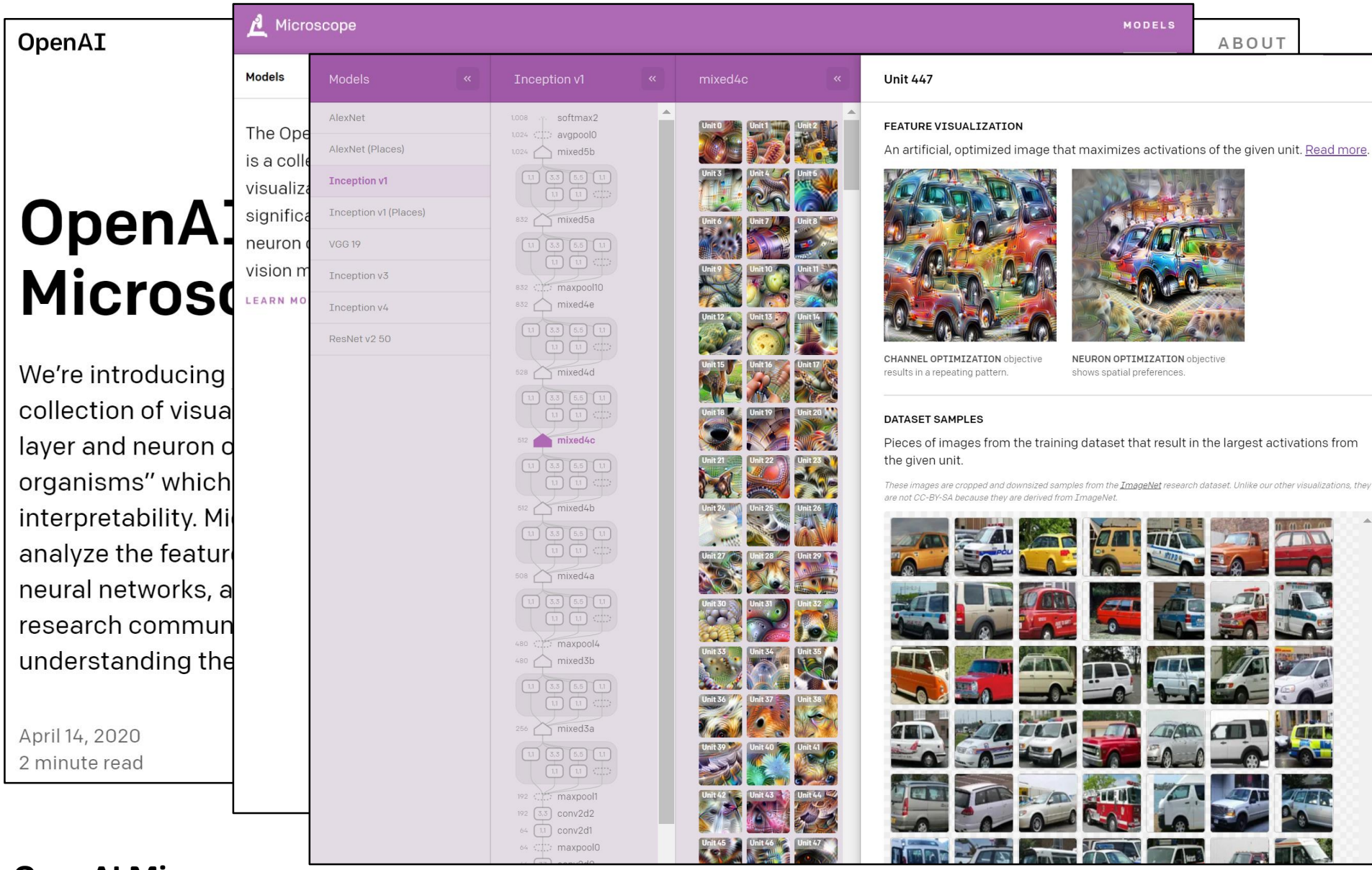


Neuronen in **RNNs** haben jeweils einen **Speicher (Internal Memory / Hidden State).**

RNNs eignen sich gut für **kurzfristige Erinnerungen,**
weniger gut für **langfristige Erinnerungen** (Vanishing Gradient Problem).

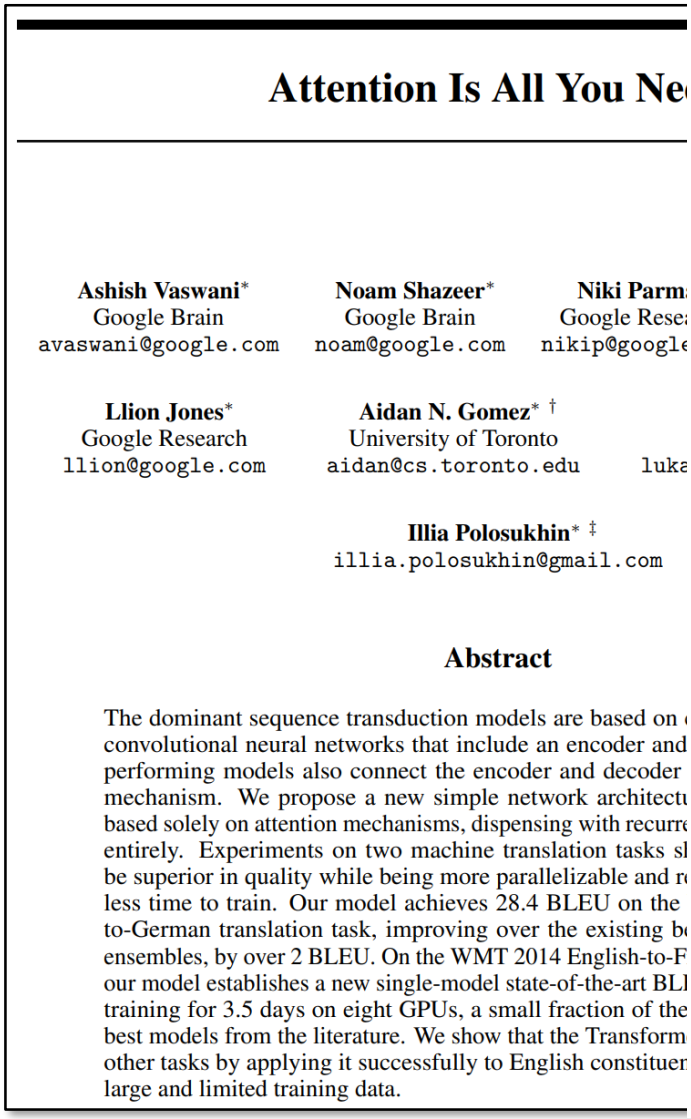
Illustrated Guide to Recurrent Neural Networks, 2018
towardsdatascience.com/illustrated-guide-to-recurrent-neural-networks-79e5eb8049c9

OpenAI Microscope



OpenAI Microscope
microscope.openai.com/models

Google, 2017: Attention is All You Need



Attention Is All You Ne

Ashish Vaswani* Google Brain avaswani@google.com

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Niki Parm Google Rese nikip@google

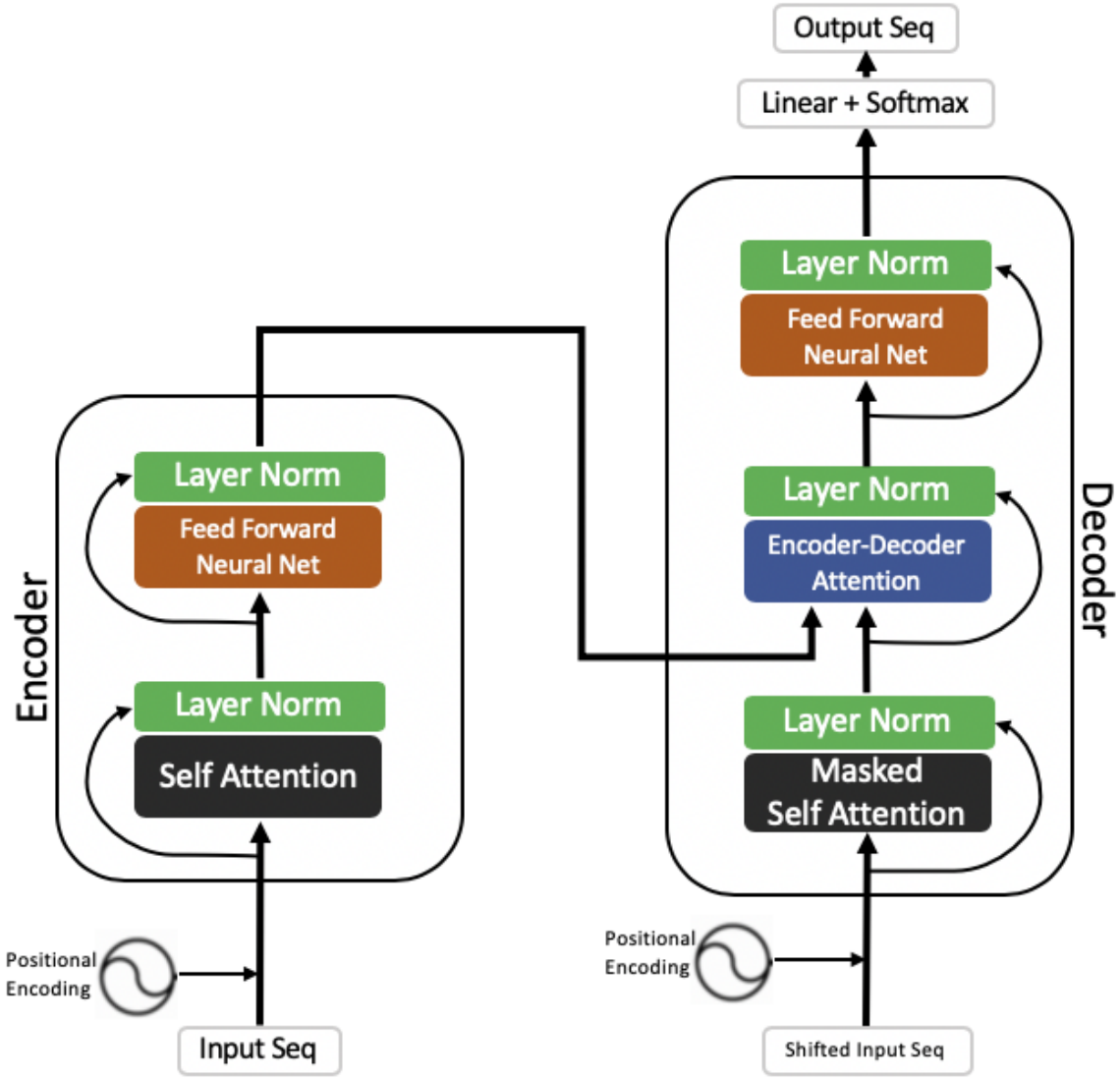
Llion Jones* Google Research llion@google.com

Aidan N. Gomez* † University of Toronto aidan@cs.toronto.edu luka

Illia Polosukhin* ‡ illia.polosukhin@gmail.com

Abstract

The dominant sequence transduction models are based on
convolutional neural networks that include an encoder and
performing models also connect the encoder and decoder
mechanism. We propose a new simple network architectu
based solely on attention mechanisms, dispensing with recurr
entirely. Experiments on two machine translation tasks sl
be superior in quality while being more parallelizable and r
less time to train. Our model achieves 28.4 BLEU on the
to-German translation task, improving over the existing b
ensembles, by over 2 BLEU. On the WMT 2014 English-to-F
our model establishes a new single-model state-of-the-art BL
training for 3.5 days on eight GPUs, a small fraction of the
best models from the literature. We show that the Transform
other tasks by applying it successfully to English constituer
large and limited training data.



Google et.al., 2017: Attention Is All You Need
arxiv.org/pdf/1706.03762.pdf

OpenAI: Image GPT, Juni 2020

Generative Pretraining from Pixels

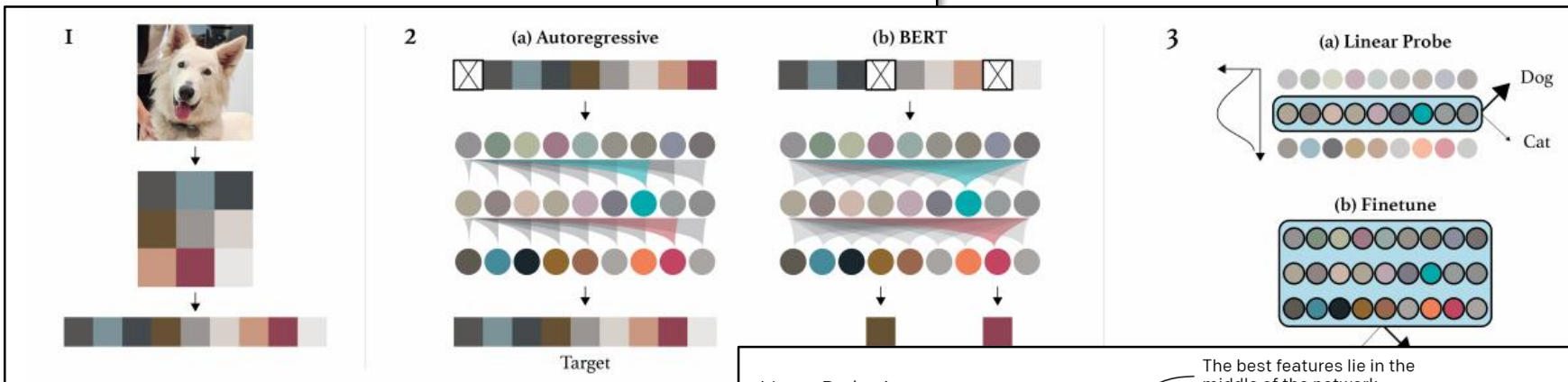


Figure 1. An overview of our approach. First, we pre-process r
We then chose one of two pre-training objectives, auto-regres
the representations learned by these objectives with linear pro

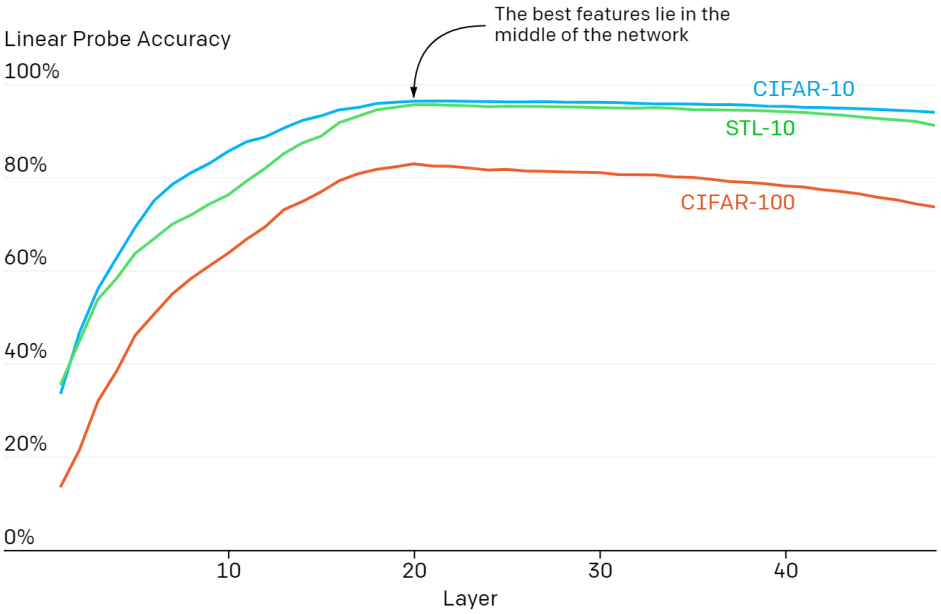
ture of ImageNet and web images is competitive with self-supervised benchmarks on ImageNet, achieving 72.0% top-1 accuracy on a linear probe of our features.

1. Introduction

Unsupervised pre-training played a central role in the resurgence of deep learning. Starting in the mid 2000's, approaches such as the Deep Belief Network (Hinton et al., 2006) and Denoising Autoencoder (Vincent et al., 2008) were commonly used in neural networks for computer vision (Lee et al., 2009) and speech recognition (Mohamed et al., 2009). It was believed that a model which learned the data distribution $P(X)$ would also learn beneficial fea-

prediction of corrupted inputs, clos
Denoising Autoencoder, which was
images.

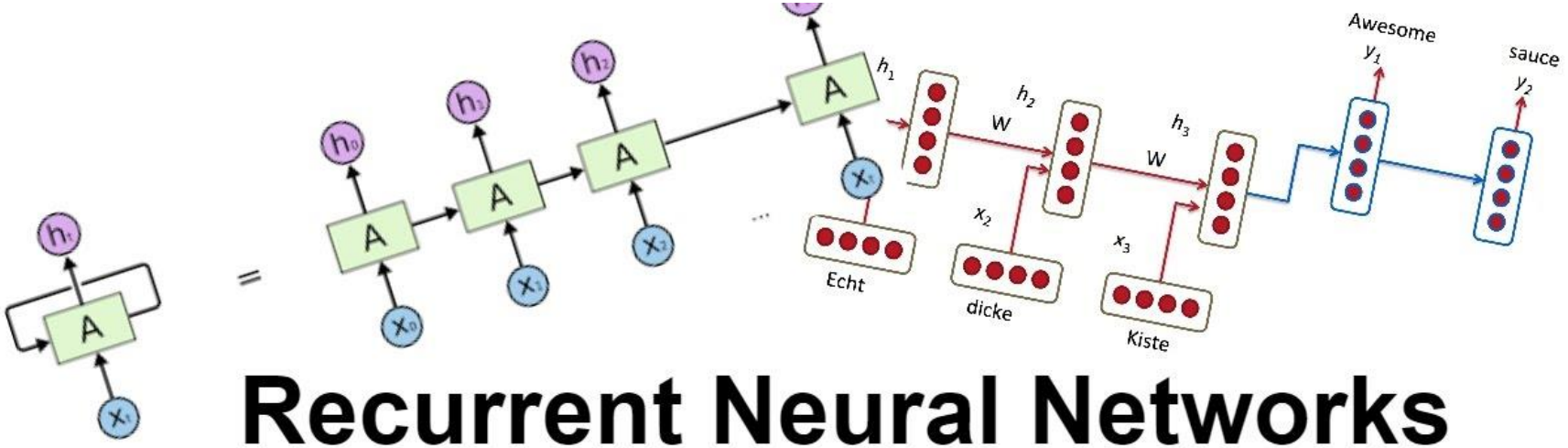
As a higher dimensional, noisier, ar
ity than text, images are believed t
tive modeling. Here, self-supervise
encourage the modeling of more g
et al., 2015) have shown significant
of new training objectives (Oord e
architectures (Gomez et al., 2017),
pacity (Kolesnikov et al., 2019) ha
to achieve state of the art performa
(Hénaff et al., 2019) and sometime
vised representations in transfer le
2019; Misra & van der Maaten, 20



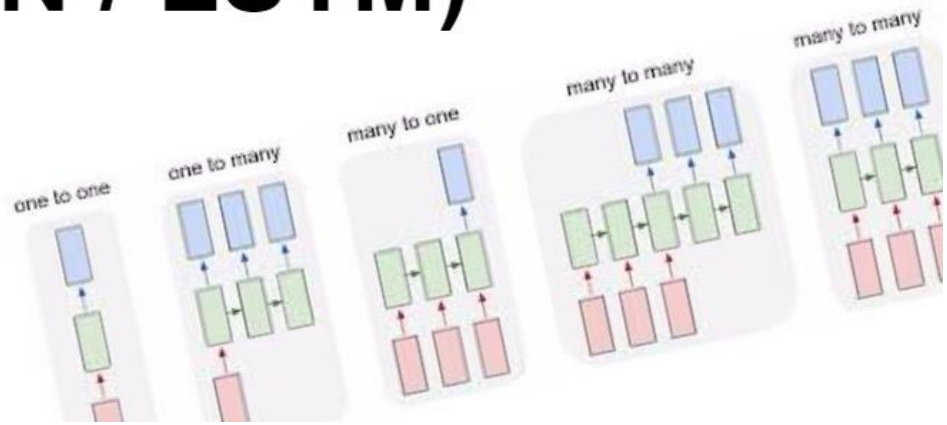
Feature quality depends heavily on the layer we choose to evaluate. In contrast with supervised models, the best features for these generative models lie in the middle of the network.

cdn.openai.com/papers/Generative_Pretraining_from_Pixels_V2.pdf

3. RNN & LSTM Networks

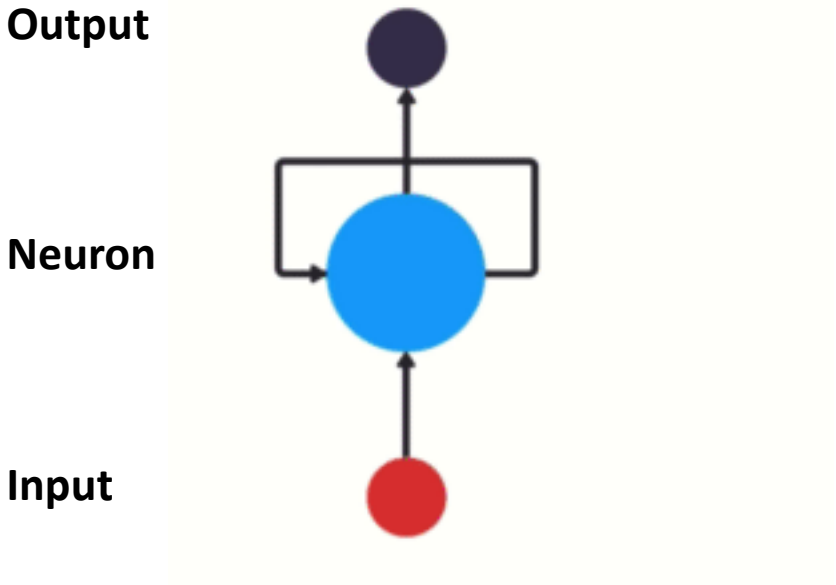


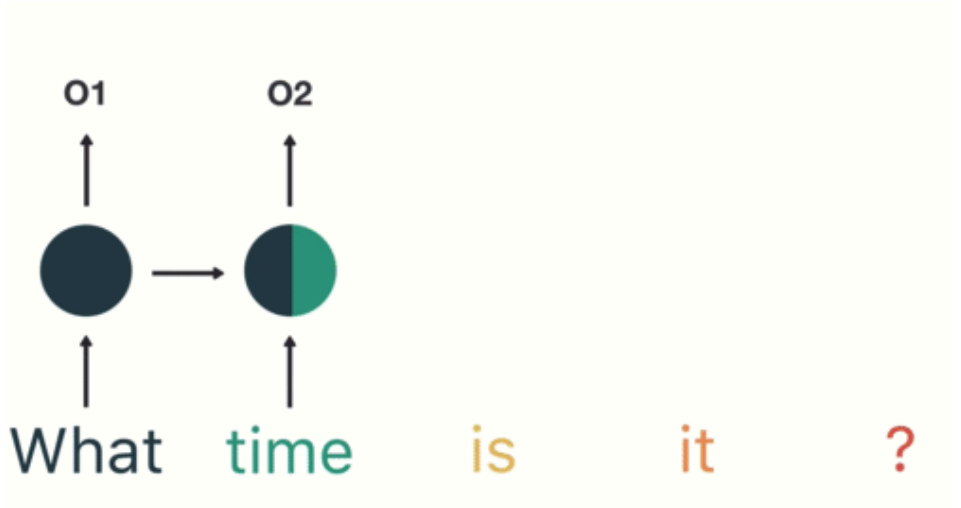
Recurrent Neural Networks (RNN / LSTM)



Recurrent Neural Networks (RNN)

Textanalyse mit einem **RNN** (Beispiel)





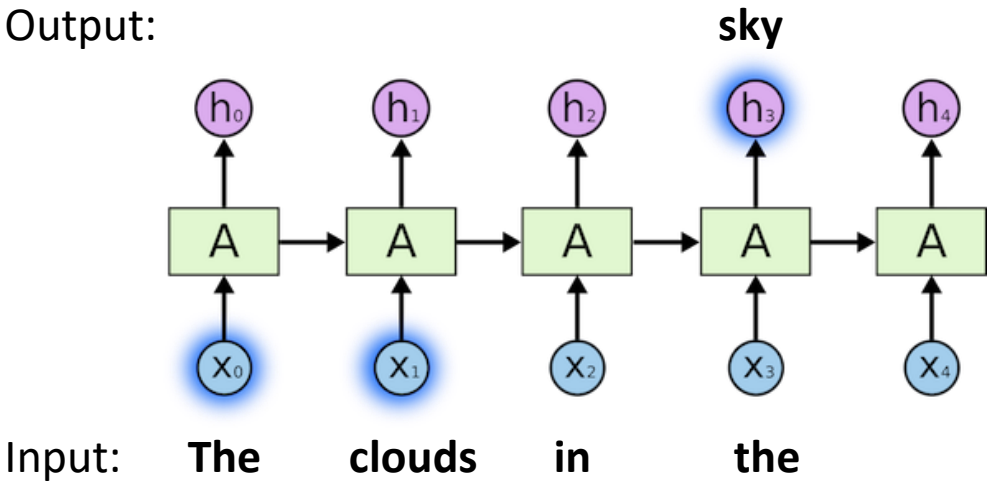
Neuronen in **RNNs** haben jeweils einen **Speicher (Internal Memory / Hidden State).**

Es gibt **verschiedene Arten** von **RNN-Netzen.**

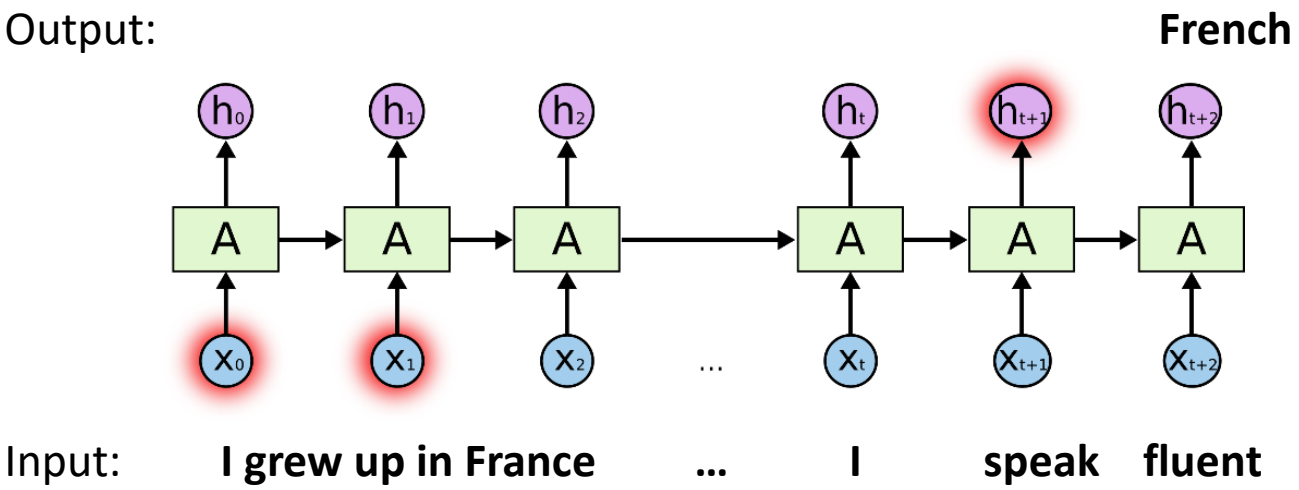
Illustrated Guide to Recurrent Neural Networks, 2018
towardsdatascience.com/illustrated-guide-to-recurrent-neural-networks-79e5eb8049c9

Recurrent Neural Networks (RNN)

Beispiel Textvorhersage (wenig Kontext)

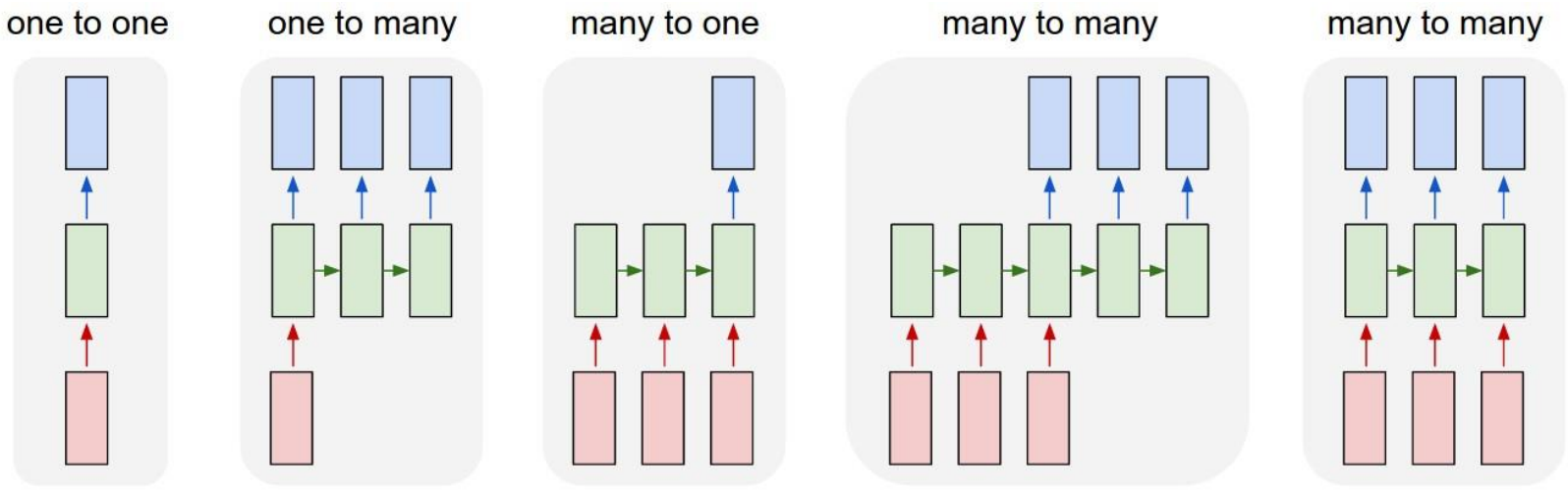


Beispiel Textvorhersage (mehr Kontext)



RNNs eignen sich gut für **kurzfristige Erinnerungen,**
weniger gut für **langfristige Erinnerungen** (Vanishing Gradient Problem).

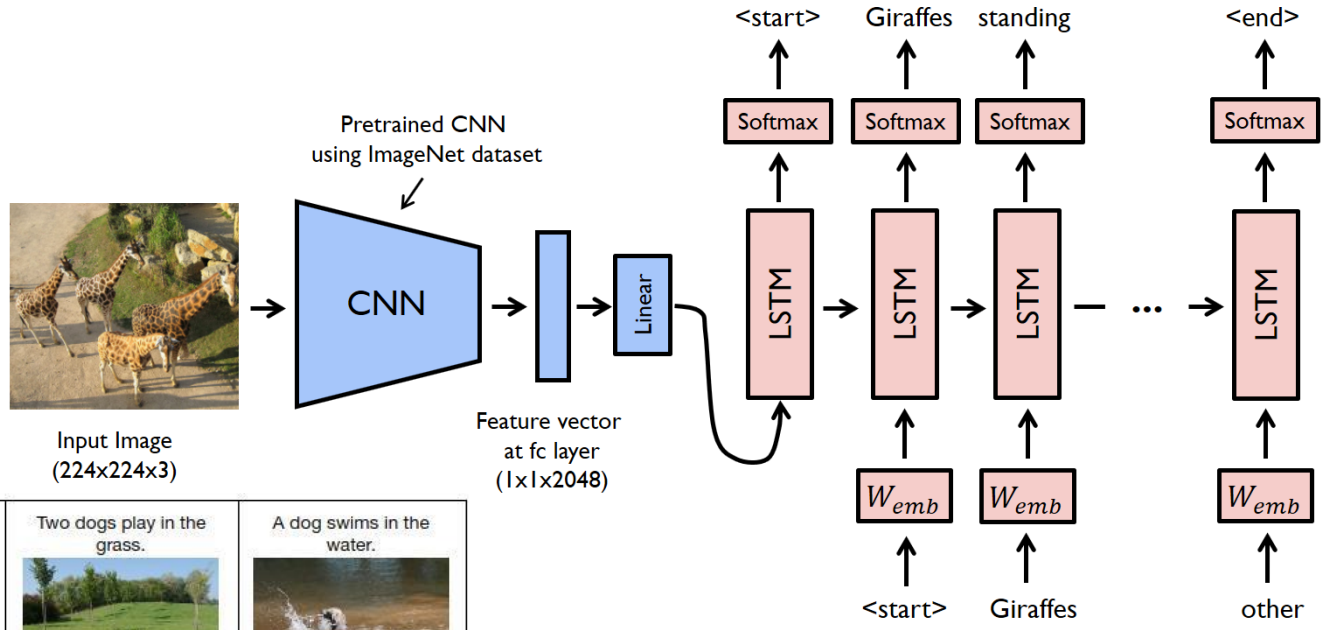
Grundlegende RNN-Architekturen



One-To-One: Für einfache Anwendungen
One-To-Many: Z.B. **Image Captioning** (Image -> Sequenz von Worten)
Many-To-One: Z.B. **Sentiment-Klassifikation** (Sequenz von Worten -> Sentiment)
Textvorhersage (Sequenz von Worten -> Wort)
Many-To-Many: Z.B. **Übersetzung** (Sequenz von Worten -> Sequenz von Worten)
Many-To-Many: (synched) Z.B. **Video-Klassifikation** von Frames

Standford: Recurrent Neural Networks, 2017
www.youtube.com/watch?v=6niqTuYFZLQ

Kombinierter Einsatz von RNN und LSTM



RNN und **LSTM** können auch mit **Feed-Forward-Netze** (z.B. **Convolutional Neural Networks)** kombiniert werden. Sie bringen damit „**Memory**“ hinein.

Anwendungen sind z.B.:
Textuelle Beschreibung von Bildern (**Image Captioning**) oder Automatische Generierung von Untertiteln (**Video Captioning**).

Generierung von Musik mit RNN und LSTM

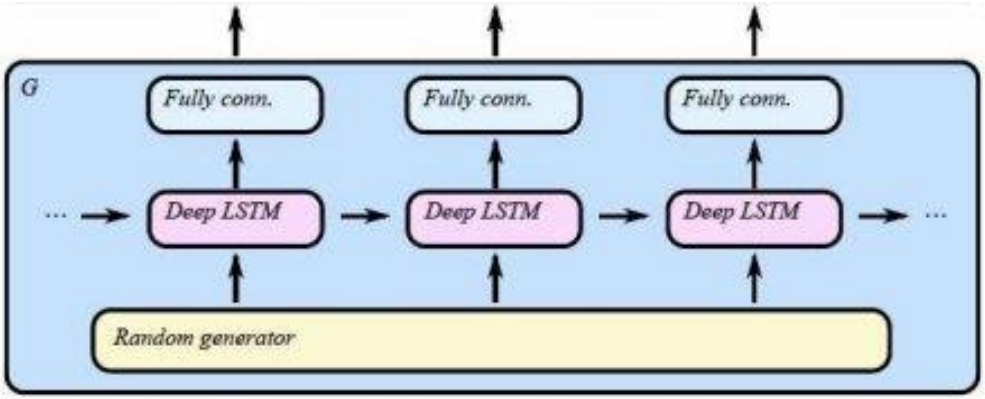


Fig. 7.27 C-RNN-GAN architecture.

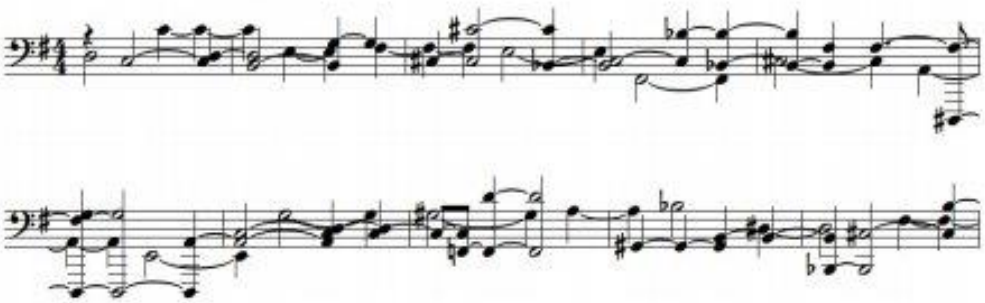


Fig. 7.28 C-RNN-GAN generated examples.

Musik ist auch eine Sequenz (Sequence). Mit RNN und LSTMs kann man Musik generieren.

Music Composition using Recurrent Neural Networks
web.stanford.edu/class/archive/cs/cs224n/cs224n.1174/reports/2762076.pdf

Transformer Networks (machine learning model)

Transformer (machine learning model)

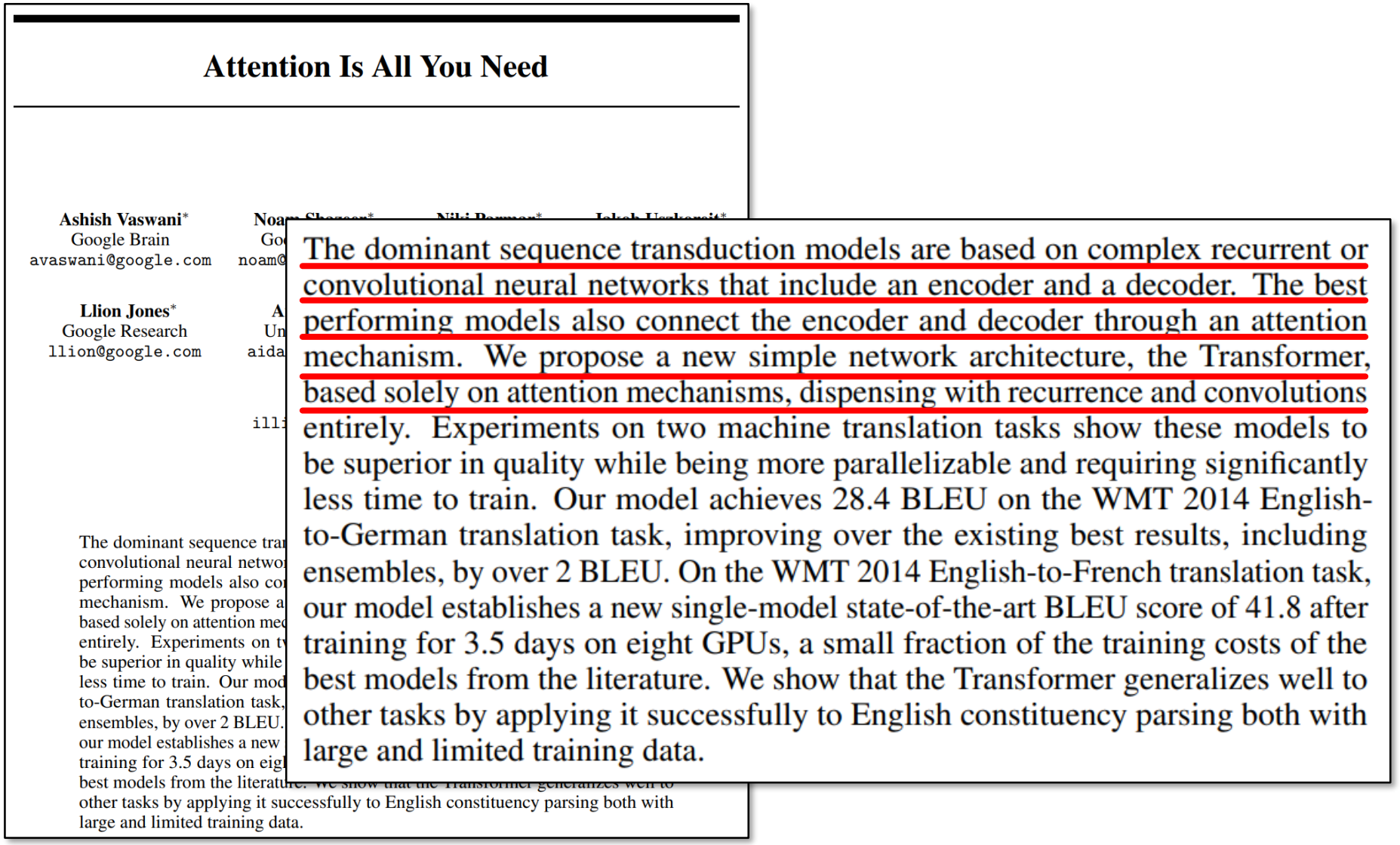
From Wikipedia, the free encyclopedia

The **Transformer** is a deep learning model introduced in 2017, used primarily in the field of natural language processing (NLP).[1]

Like recurrent neural networks (RNNs), Transformers are designed to handle sequential data, such as natural language, for tasks such as translation and text summarization. However, unlike RNNs, Transformers do not require that the sequential data be processed in order. For example, if the input data is a natural language sentence, the Transformer does not need to process the beginning of it before the end. Due to this feature, the Transformer allows for much more parallelization than RNNs and therefore reduced training times.[1]

Transformers have rapidly become the model of choice for NLP problems,[2] replacing older recurrent neural network models such as the long short-term memory (LSTM). Since the Transformer model facilitates more parallelization during training, it has enabled training on larger datasets than was possible before it was introduced. This has led to the development of pretrained systems such as BERT (Bidirectional Encoder Representations from Transformers) and GPT (Generative Pre-trained Transformer), which have been trained with huge general language datasets, such as Wikipedia Corpus, and can be fine-tuned to specific language tasks.[3][4]

Google, 2017: Attention is All You Need



Attention Is All You Need

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The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

Google et.al., 2017: Attention Is All You Need
arxiv.org/pdf/1706.03762.pdf

Google, 2017: Attention is All You Need

Attention Is All You Need

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Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

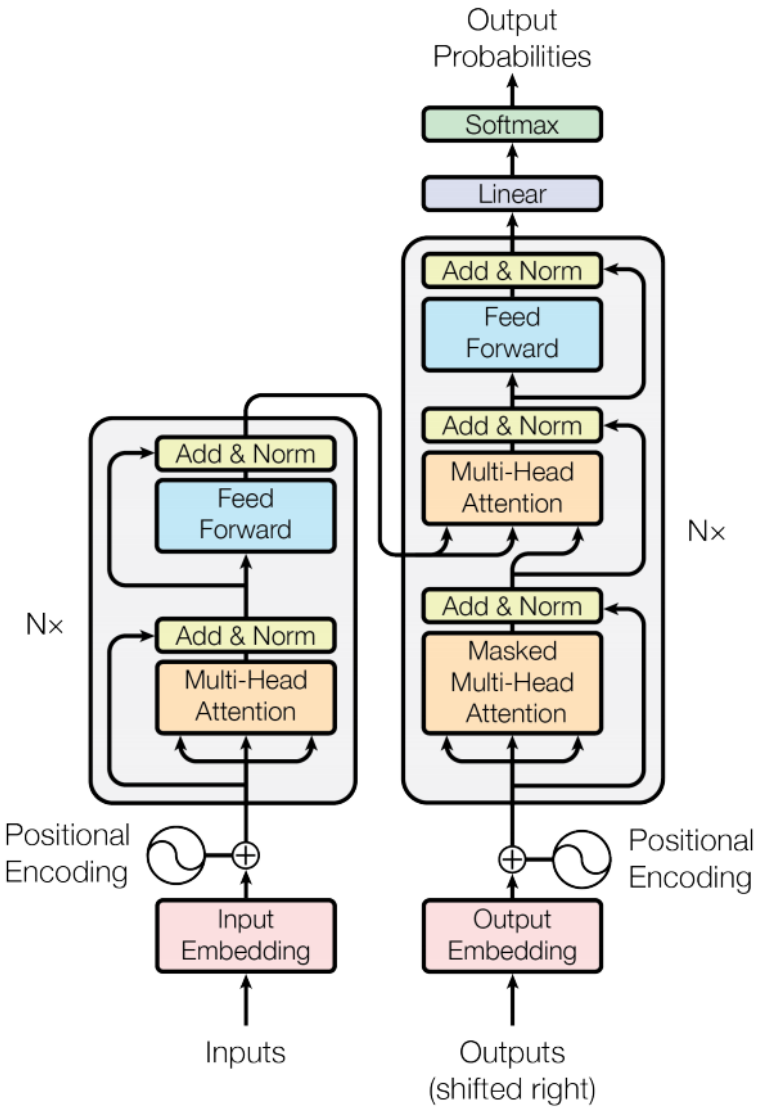

Figure 1: The Transformer - model architecture.

Google et.al., 2017: Attention Is All You Need
arxiv.org/pdf/1706.03762.pdf

GPT-3: Trainingsdaten

Since Neural Networks are compressed/compiled version of the training data, the size of the dataset has to scale accordingly with the size of the model. GPT-3 175B is trained with 499 Billion tokens. Here is the breakdown of the data:

Dataset	# Tokens (Billions)
Total	499
Common Crawl (filtered by quality)	410
WebText2	19
Books1	12
Books2	55
Wikipedia	3

How GPT3 Works - Visualizations and Animations, 2020
jalammar.github.io/how-gpt3-works-visualizations-animations/