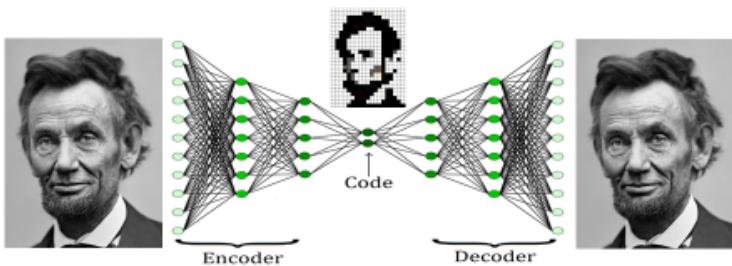


# 8 Machine Learning III

## - Specialized Areas in Machine Learning (3) Autoencoder



Autoencoder



Der Encoder nimmt Rohdaten (z.B. Bilder oder Audio) und komprimiert die Daten auf eine mehrfach kleinere Menge.

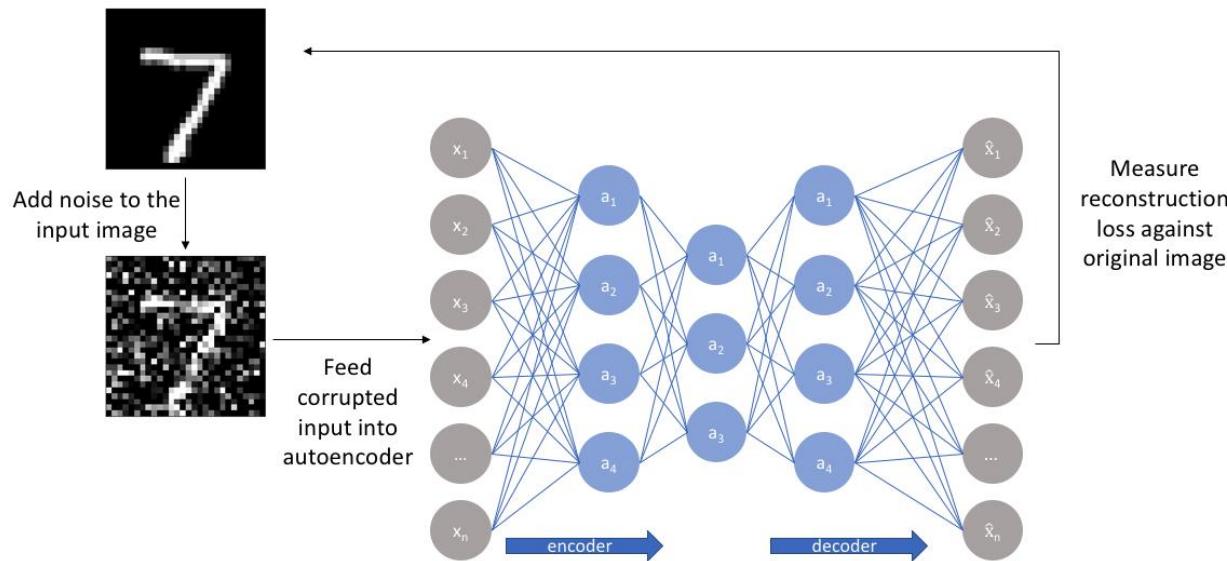
Der Decoder nimmt diese kleine Menge an Daten und versucht daraus das Original wieder herzustellen.

Weil das Modell Ende-zu-Ende trainiert wurde, funktionieren sowohl Decoder und Encoder auch einzeln, z.B. nur Encoder oder Decoder, (vgl. MP3, Video-Upscaling).

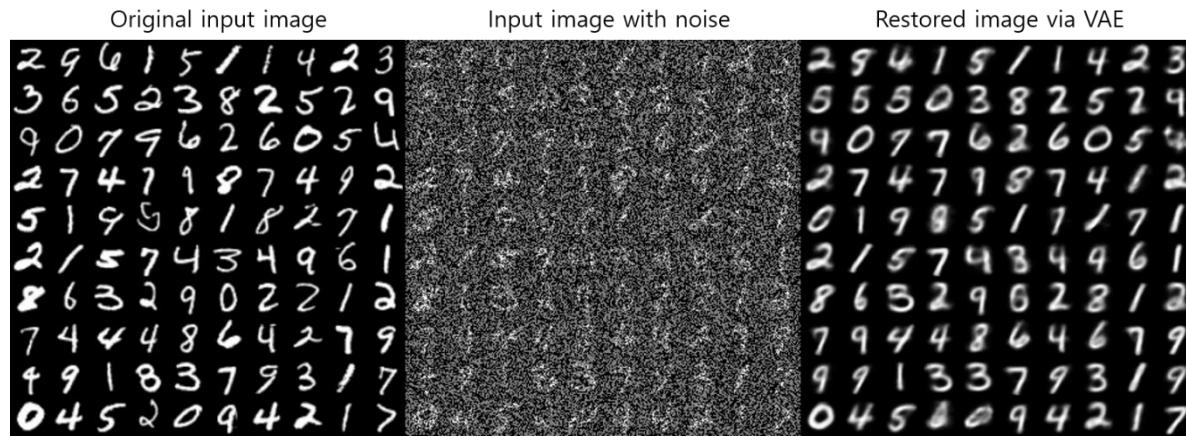


DLSS ON (QUALITY MODE)  
Ray Tracing - Epic, 1080p, RTX 2060

# Denoise Autoencoder (DAE)

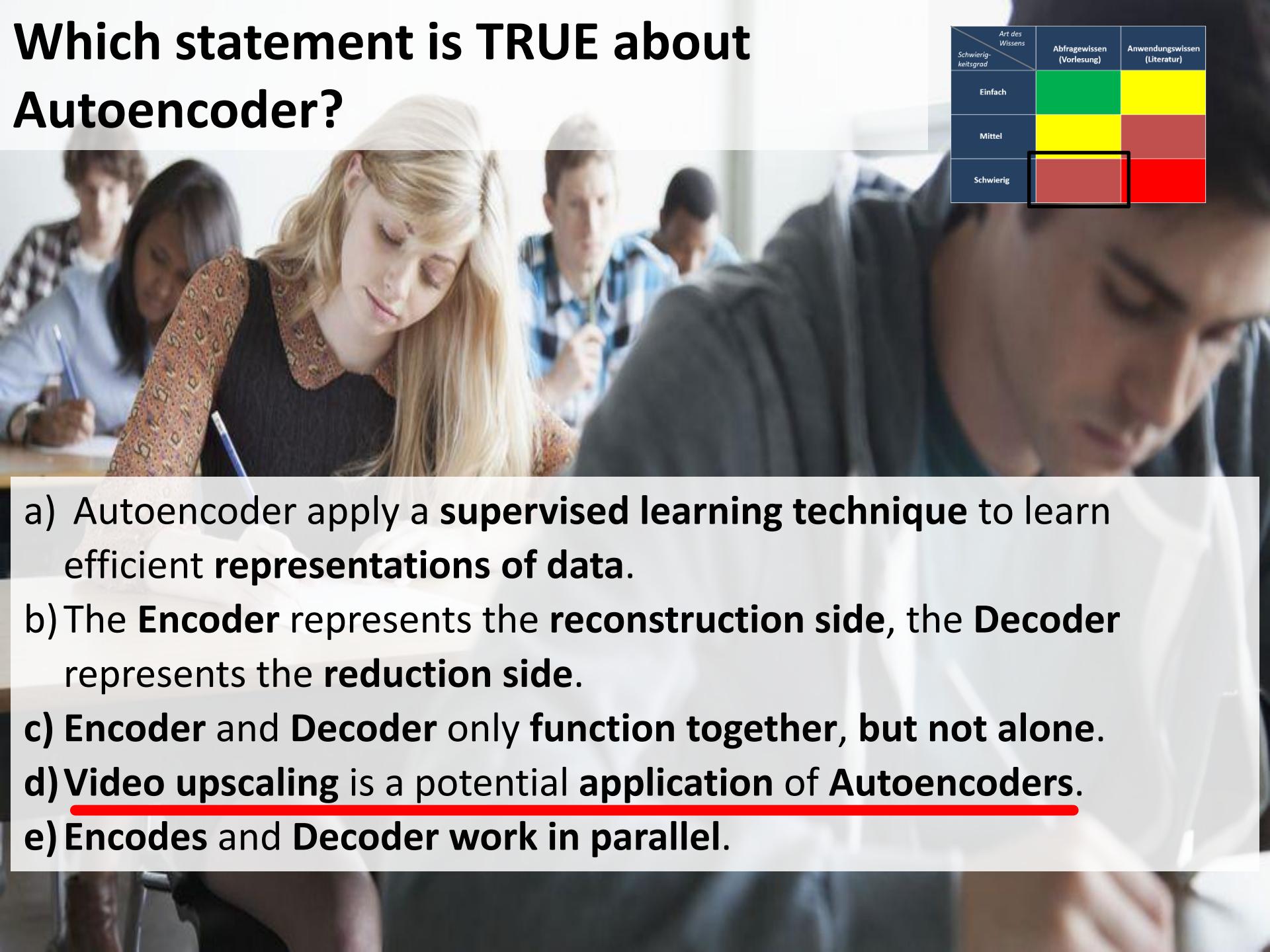


Ein Denoise Autoencoder (DAE) lernt Rauschen zu entfernen.



# Which statement is TRUE about Autoencoder?

Schwierigkeitsgrad	Art des Wissens	Abfragewissen (Vorlesung)	Anwendungswissen (Literatur)
Einfach		Green	Yellow
Mittel		Yellow	Red
Schwierig		Red	Red

- 
- A photograph showing several students in a classroom setting, focused on their work at their desks.
- a) Autoencoder apply a **supervised learning technique** to learn efficient **representations of data**.
  - b) The **Encoder** represents the **reconstruction side**, the **Decoder** represents the **reduction side**.
  - c) **Encoder** and **Decoder** only function together, but not alone.
  - d) **Video upscaling** is a potential application of Autoencoders.
  - e) Encodes and Decoder work in parallel.

# What is NOT a type of Autoencoder?

Schwierigkeitsgrad	Art des Wissens	Abfragewissen (Vorlesung)	Anwendungswissen (Literatur)
Einfach		Green	Yellow
Mittel		Yellow	Red
Schwierig		Red	Red

- a) Variational Autoencoder
- b) Denoise Autoencoder
- c) Sparse Autoencoder
- d) Reinforced Autoencoder
- e) None (i.e., all valid)

# 8 Machine Learning III

## - Specialized Areas in Machine Learning

### Content:

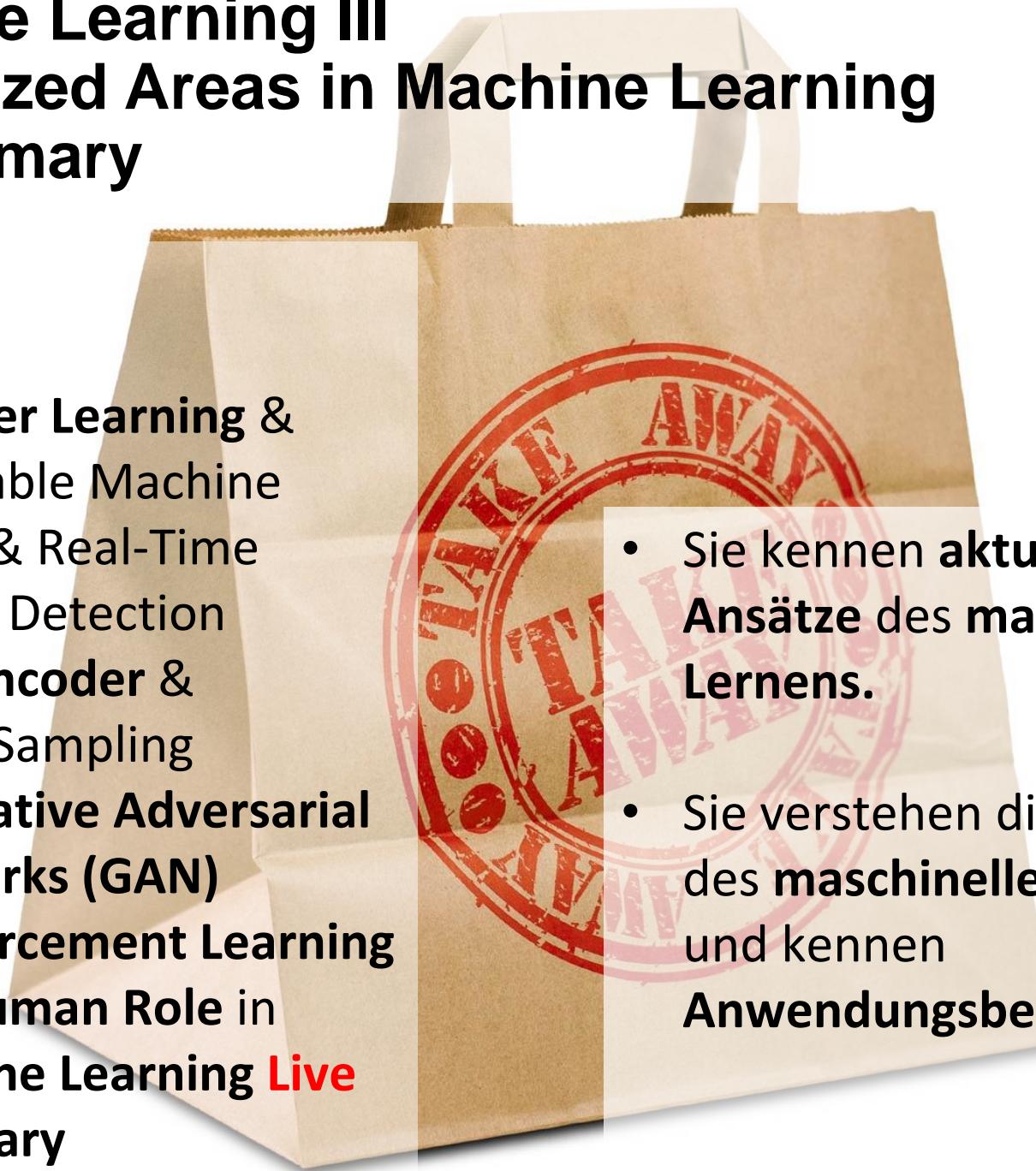
1. Transfer Learning & Teachable Machine
2. YOLO & Real-Time Object Detection
3. Autoencoder & Super Sampling
4. Generative Adversarial Networks (GAN)
5. Reinforcement Learning
6. The Human Role in Machine Learning **Live**
7. Summary



# 8 Machine Learning III

## - Specialized Areas in Machine Learning (7) Summary

### Content:

- 
1. Transfer Learning & Teachable Machine
  2. YOLO & Real-Time Object Detection
  3. Autoencoder & Super Sampling
  4. Generative Adversarial Networks (GAN)
  5. Reinforcement Learning
  6. The Human Role in Machine Learning **Live**
  7. Summary
- Sie kennen **aktuelle Ansätze des maschinellen Lernens.**
  - Sie verstehen die **Ansätze des maschinellen Lernens** und kennen **Anwendungsbeispiele.**

# Michael Amberg

## Todays Content:

1. Transfer Learning & Teachable Machine
2. YOLO & Real-Time Object Detection
3. Autoencoder & Super Sampling
4. Generative Adversarial Networks (GAN)
5. Reinforcement Learning
6. The Human Role in Machine Learning **Live**
7. Summary



### 3. Autoencoder

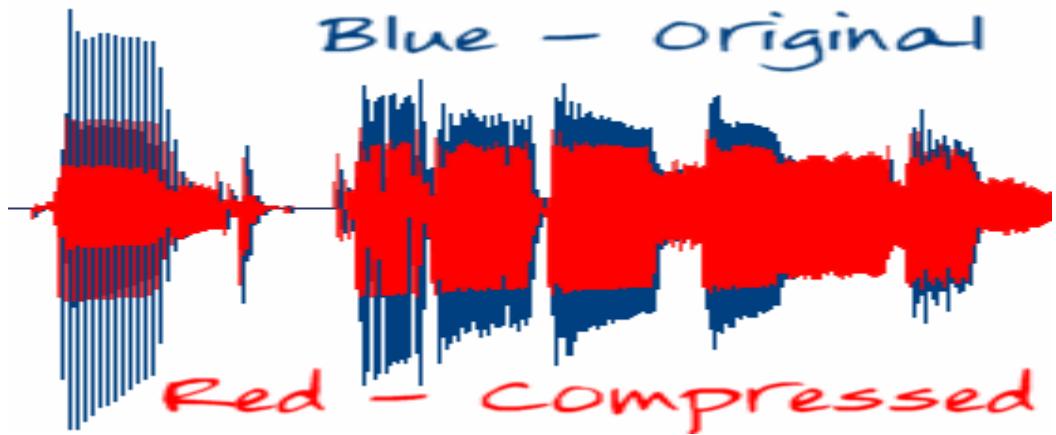


**Deliver Us The Moon | NVIDIA DLSS Performance & Image Quality Boost, 2020**  
[www.youtube.com/watch?v=via-LSKo\\_q4](https://www.youtube.com/watch?v=via-LSKo_q4)

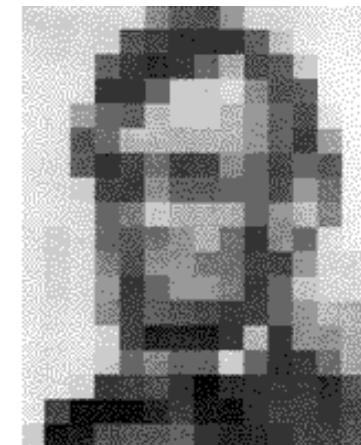
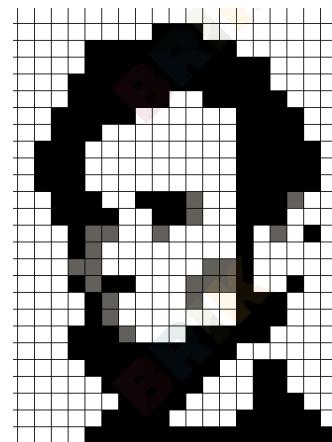
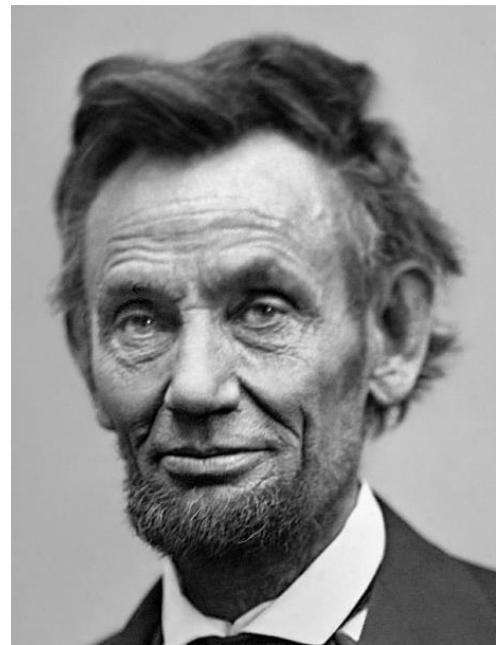
# Motivation Autoencoder



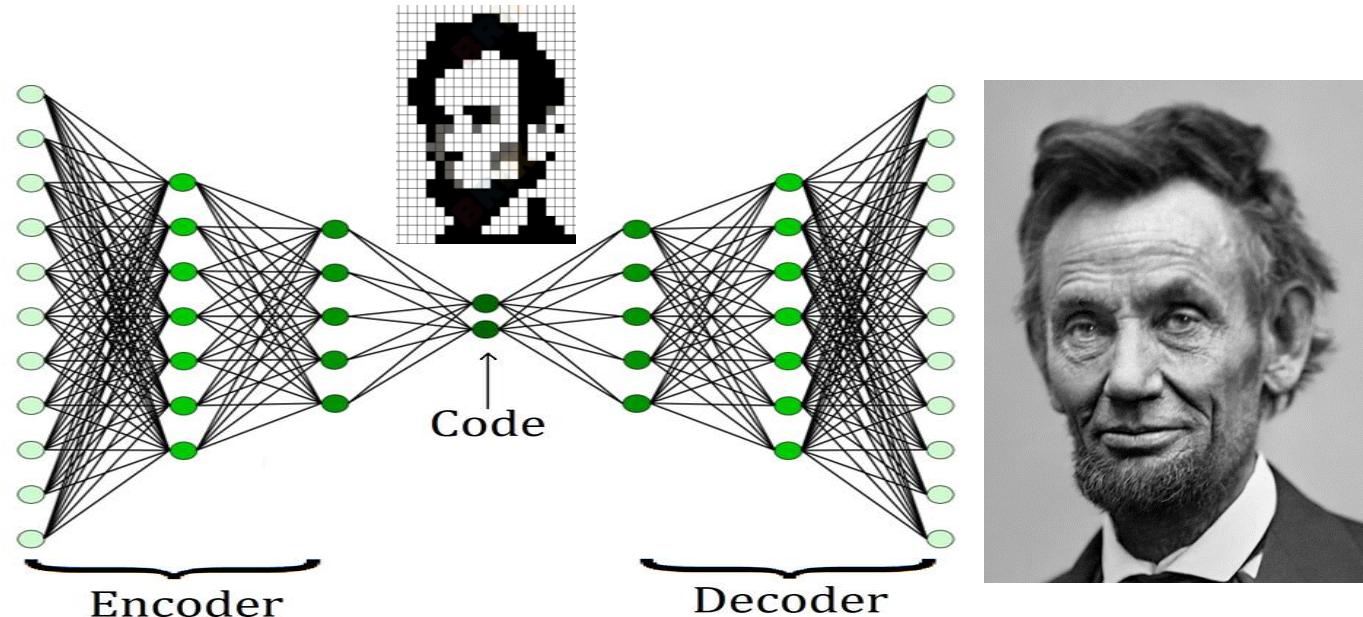
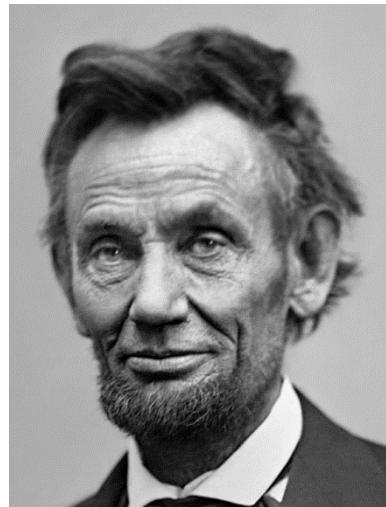
MP3 Audioformat: Verlustlose Kompression



# Motivation Autoencoder



# Autoencoder

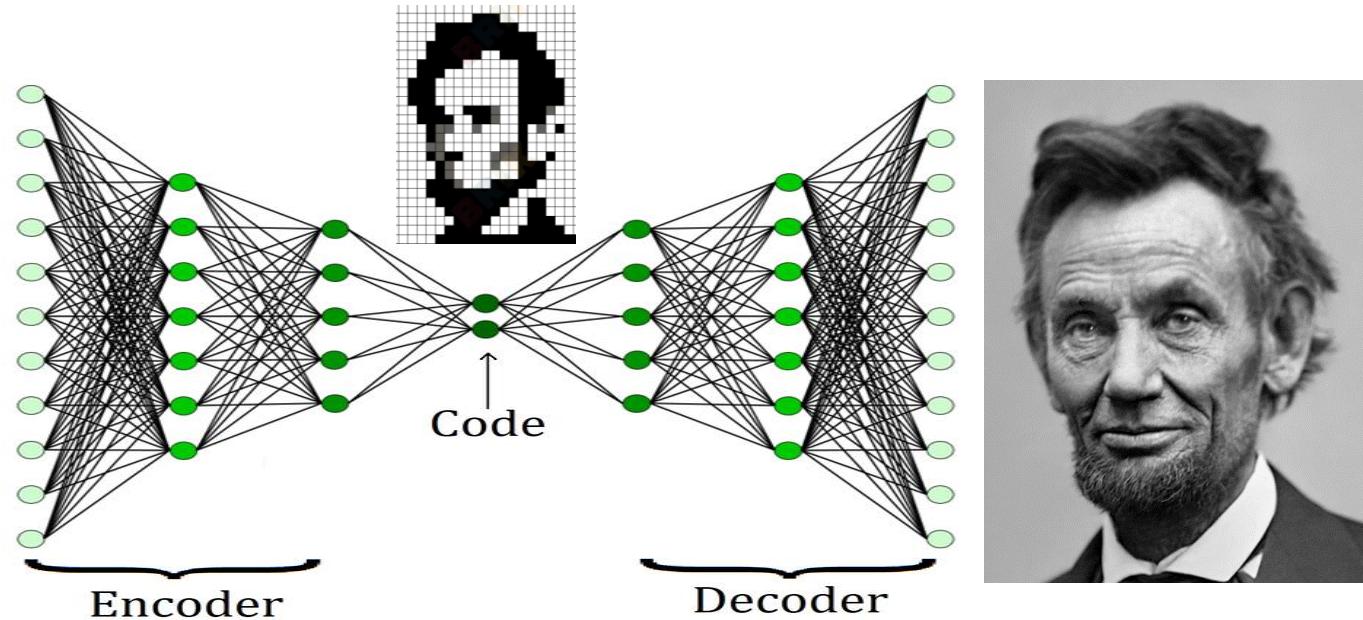
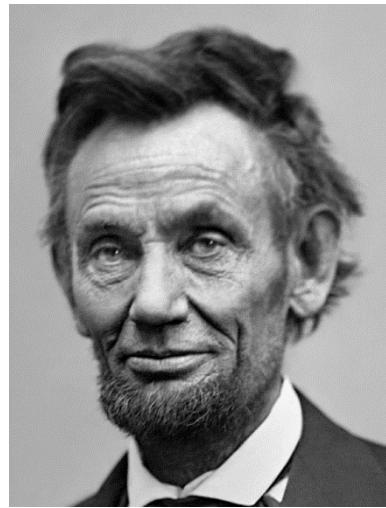


An **Autoencoder** is a type of artificial **neural network** used to **learn efficient data codings** in an **unsupervised manner**.

The aim of an **Autoencoder** is to learn a **representation (encoding)** for a **set of data**, typically for **dimensionality reduction**, by training the network to **ignore signal “noise”**.

Along with the **reduction side (Encoder)**, a **reconstructing side (Decoder)** is learnt, where the **Autoencoder** tries to **generate** from the **reduced encoding** a **representation** as **close as possible** to its **original input**, hence its name. ([Wikipedia](#))

# Autoencoder

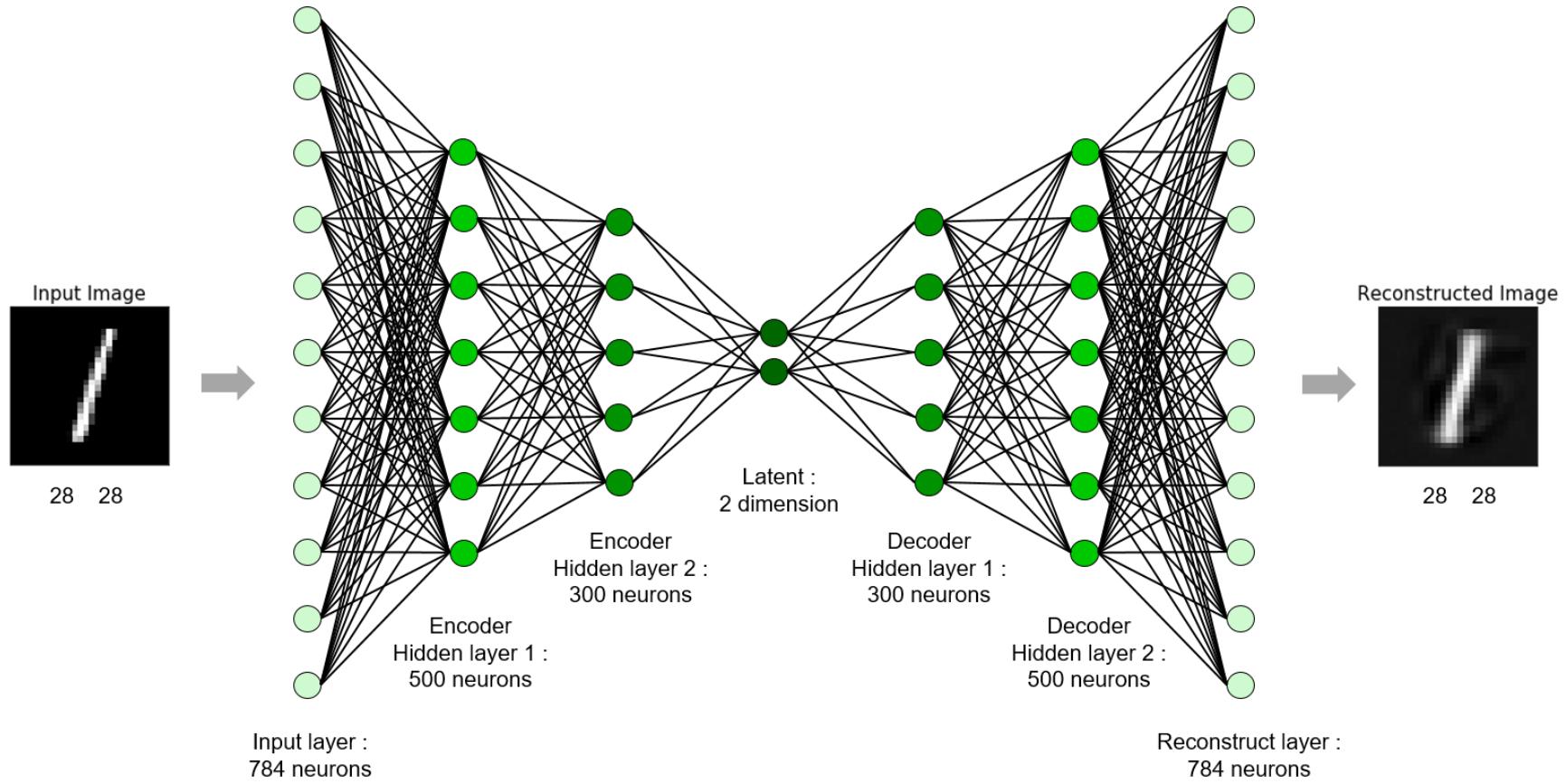


Der **Encoder** nimmt **Rohdaten** (z.B. Bilder oder Audio) und komprimiert die **Daten** auf eine **mehrfach kleinere Menge**.

Der **Decoder** nimmt diese **kleine Menge an Daten** und versucht daraus das **Original** wieder herzustellen.

Weil das **Modell Ende-zu-Ende trainiert** wurde, funktionieren sowohl **Decoder** und **Encoder** auch einzeln, z.B. nur **Encoder** oder **Decoder**, (vgl. **MP3, Video-Upscaling**).

# Autoencoder

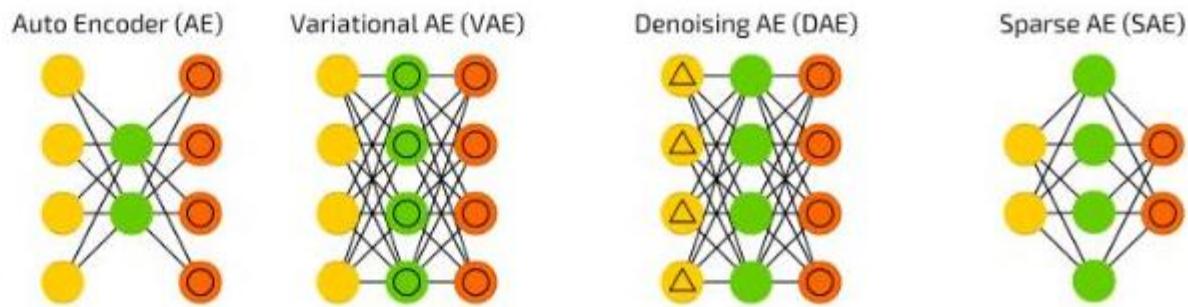


The ideal **Autoencoder** model balances the following:

- **Sensitive to the inputs enough to accurately build a reconstruction.**
- **Insensitive enough to the inputs that the model doesn't simply memorize or overfit the training data.**

# Autoencoder Architectures

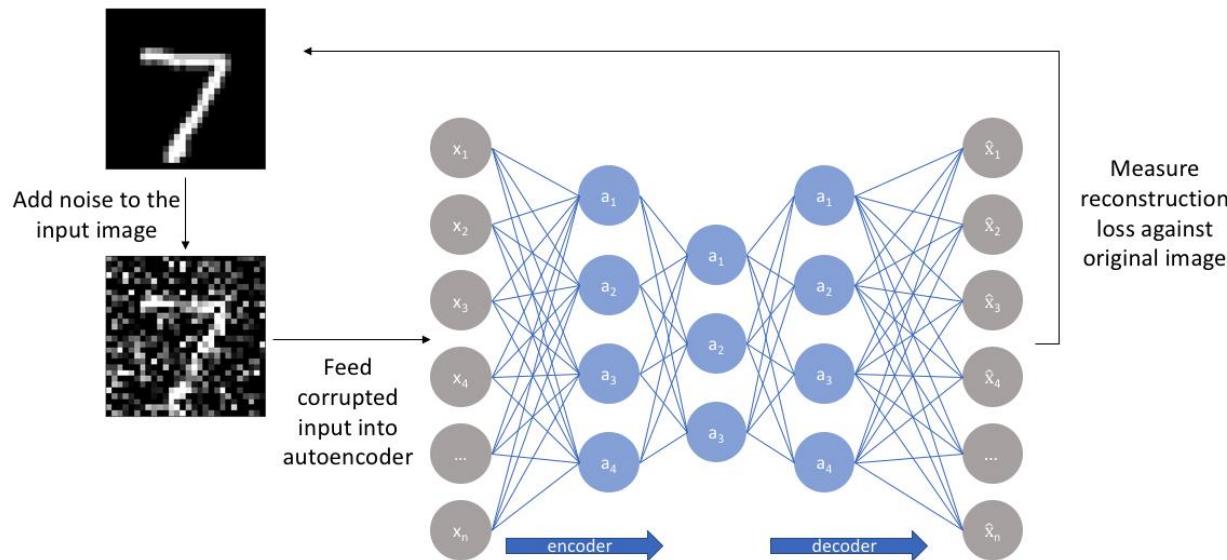
- (○) Backfed Input Cell
- (○) Input Cell
- (△) Noisy Input Cell
- (●) Hidden Cell
- (●) Probabilistic Hidden Cell
- (△) Spiking Hidden Cell
- (●) Output Cell
- (●) Match Input Output Cell
- (●) Recurrent Cell
- (●) Memory Cell
- (△) Different Memory Cell
- (●) Kernel
- (○) Convolution or Pool



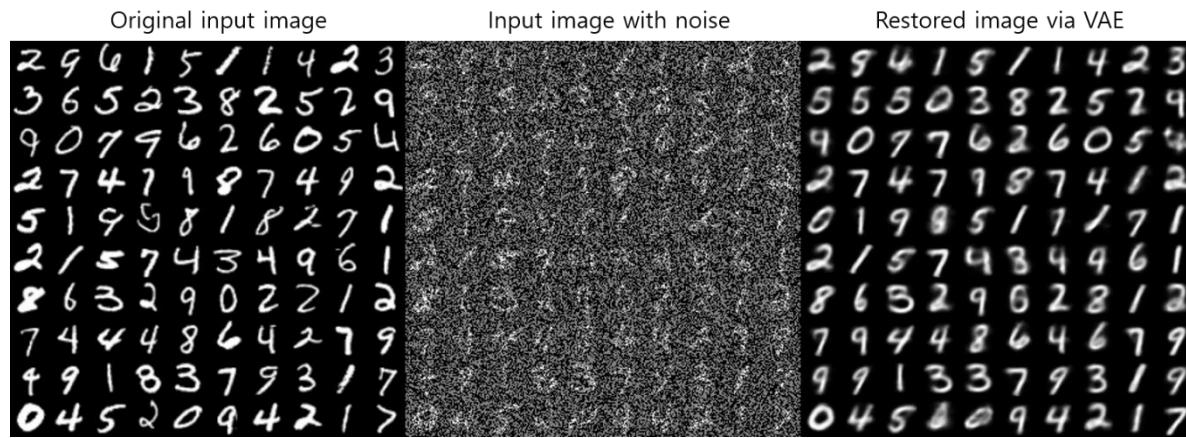
Es gibt unterschiedliche Autoencoder-Architekturen, z.B.:

- **Autoencoder (AE)**
- **Variational Autoencoder (VAE)**
- **Denoise Autoencoder (DAE)**
- **Sparse Autoencoder (SAE)**
- **Convolutional Autoencoder**

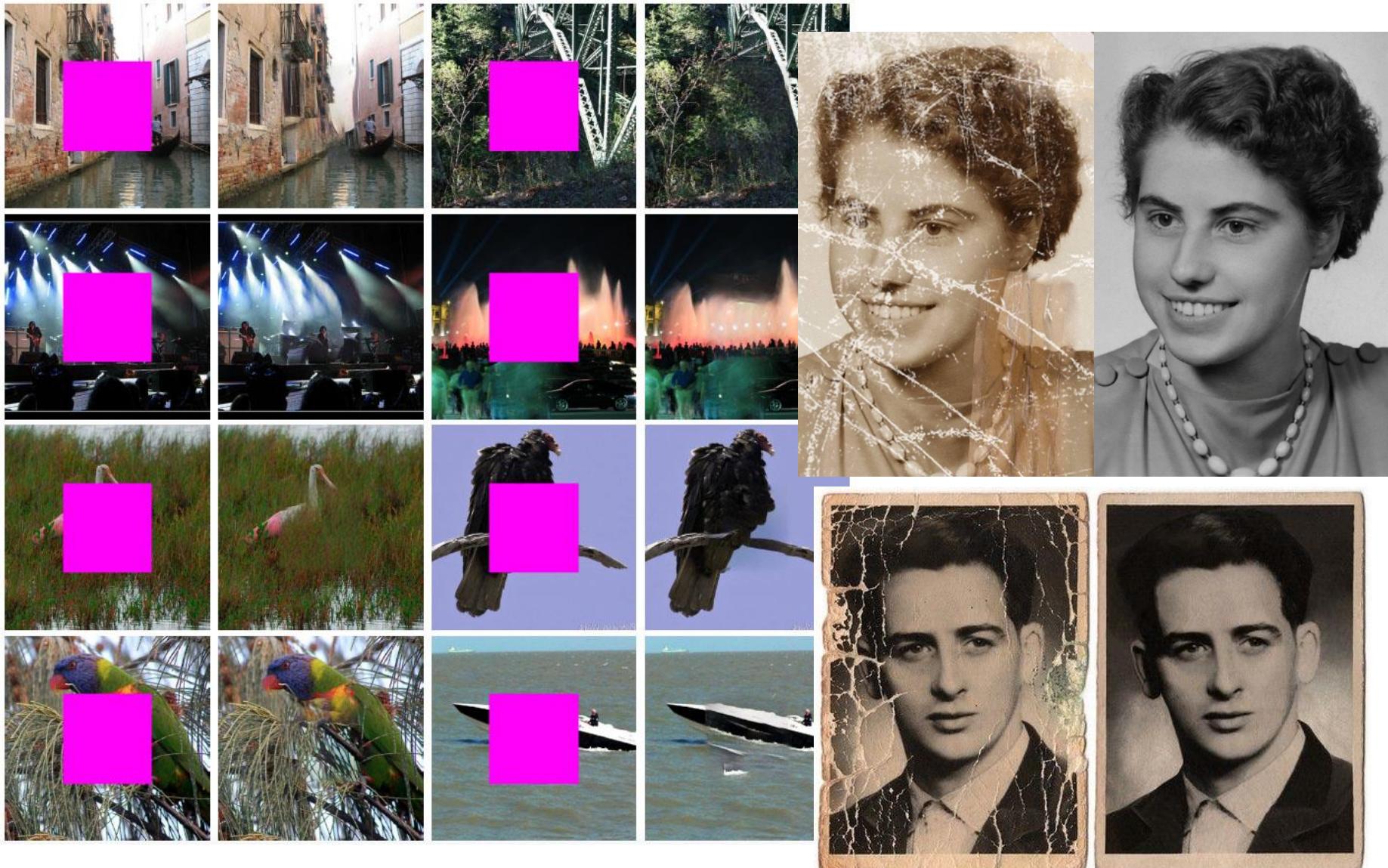
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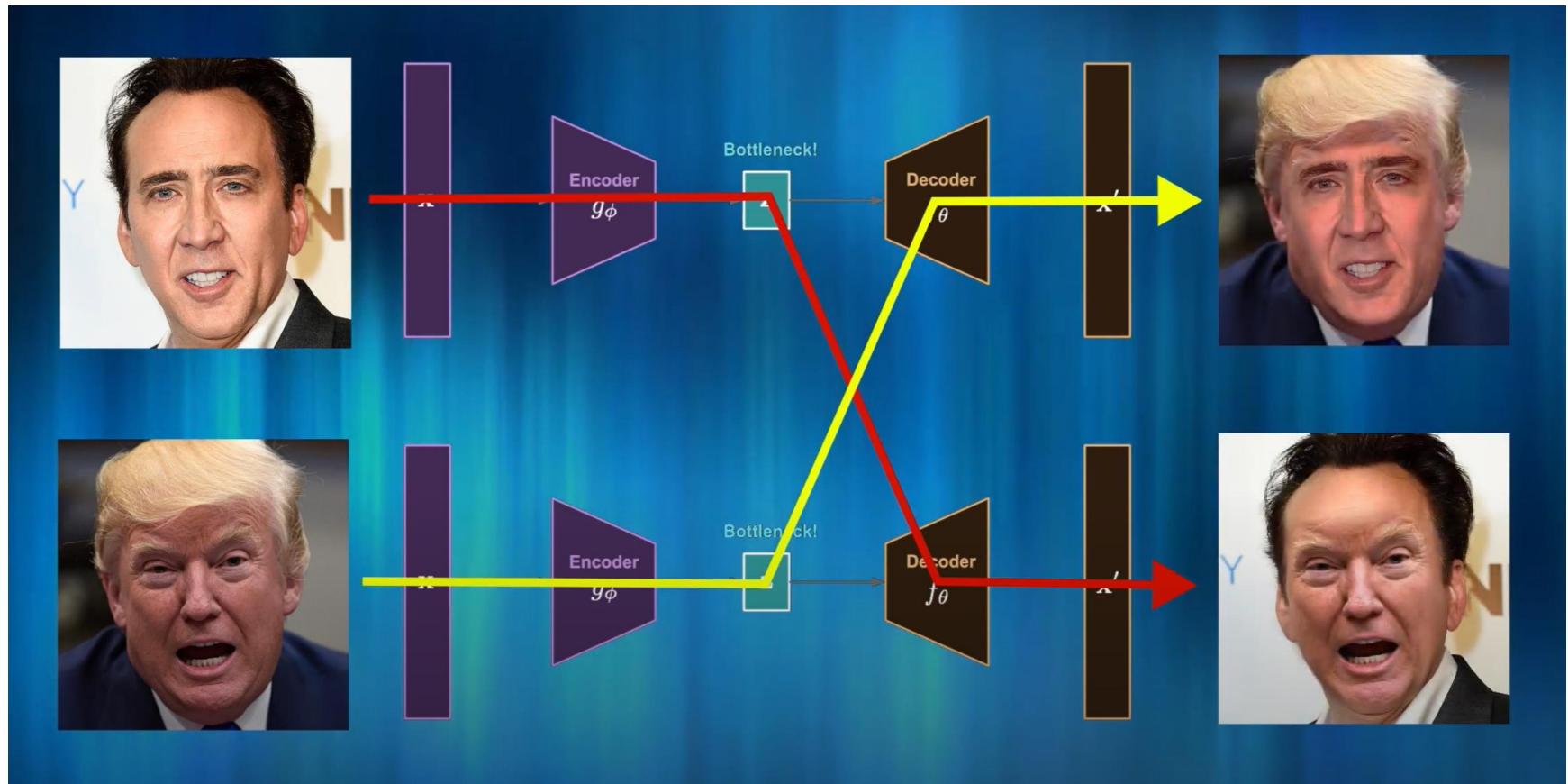


# Autoencoder for Image Inpainting



Guide to Image Inpainting: Using machine learning to edit and correct defects in photos, 2019  
[heartbeat.fritz.ai/guide-to-image-inpainting-using-machine-learning-to-edit...](http://heartbeat.fritz.ai/guide-to-image-inpainting-using-machine-learning-to-edit...)

# Autoencoder & Deep Fakes am Beispiel

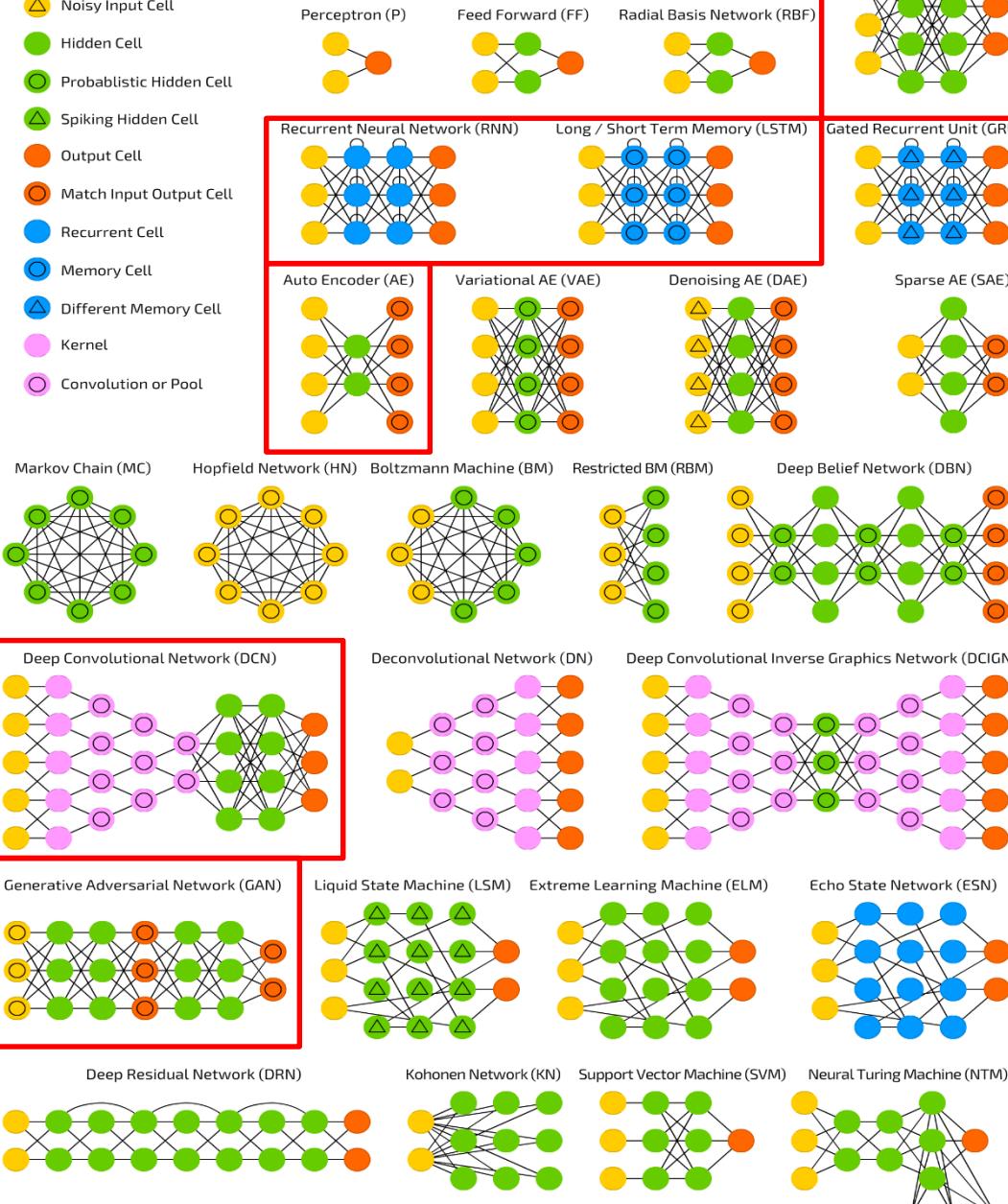


Fun With Autoencoders (Deep Fakes, Recommendation Engines & more), 2019  
[www.youtube.com/watch?v=LeeBnIZLTBs](https://www.youtube.com/watch?v=LeeBnIZLTBs)

# Neural Networks

©2016 Fjodor van Veen - [asimovinstitute.org](http://www.asimovinstitute.org)

- Backfed Input Cell
- Input Cell
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- Hidden Cell
- Probabilistic Hidden Cell
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- Memory Cell
- △ Different Memory Cell
- Kernel
- Convolution or Pool



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

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

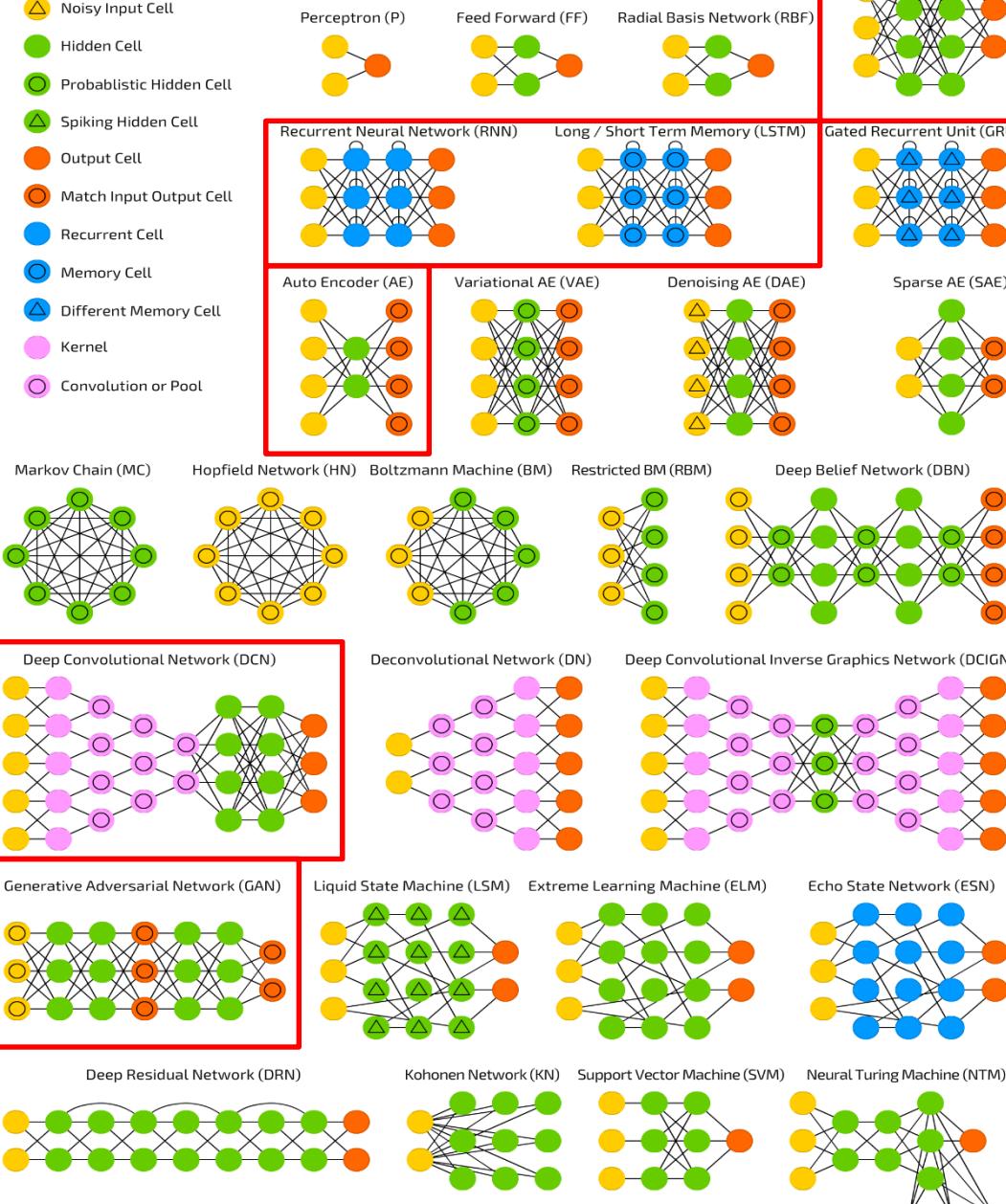
Die Wahl der **Architektur** hängt von der **Datenstruktur**, den **Dateninhalten** und der **Aufgabenstellung** ab.

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

# Neural Networks

©2016 Fjodor van Veen - [www.asimovinstitute.org](http://www.asimovinstitute.org)

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# OpenAI: Image GPT, Juni 2020

## Generative Pretraining from Pixels

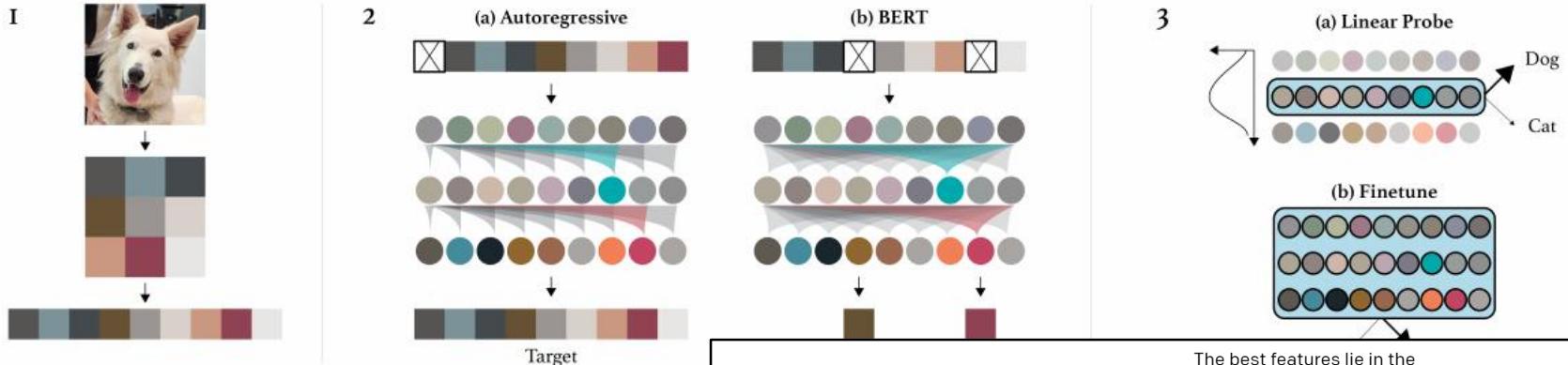


Figure 1. An overview of our approach. First, we pre-process raw images into a 16x1 vector. We then chose one of two pre-training objectives, auto-regressive or BERT, to learn representations. Finally, we fine-tuned the representations learned by these objectives with linear probes.

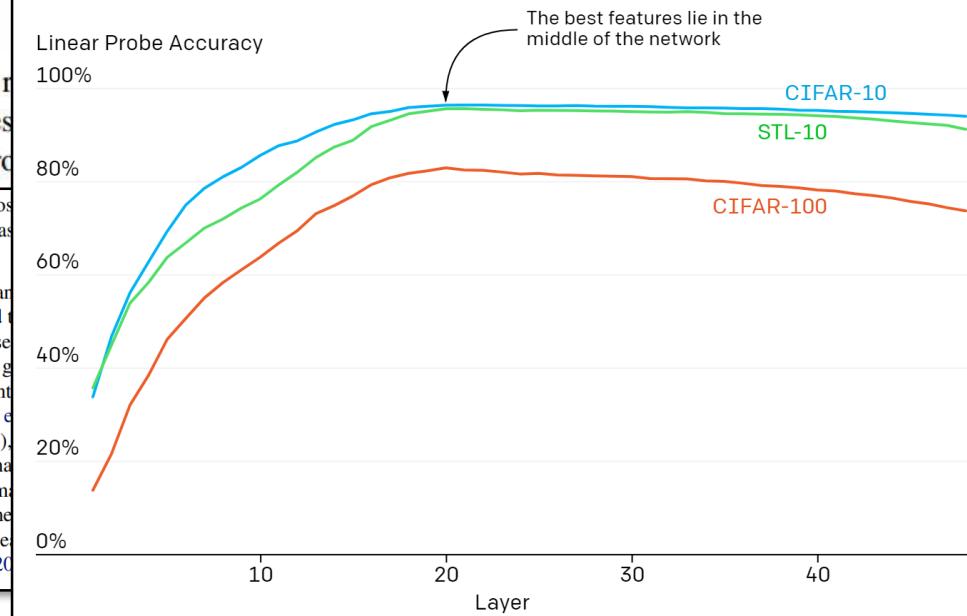
ture of ImageNet and web images is competitive with self-supervised benchmarks on ImageNet, achieving 72.0% top-1 accuracy on a linear probe of our features.

prediction of corrupted inputs, closely matching the Denoising Autoencoder, which was trained on raw images.

As a higher dimensional, noisier, and more complex than text, images are believed to require more sophisticated modeling. Here, self-supervised learning objectives encourage the modeling of more general features. Recent work (Ordóñez et al., 2015) have shown significant improvements in the quality of new training objectives (Ordóñez et al., 2015). In addition, new architectures (Gomez et al., 2017), and new training strategies (Kolesnikov et al., 2019) have enabled generative models to achieve state of the art performance (Hénaff et al., 2019) and sometimes even surpass supervised representations in transfer learning (Misra & van der Maaten, 2019).

## 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-



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.