technische universität
dortmund

Lehrstuhl 11
Fakultät für Informatik

Maschinelles Lernen und Visualisierung

Praktische Beispiele und Umsetzung in Python

Marco Pleines | Kamp-Lintfort, 04.06.2019

Source Code and Slides

- Source Code: https://bit.ly/2Kr64AG
- Slides: https://bit.ly/2WKZawv

PC-Pool Accounts

- Password: Besuch#2019
- Fill in the passed out sheet and sign it

Hi!

I am Marco Pleines

- PhD at TU Dortmund
- Former Hochschule Rhein-Waal
- Deep Reinforcement Learning

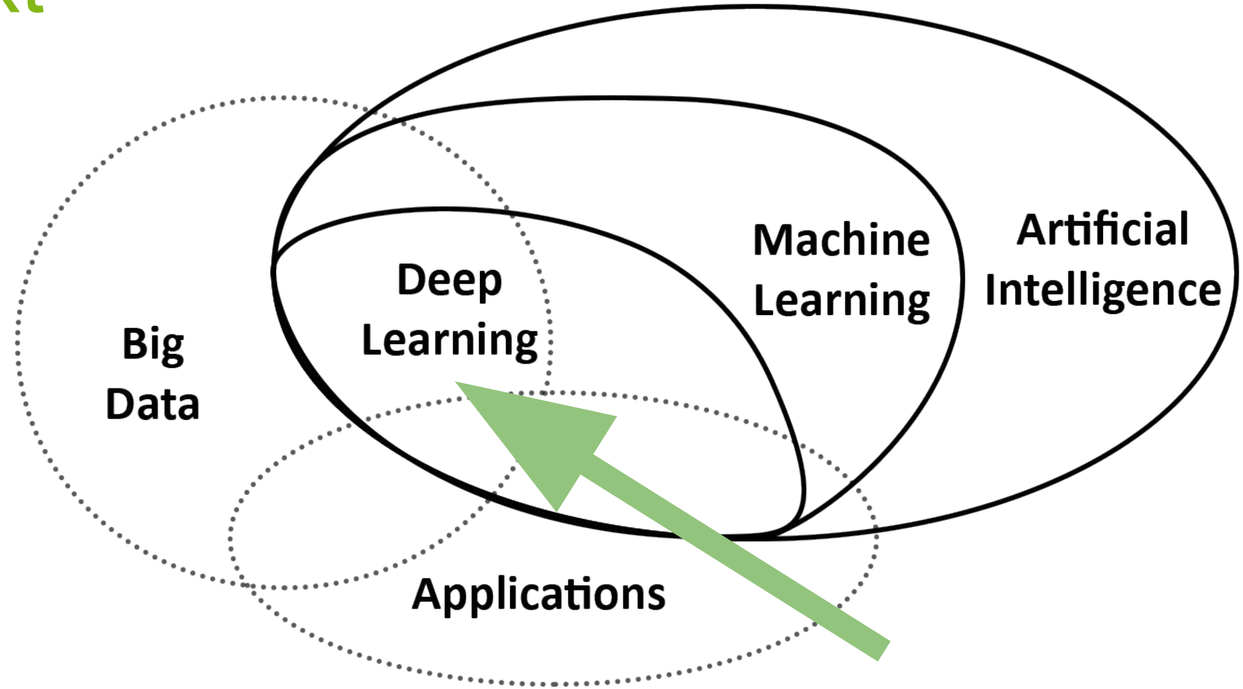
Convolutional Neural Networks & Generative Adversarial Networks

Agenda

1.	Deep Learning	15 min
2.	Convolutional Neural Networks	15 min
	+ Hands-on Session	45 min
	+ Wrap Up	5 min
3.	Break	15 min
4.	Adversarial Neural Networks	15 min
	+ Hands-on Session	20 min
5.	Conclusion	5 min

Deep Learning

Context

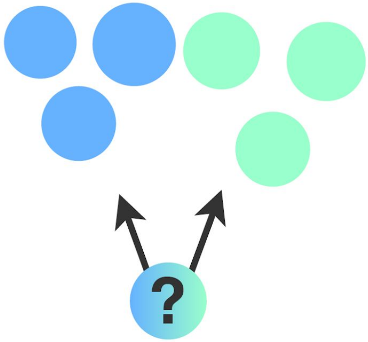

Machine
Learning
Artificial
Intelligence
Deep
Learning
Big
Data
Applications

Machine Learning Types

Supervised Learning

Regression

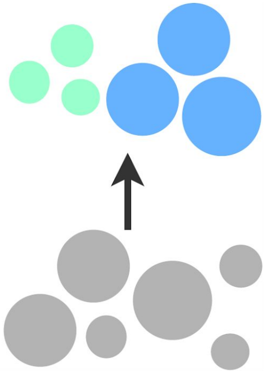
Classification



Unsupervised Learning

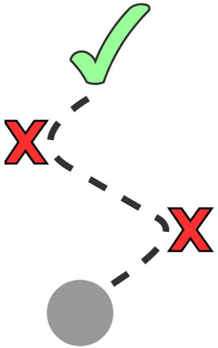
Clustering

Association



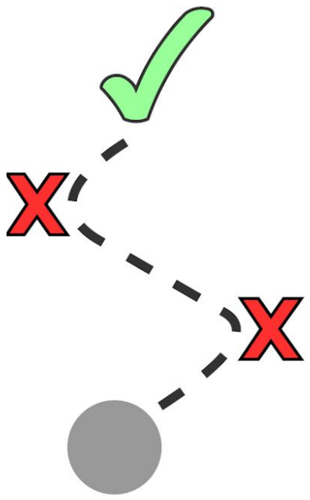
Reinforcement Learning

Sequential Decision Making



Reinforcement Learning

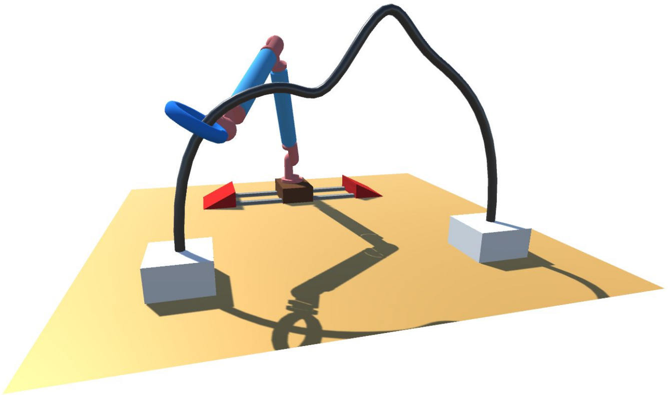
- Sequential decision making in a trial-and-error manner
- Normally no pre-existing dataset
- Data is being generated dynamically
- Agent learns based on reward signals
- Rewards may be sparse and delayed



Reinforcement Learning

Examples:

- Autonomous driving
- Robotics
- Playing games
- Controlling cooling systems



https://youtu.be/cMpzwoR6okY

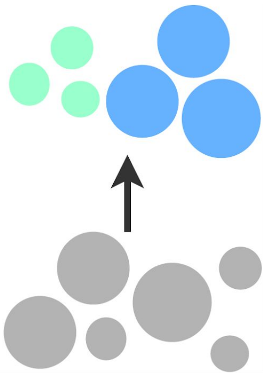
Unsupervised Learning

- Goal: Modelling the structure and distribution of data

- Association: Discovering rules, which describe portions of the data
- Clustering: Finding distinctive groups within data

Milk → Diaper → Eggs → Beer

Association



Clustering

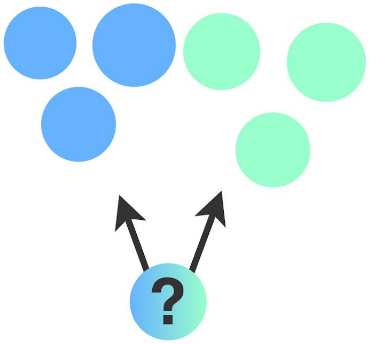
Unsupervised Learning

Examples:

- Customer segmentation
- Anomaly detection
- Fraud detection
- Analyzing customer behavior

Supervised Learning

- Mapping input to an output $f(\overrightarrow{x}) = \overrightarrow{y}$
- Classification: output represents categories
  - i.e. classes, e.g. cats and dogs
- Regression: output represents real numbers
  - e.g. real estate numbers



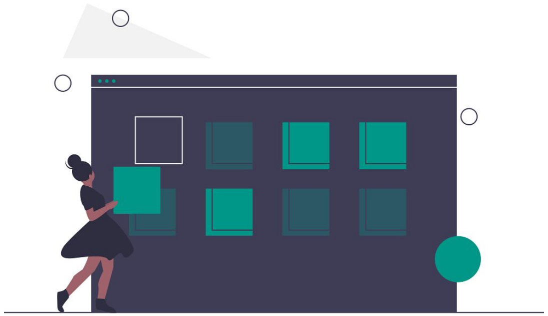
Classification

Regression

Supervised Learning

Examples:

- Medical diagnosis
- Speech recognition
- Prediction of stock prices
- Image classification



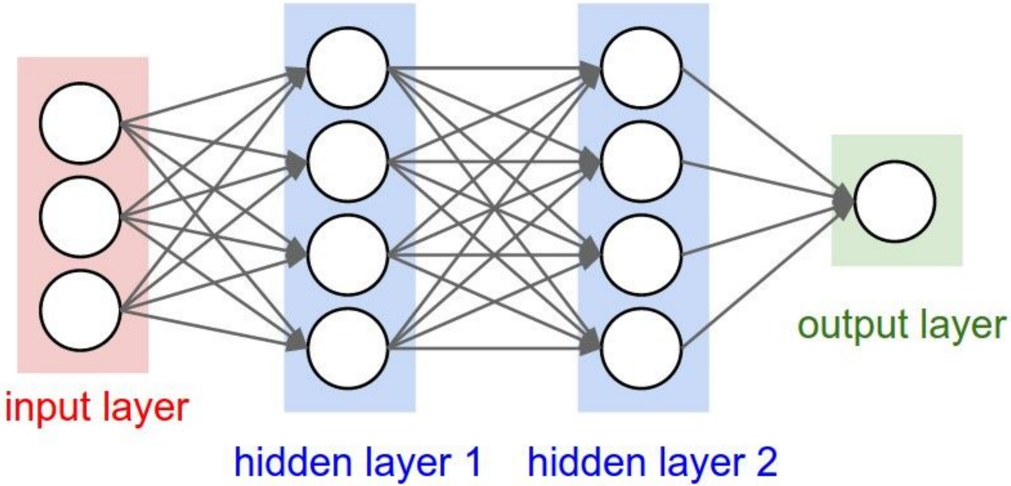
Deep Learning

- **Deep Learning**: A function made of simpler functions
- The world: A hierarchy of concepts based on experience
- Computers learn from complicated concepts by building them out of simpler ones
- A representation as graph would feature many layers that make it **deep**

(see Goodfellow et al., 2016)

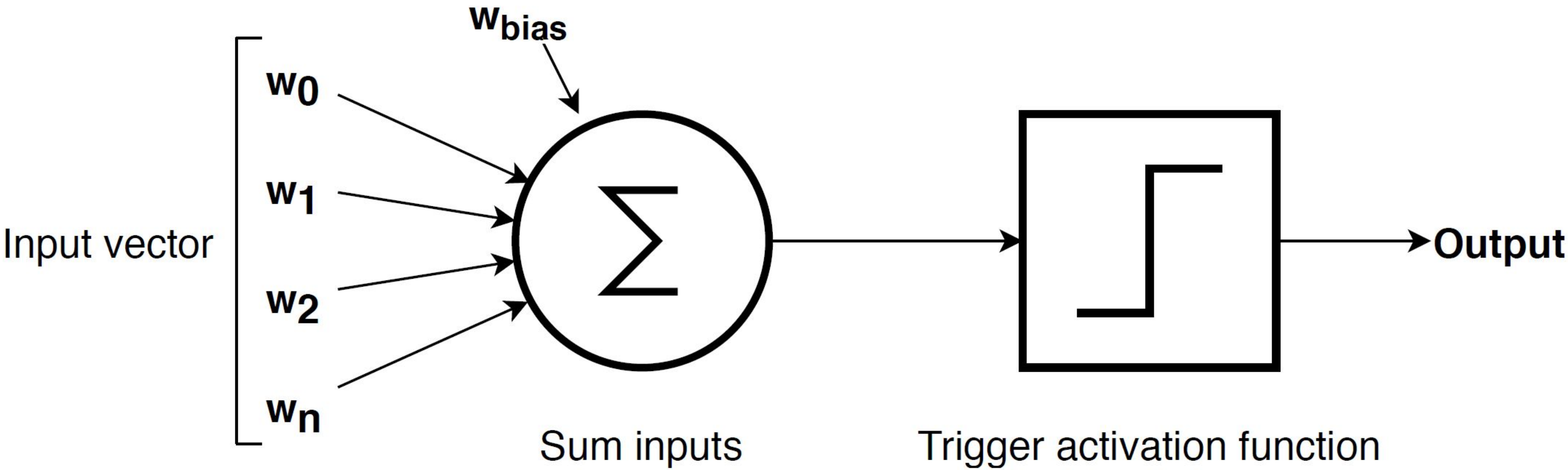
Convolutional Neural Networks

Artificial Neural Networks

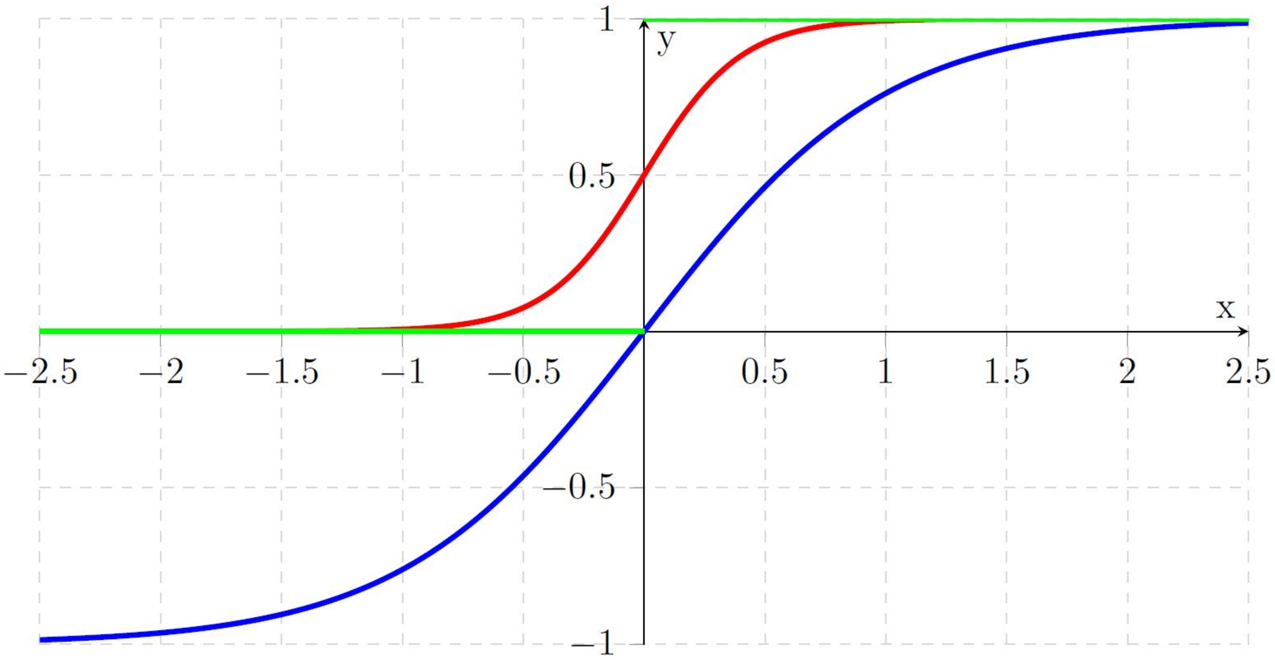


(Karpathy, 2019)

The Perceptron



Activation Functions



Step Function
Sigmoid Function
Hyperbolic Tangent Function

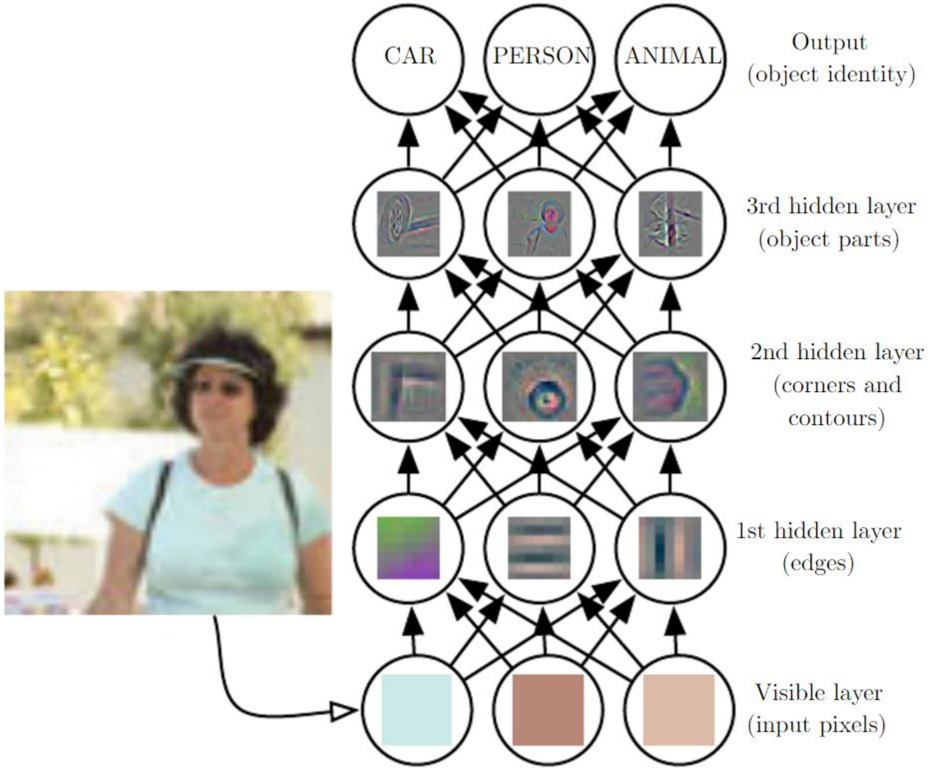
Training the Network

1. Data is fed to the neural network
2. The output predictions are compared to the real labels
3. A loss function determines how much apart the predictions are from the labels
4. The weights of the neural net are slowly adjusted to make better predictions (minimizing the loss)

3blue1brown Youtube Channel

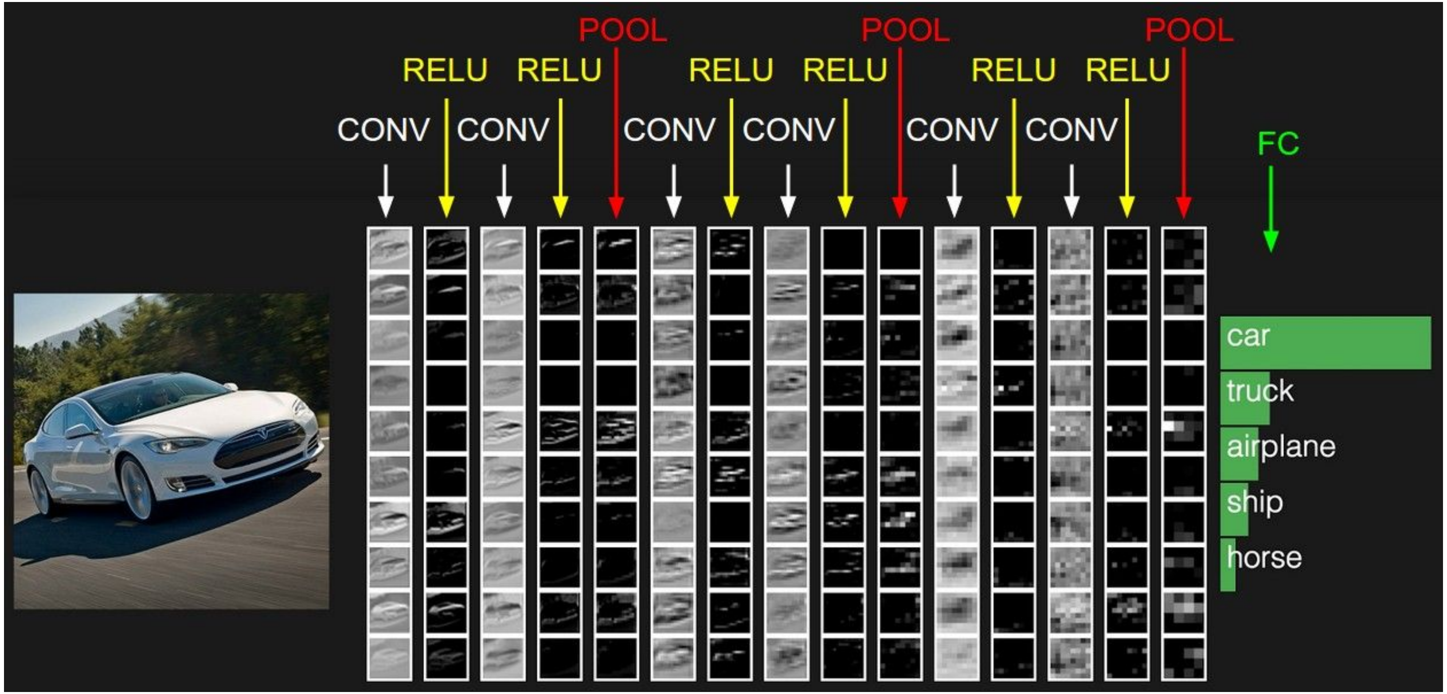
Convolutional Layers

- Image input
- Extracts spatial information



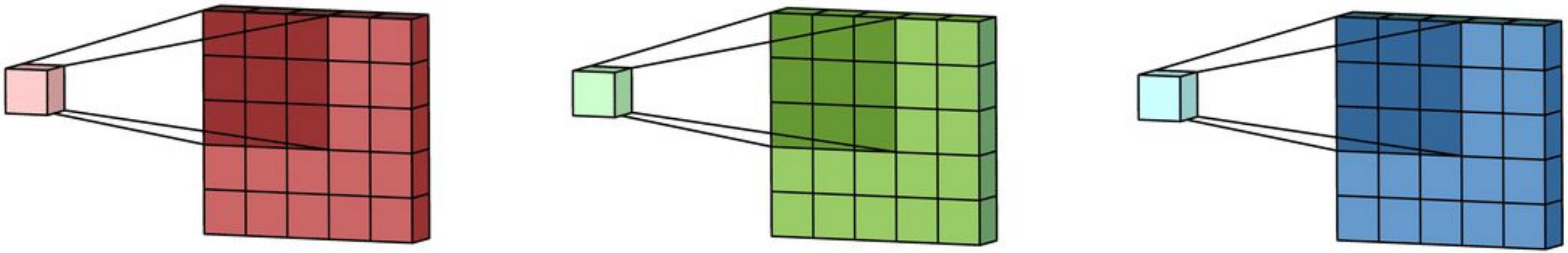
(Goodfellow et al., 2016)

Convolutional Layers



(Karpathy, 2019)

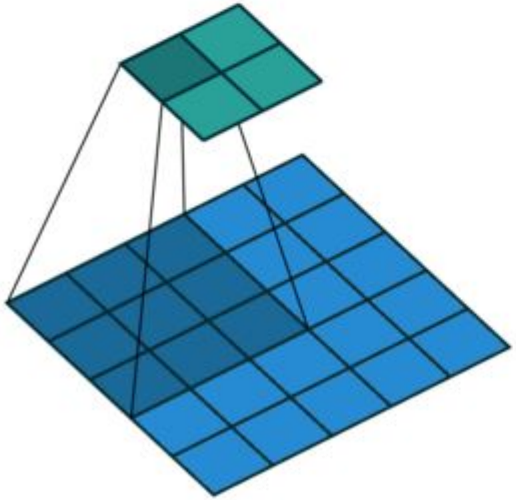
Convolutional Layers



(Shafkat, 2018)

Pooling Layers

- Purpose: Reduce input size
- The average or maximum value across a number of pixels is extracted



(Shafkat, 2018)

Hands-On Session!

Hands-On Session - CNN

Your task:

1. Create a custom dataset

2. Train a Convolutional Neural Network on your dataset

Hands-On Session - CNN

Instructions:

1. Open “Anaconda Prompt”
2. Type “activate visualize-2019” and hit enter
3. Type “cd visualize-2019” and hit enter
4. Type “jupyter notebook” and hit enter
5. Open “Convolutional-Neural-Network.ipynb”

Wrap Up!

Who achieved the best accuracy?

Generative Adversarial Networks

Marco Pleines | Kamp-Lintfort, 04.06.2019

Phoney Obama Speech

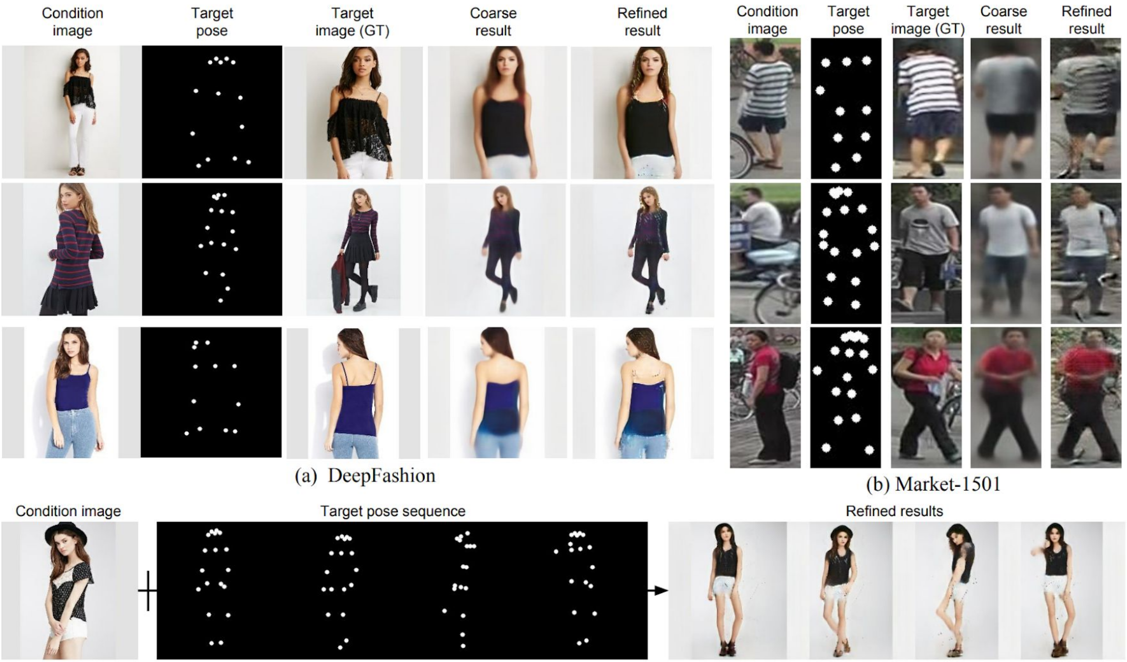
https://youtu.be/cQ54GDm1eL0

Generative Adversarial Networks can generate new data that match the scheme of its training data!

Anime Faces using Style GAN

https://twitter.com/gwern/status/1095131651246575616?lang=en

Pose Guided Person Image Generation



(Ma et al., 2017)

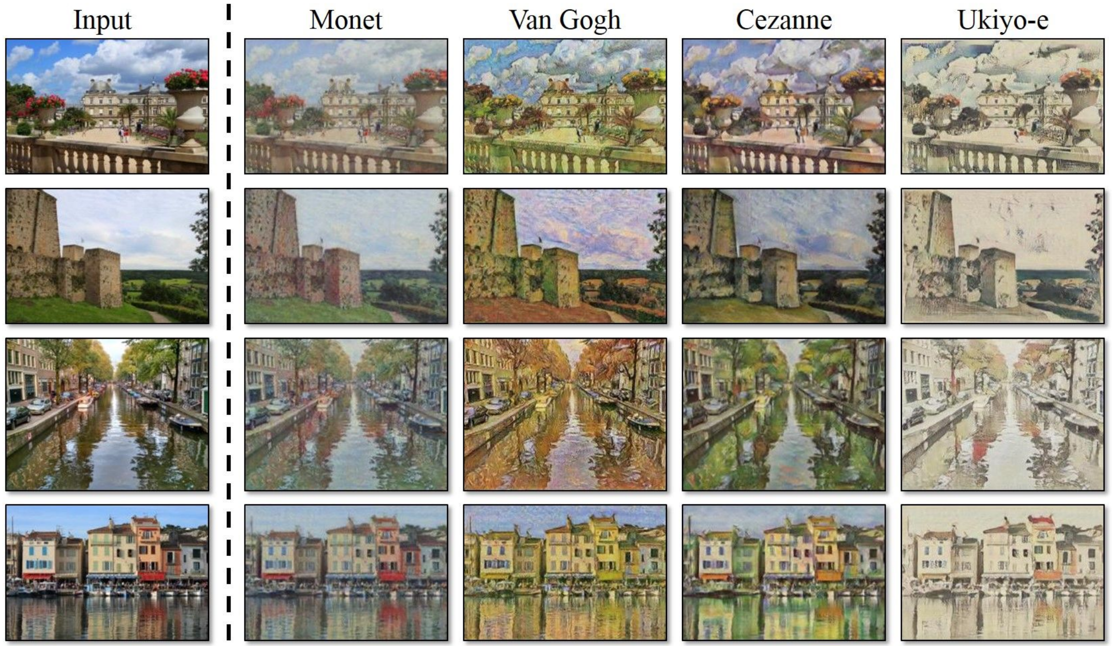
Cycle GAN - Horse to Zebra

(Zhu et al., 2017), https://github.com/junyanz/CycleGAN

Cycle GAN - Failures

(Zhu et al., 2017), https://github.com/junyanz/CycleGAN

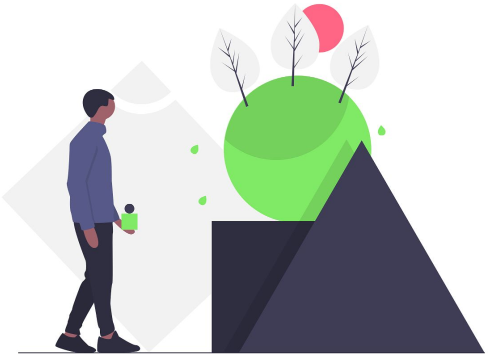
Cycle GAN - Style Transfer



(Zhu et al., 2017)

And much more …

- 3D Models
- Hotel room proposals
- Music
- Change seasons of a landscape in an image
- Black & White to Color

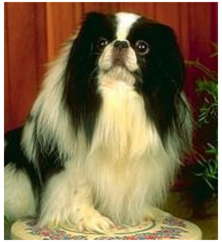


And much more …

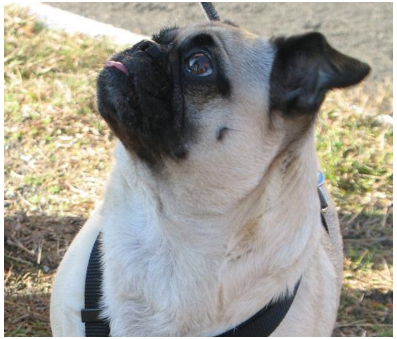
- https://github.com/nashory/gans-awesome-applications
- https://medium.com/@jonathan_hui/gan-some-cool-applications-of-gans-4c9ecca35900
- https://www.gwern.net/Faces#applications

But how does a GAN work

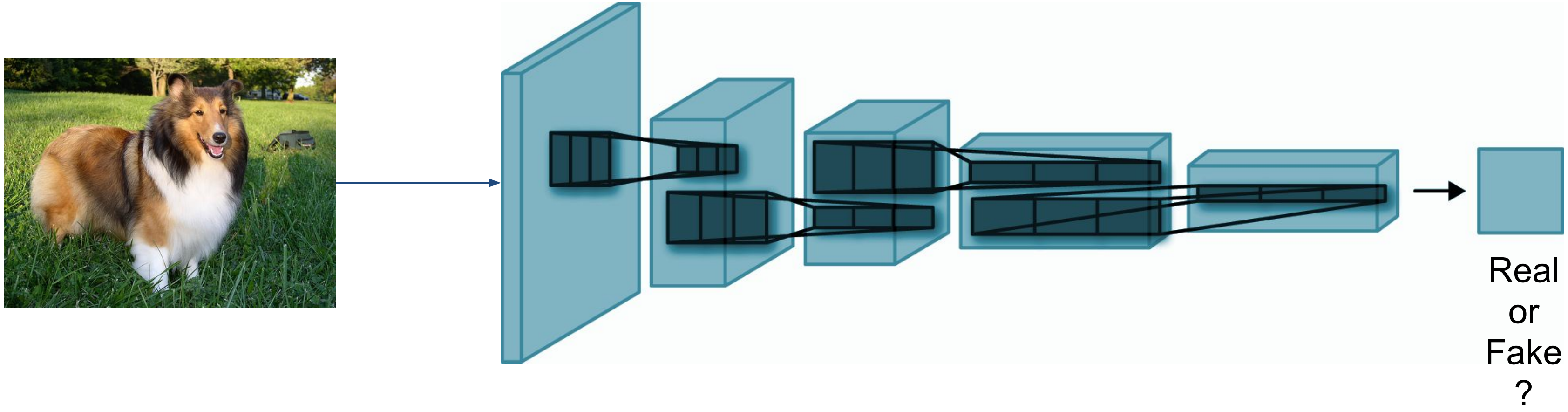
Lets assume this is our dataset …



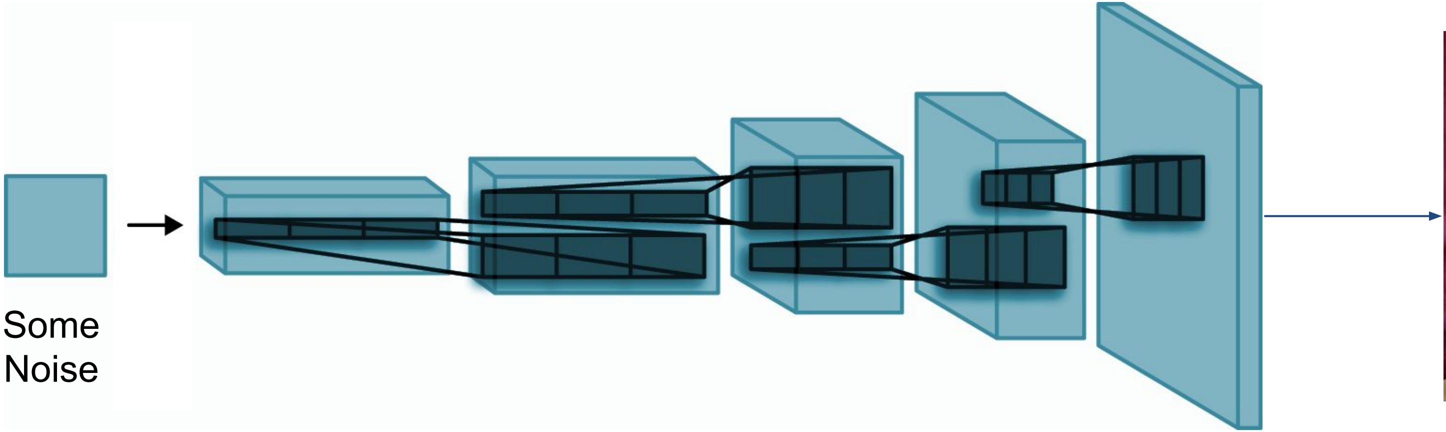
True dogs …



Discriminator

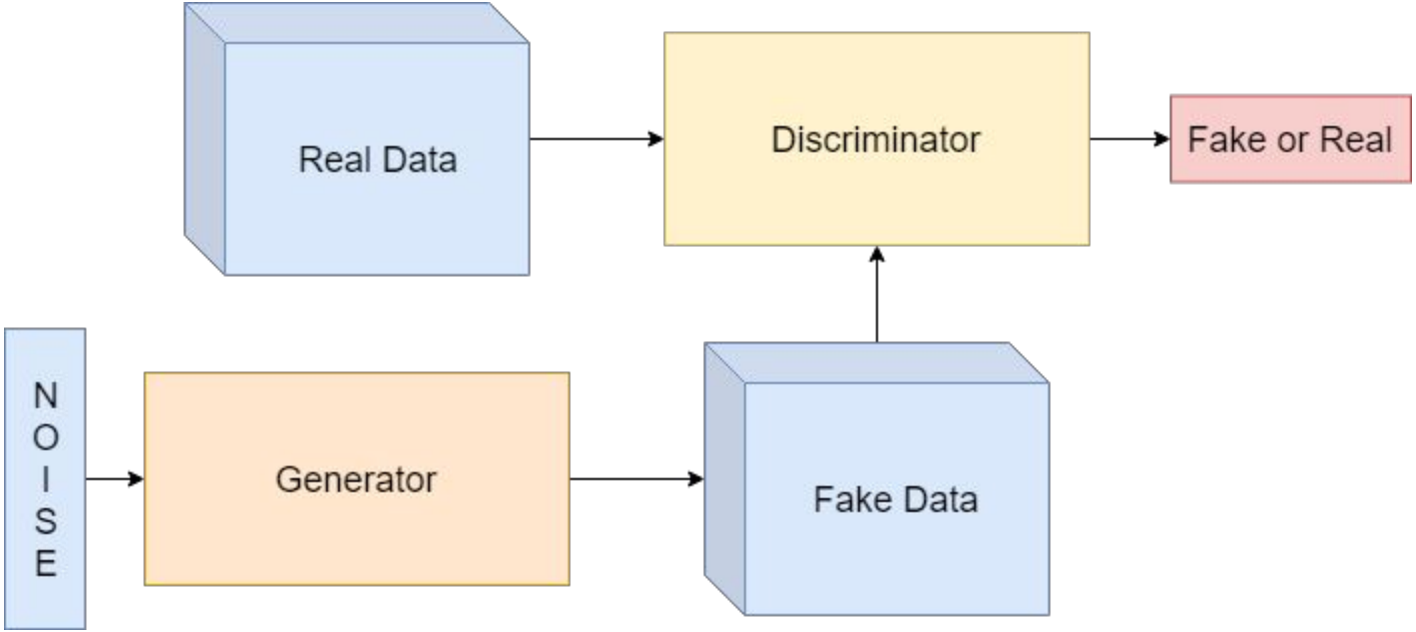


Generator



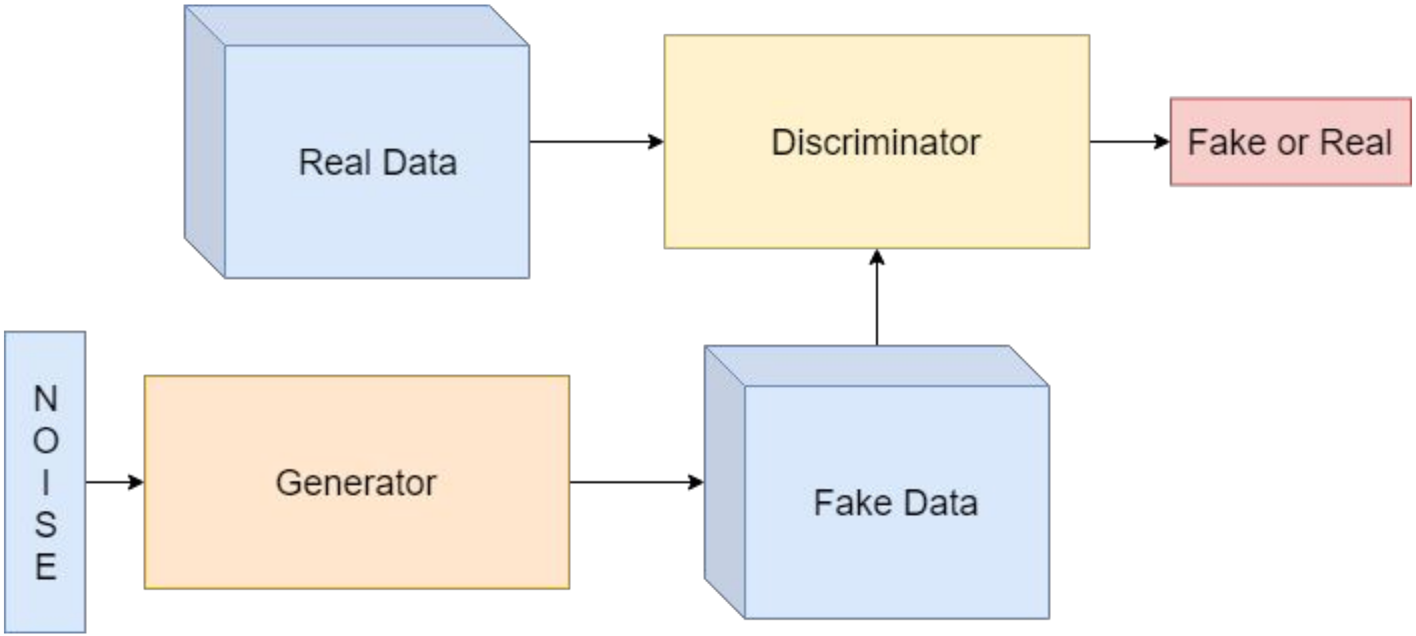
Discriminator and Generator Interplay

The generator tries to outsmart the discriminator.



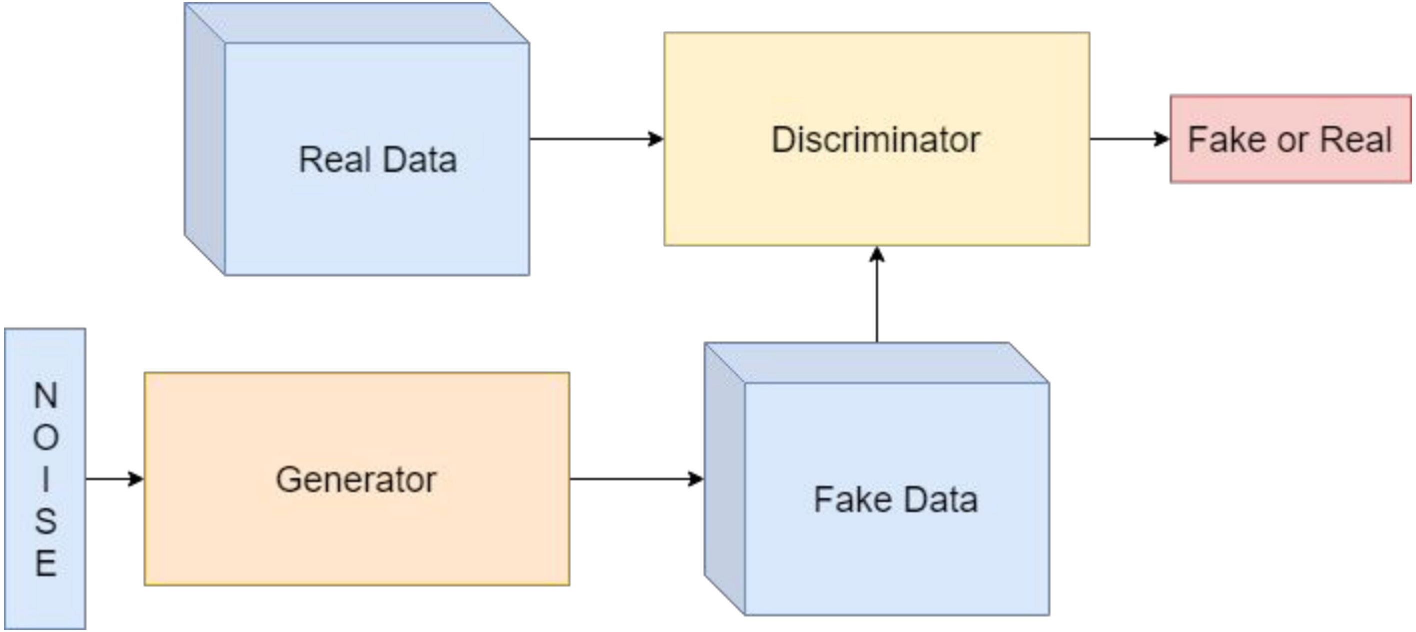
Discriminator and Generator Interplay

The generator tries to minimize the probability of fake data.



Discriminator and Generator Interplay

The discriminator tries to maximize the probability of real data.



Training the Networks

1. Generate fake data from generator

2. Optimize discriminator on real and fake data

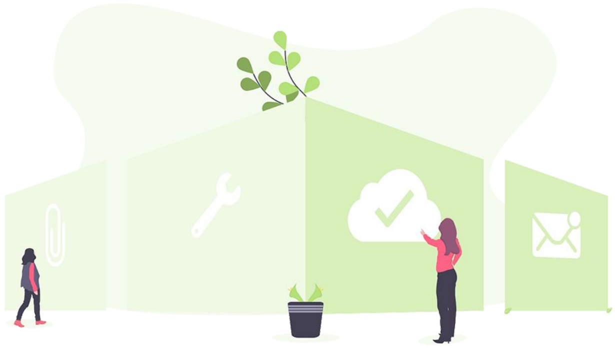
3. Optimize generator depending on the discriminator’s performance

Hands-On Session!

Hands-On Session - GAN

Task

- Try out different GAN demos!



Instructions:

- Open “Generative-Adversarial-Networks.ipynb”

Conclusion

Where will we go from here?

Thank you for participating!

References

Goodfellow, I., Bengio, Y., and Courville, A. (2016). Deep Learning. MIT Press. Available at http://deeplearningbook.org retrieved May 27, 2019

Karpathy, A. (2019), Convolutional Neural Networks: Architectures, Convolution / Pooling Layers. Available at http://cs231n.github.io/convolutional-networks/ retrieved May 27, 2019

Sanderson, G. (2017), Neural networks. Available at https://www.youtube.com/playlist?list=PLZHQObOWTQDNU6R1_67000Dx_ZCJB-3pi retrieved May 27, 2019

References

Shafkat, I. (2018). Intuitively Understanding Convolutions for Deep Learning. Towards Data Science. Available at https://towardsdatascience.com/intuitively-understanding-convolutions-for-deep-learning-1f6f42faee1 retrieved May 28, 2019

Ma, L., Jia, X., Sun, Q., Schiele, B., Tuytelaars, T., Van Gool, L. (2017). Pose Guided Person Image Generation. NIPS. Available at https://papers.nips.cc/paper/6644-pose-guided-person-image-generation.pdf retrieved May 28, 2019.

Zhu, J., Park T., Isola, P., Efros, A. (2017). Unpaired Image-to-Image Translation using Cycle-Consistent Adversarial Networks. IEEE 2017 Conference on Computer Vision (ICCV).