

Deep Learning Summer School – 25.08.2022

Dr. Pedro Achanccaray Diaz p.diaz@tu-braunschweig.de

Outline

1. Introduction

- 1) Deep Learning
- 2) Machine Learning
- 3) Artificial Neural Networks
- 4) Computer Vision
- 5) Remote Sensing
- 6) Computer Vision tasks
- 2. Application: Automatic detection of system halls
- 3. Lab







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Artificial Intelligence (AI)

A technology with wich we can create intelligent systems that can simulate human intelligence.

• Weak / General Al













 Hello! May I help you?
 Check availability
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 Please, tell me your address
 1013 Centre Rd, Suite 403-B Wilmington, Delaware 19805
 Delivery will take 2-3 days A technology with wich we can create intelligent systems that can simulate human intelligence.

• Weak / General Al



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Artificial Intelligence (AI)



A technology with wich we can create intelligent systems that can simulate human intelligence.

- Weak / General Al
- Strong AI (reasoning, judging, learning, communicating, awarenss, self-awareness)







Artificial Intelligence (AI)

Machine Learning (ML)

Al's subfield which allows machines to learn from data or past experience without being explicitly programmed.

A technology with wich we can create intelligent systems that can simulate human intelligence.



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Artificial Intelligence (AI)

Machine Learning (ML)

Machine Learning Examples



Al's subfield which allows machines to learn from data or past experience without being explicitly programmed.

A technology with wich we can create intelligent systems that can simulate human intelligence.







Artificial Intelligence (AI)

Machine Learning (ML)

Deep Learning (DL)

A type of ML algorithms that uses multiple layers to progressively extract higher-level features.

Image processing:

- Lower layers: identify edges
- Higher layers: identify relevant concepts for a human being (digits, letters, faces)

Al's subfield which allows machines to learn from data or past experience without being explicitly programmed.

A technology with wich we can create intelligent systems that can simulate human intelligence.







Artificial Intelligence (AI)

Low Level Features

Machine Learning (ML)

Deep Learning (DL)

A type of ML algorithms that uses multiple layers to progressively extract higher-level features.

Image processing:

- Lower layers: identify edges
- Higher layers: identify relevant concepts for a human being (digits, letters, faces)



Mid Level Features



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Autonomous driving









Autonomous driving



Sentiment analysis









Autonomous driving



Text synthesis

README.md

GOT Book 6 Generator

Are you tired of waiting for the next GOT book to come out? I know that I am, which is why I decided to train a RNN on the first five GOT books and use predictions from the network to create the sixth book in the series. The first five chapters of the generated sixth book are now available and are packed with as many twists and turns as the books we've all come to know and love. Here's the sparknotes summary:









Autonomous driving



Text synthesis

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Sentiment analysis



Automatic translation





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1.2. Machine Learning – Algorithms

Algorithms that can learn from *data*.







1.2. Machine Learning – Algorithms

Algorithms that can learn from *data*.

"A computer program is said <u>to learn</u> from experience *E* with respect to some class of tasks *T*, and performance measure *D*, if its performance on tasks *T*, as measured by *D*, improves with experience *E*." – Mitchell, 1997.





1.2. Machine Learning – Algorithms

Algorithms that can learn from *data*.









Tasks are described in terms of how the machine learning system should process a sample.





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A **sample** is a collection of *features* that have been *quantitatively* measured from some *object* or *event*.





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A **sample** is a collection of *features* that have been *quantitatively* measured from some *object* or *event*.

Representation of a **sample**:

$$x \in \mathbb{R}^n$$
, $x = [x_1, x_2, ..., x_n]$, $x_i \Rightarrow$ feature, attribute, characteristic





- Classification
- Regression
- Automatic translation
- Sampling and synthesis



. . .

.



- Classification
- Regression
- Automatic translation
- Sampling and synthesis



. . .

Specify which of the k categories a sample belongs to.









•

•



- Classification
- Regression
- Automatic translation
- Sampling and synthesis

Specify which of the k categories a sample belongs to.

output, categories

identified by a



 $\mathbf{y} = f(\mathbf{x})$



. . .





input

 $x = [x_1, x_2, \dots, x_n]$

Predict a numerical value given an input.

- Classification
- Regression
- Automatic translation
- Sampling and synthesis



. . .

.





Classification

Regression

- Automatic translation
- Sampling and synthesis

Predict a numerical value given an input.





. . .

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igp

Input: a sequence of symbols in some language *Output:* a sequence of symbols in another language

- Classification
- Regression
- Automatic translation
- Sampling and synthesis



. . .





- Classification
- Regression
- Automatic translation
- Sampling and synthesis

Input: a sequence of symbols in some language *Output:* a sequence of symbols in another language



Old offline translation New offline translation ● ENGLISH ☆ The evenings are likely to rain, please take the umbrella with your ● ENGLISH ③ offline □ ③ offline □



. . .



Generate new samples that are similar to those of the training data.

- Classification
- Regression
- Automatic translation
- Sampling and synthesis



. . .

.



- Classification
- Regression
- Automatic translation
- Sampling and synthesis

Generate new samples that are similar to those of the training data.

https://www.thispersondoesnotexist.com/







. . .

1.2. Machine Learning – Performance measure *D*

The *performance measure D* is specific to the *task T*.





1.2. Machine Learning – Performance measure *D*

The *performance measure D* is specific to the *task T*.

Task: classification, accuracy is usually measured

- Proportion of samples for which the model produces the correct output.
- *Error rate:* proportion of samples for which the model produces an incorrect output.





1.2. Machine Learning – Experience E

Unsupervised learning

• Supervised learning





1.2. Machine Learning – Experience *E*

Unsupervised learning

Learns from samples represented by features

• Supervised learning









1.2. Machine Learning – Experience *E*

Recommender systems



Learns from samples represented by features

Supervised learning



Bedsure Dog Cushion, Washable rh. Waterproof Dog Bed L for Large, Medium Dogs, Padded Mat, Grey in 10 cm Height, 90 x 68 cm Visit the Bedsure Store azon's Choice for "hunde bett"



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BuenoPet - Orthopaedic Dog Cushion | Dog Mat | Ergonomic Dog Bed Washable Mat | D...

OLNIRA Strong Mink Dog Bed and Sofa with Oeko-Tex Certificate, Removable Washable C...

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MSRNSIY Plush Dog Bed, medium dog sofa, washable super soft dog basket, dog basket

JOYELF Memory Foam Dog Bed, Orthopaedic Dog Bed & Sofa with Removable Washable ..






Recommender systems

Unsupervised learning

Learns from samples represented by features

Supervised learning





Más títulos similares a este







Nuevo

14 2019

Mike Ross, un joven brillante, pero que nunca terminó la universidad, impresiona a un importante abogado y consigue trabajo en un prestigioso bufete.

89 % para ti

018

Después de una crisis, los empleados de una exitosa agencia de talentos en París luchan por mantener felices a sus clientes superestrellas y el negocio a flote. 16 2021 Un veterano de la Guerra Civil que va de pueblo en pueblo para leer las noticias emprende un arriesgado viaje para darle un nuevo hogar a

una niña huérfana.





Unsupervised learning

Learns from samples represented by features

Supervised learning

Learns from samples represented by features and labels





Face recognition



Unsupervised learning

Learns from samples represented by features

Supervised learning

Learns from samples represented by features and labels





Face recognition



Unsupervised learning

Learns from samples represented by features

Supervised learning

Learns from samples represented by features and labels







Face recognition



Unsupervised learning

Learns from samples represented by features

Supervised learning .

> Learns from samples represented by features and labels



this small bird has a pink breast and crown, and black primaries and secondaries.

this magnificent fellow is almost all black with a red crest, and white cheek patch.



the flower has petals that are bright pinkish purple with white stigma



this white and yellow flower have thin white petals and a round yellow stamen





Text-to-Image translation



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Watanabe, S., Sakamoto, J., & Wakita, M. (1995). **Pigeons'** discrimination of paintings by Monet and Picasso. Journal of the experimental analysis of behavior, 63(2), 165-174.





Watanabe, S., Sakamoto, J., & Wakita, M. (1995). **Pigeons'** discrimination of paintings by Monet and Picasso. Journal of the experimental analysis of behavior, 63(2), 165-174.



Experiment:

• Pigeon in a *Skinner box*.







Watanabe, S., Sakamoto, J., & Wakita, M. (1995). Pigeons' discrimination of paintings by Monet and Picasso. Journal of the experimental analysis of behavior, 63(2), 165-174.

Experiment:

- Pigeon in a *Skinner box*.
- Paintings by two artists are presented: Monet and Picasso.





"Three musicians masks" - Picasso



"Pathway in Monet's Garden at Giverny" – C. Monet





Watanabe, S., Sakamoto, J., & Wakita, M. (1995). Pigeons' discrimination of paintings by Monet and Picasso. Journal of the experimental analysis of behavior, 63(2), 165-174.

Experiment:

- Pigeon in a *Skinner box*.
- Paintings by two artists are presented: Monet and Picasso.
- The pigeon *receives a reward* if it presses the button when *Picasso paintings* are presented.





"Three musicians masks" - Picasso



"Pathway in Monet's Garden at Giverny" – C. Monet





• The pigeons were able to *discriminate* between both paints with an accuracy of **95%** *during training* (e.g. paintings seen many times).





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- They can *extract* and *recognize* patterns => *style*.
- They are able to *generalize* from what has already been seen to *make decisions*.





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Capacity of Neural Networks (biological and artificial)!









ligp

Biological neuron

Artificial neuron





























Artificial neuron





























Biological neural network









Biological neural network



Artificial neural network









Biological neural network





























1.3. Neural Networks and Deep Learning

Neural Network









1.3. Neural Networks and Deep Learning

Neural Network



Deep Learning Neural Network









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1.4. Computer Vision

Computer Vision

how computers can **understand** digital images or videos and **extract information**





1.4. Computer Vision

Computer Vision

how computers can **understand** digital images or videos and **extract information**







1.4. Computer Vision

Computer Vision

how computers can **understand** digital images or videos and **extract information**





Abnormalities identification [Source]



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1.4. Computer Vision

Computer Vision

how computers can **understand** digital images or videos and **extract information**





Abnormalities identification [Source]



Land Use, Land Cover | Road extraction [Source]





1.4. Computer Vision

Computer Vision

how computers can **understand** digital images or videos and **extract information**





Abnormalities identification [Source]



Land Use, Land Cover | Road extraction [Source]



Scene understanding | Visual Question and Answer (VQA) [<u>Source</u>]




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Remote Sensing

acquisition of information about an object or phenomenon *without making physical contact with it*





Remote Sensing

acquisition of information about an object or phenomenon *without making physical contact with it*







Remote Sensing

acquisition of information about an object or phenomenon *without making physical contact with it*



Lidar [Source]









Remote Sensing

acquisition of information about an object or phenomenon *without making physical contact with it*

Lidar [<u>Source</u>]













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Classification

Cat



http://cs231n.stanford.edu/slides/2020/le

"assign a label to the whole image"







Classification Cat



http://cs231n.stanford.edu/slides/2020/lecture_12.pdf

"assign a label to the whole image" "assign a label to each pixel in the image"





Classification Segmentation Cat Sky Trees Cat Grass

http://cs231n.stanford.edu/slides/2020/lecture_12.pdf

"assign a label to the whole image"

"assign a label to each" pixel in the image"

Semantic

"find where an object is in the image"







Object

Detection



1.6. Computer Vision tasks (remote sensing)

Classification



"assign a label to the whole image"







1.6. Computer Vision tasks (remote sensing)

Classification

Semantic Segmentation



"assign a label to the whole image" Hall



"assign a label to each pixel in the image"





1.6. Computer Vision tasks (remote sensing)



"assign a label to the whole image"

pixel in the image"

the image"





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2. Application

Mass Monument Industrial Hall?

Classification of steel construction system halls of the High Modernism period and their attribution for an automated airborne image-based acquisition

P. Achanccaray · M. Gerke · L. Wesche · S. Hoyer · K. Thiele · U. Knufinke · C. Krafczyk





Niedersächsisches Landesamt für Denkmalpflege



Site: https://kulturerbe-konstruktion.de/spp-2255-teilprojekt/massenphaenomen-gewerbehalle-c3/







- 2. Industrial Halls Types
- Turnhalle KT 60 L

Turnhalle – KT 60 L



• Bogenhalle – Ruhland









2. Industrial Halls – Locations





2. Industrial Halls – Samples







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2. Industrial Halls – Samples







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2. Dataset

Images:

- Digital Orthophotos DOP (appearance, texture)
- Digital Elevation Model DEM (height)
- 20 cm spatial resolution

Labels:

- Supervised learning
- Manually delineated

DOP









3. Task

Classification Semantic Segmentation

Hall

Background

Object Detection



"assign a label to the whole image"

"assign a label to each pixel in the image"



"find where an object is in the image"







3. Task



pixel in the image"

the image"





4. Deep Learning model

Model: U-Net





4. Deep Learning model

Model: U-Net

Technische

Universität Braunschweig



4. Deep Learning model

Model: U-Net





Source: Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. <u>https://doi.org/10.1007/978-3-319-24574-4_28</u>

performance



Model: U-Net



Technische Universität Braunschweig

Source: Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. <u>https://doi.org/10.1007/978-3-319-24574-4_28</u>

performance

4. Deep Learning model

Model: U-Net



Technische Universität Braunschweig

Source: Ronneberger O., Fischer P., Brox T. (2015) U-Net: Convolutional Networks for Biomedical Image Segmentation. <u>https://doi.org/10.1007/978-3-319-24574-4_28</u>

performance

4. Deep Learning model

Model: U-Net

Technische

Universität Braunschweig



5. Results

Detection rate

System halls – Testing							
Detected	Missed	False positives					
25	1	2					

(not use during training, we know if there are halls or not)

(not use during training, we do not know if there are halls or not)

System halls – Blind testing						
Detected	False positive					
2	4					







































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3. Lab



3. Lab

Google Colaboratory .

Right click on the *Deep_Learning.ipynb* file. Go to *Open with => Connect more apps*.

CO Deep_Learning.ipynb model.h5	Image: Second secon	me Co Google Colaboratory Text Editor Connect more apps Apps on your Computer	Colaboratory Colaboratory team This allows Google Colaboratory to open and create files in Google Drive. It i ★ 4.7 * 🛓 10,000,000+	• ③ cii CO	ick on <i>Install.</i> Colaboratory This allows Google Colaboratory to open Google Drive. It is automatically installed uninstalling this will not prevent access to	and create files in on first use: • Colaboratory.	Uninstall
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Google Colaboratory

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A Right click on the Deep_Learning.ipynb file. Go to Open with => Google Colaboratory.
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Name 个								Owner
	data							me
co	Deep_Lea							me
	model.h5	\odot	Preview					me
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		0¢	Share				Text Editor	



