Machine Learning & Data Driven Business (DDB)

Prof. Dr. Michael Amberg

Criminal Machine Learning

Automated Inference on Criminality using Face Images

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Abstract

We study, for the first time, automated inference on criminality based solely on still face images, which is free of any biases of subjective judgments of human observers. Via supervised machine learning, we build four classifiers (logistic regression, KNN, SVM, CNN) using facial images of 1856 real persons controlled for race, gender, age and facial expressions, nearly half of whom were convicted criminals, for discriminating between criminals and non-criminals. All four classifiers perform consistently well and empirically establish the validity of automated face-induced inference on criminality, despite the historical controversy surrounding this line of enquiry. Also, some discriminating structural features for predicting criminality have been found by machine learning. Above all, the most important discovery of this research is that criminal and non-criminal face images populate two quite distinctive manifolds. The variation among criminal faces is significantly greater than that of the non-criminal faces. The two manifolds consisting of criminal and non-criminal faces appear to be concentric, with the non-criminal manifold lying in the kernel with a smaller span, exhibiting a law of "normality" for faces of non-criminals. In other words, the faces of general law-biding public have a greater degree of resemblance compared with the faces of criminals, or criminals have a higher degree of dissimilarity in facial appearance than non-criminals.

management science, criminology, etc.

In all cultures and all periods of recorded human history, people share the belief that the face alone suffices to reveal innate traits of a person. Aristotle in his famous work Prior Analytics asserted, "It is possible to infer character from features, if it is granted that the body and the soul are changed together by the natural affections". Psychologists have known, for as long as a millennium, the human tendency of inferring innate traits and social attributes (e.g., the trustworthiness, dominance) of a person from his/her facial appearance, and a robust consensus of individuals' inferences . These are the facts found through numerous studies [3, 39, 5, 6, 10, 26, 27, 34, 32].

Independent of the validity of pedestrian belief in the (pseudo)science of physiognomy, a tantalizing question naturally arises: what facial features influence average Joes' impulsive and yet consensual judgments on social attributes of a non-acquaintance member of their own specie? Attempting to answer the question, Todorov and Oosterhof proposed a data-driven statistical modeling method to find visual determinants of social attributes by asking human subjects to score four percepts: dominance, attractiveness, trustworthiness, and extroversion, based on first impression of static face images [33]. This method can synthesize a representative (average) face image for a set of input face images scored closely on any of the four aforementioned social percepts. The ranking of these synthesized face images by subjective scores (e.g., from least to most trustwor-

https://arxiv.org/pdf/1611.04135.pdf 2016

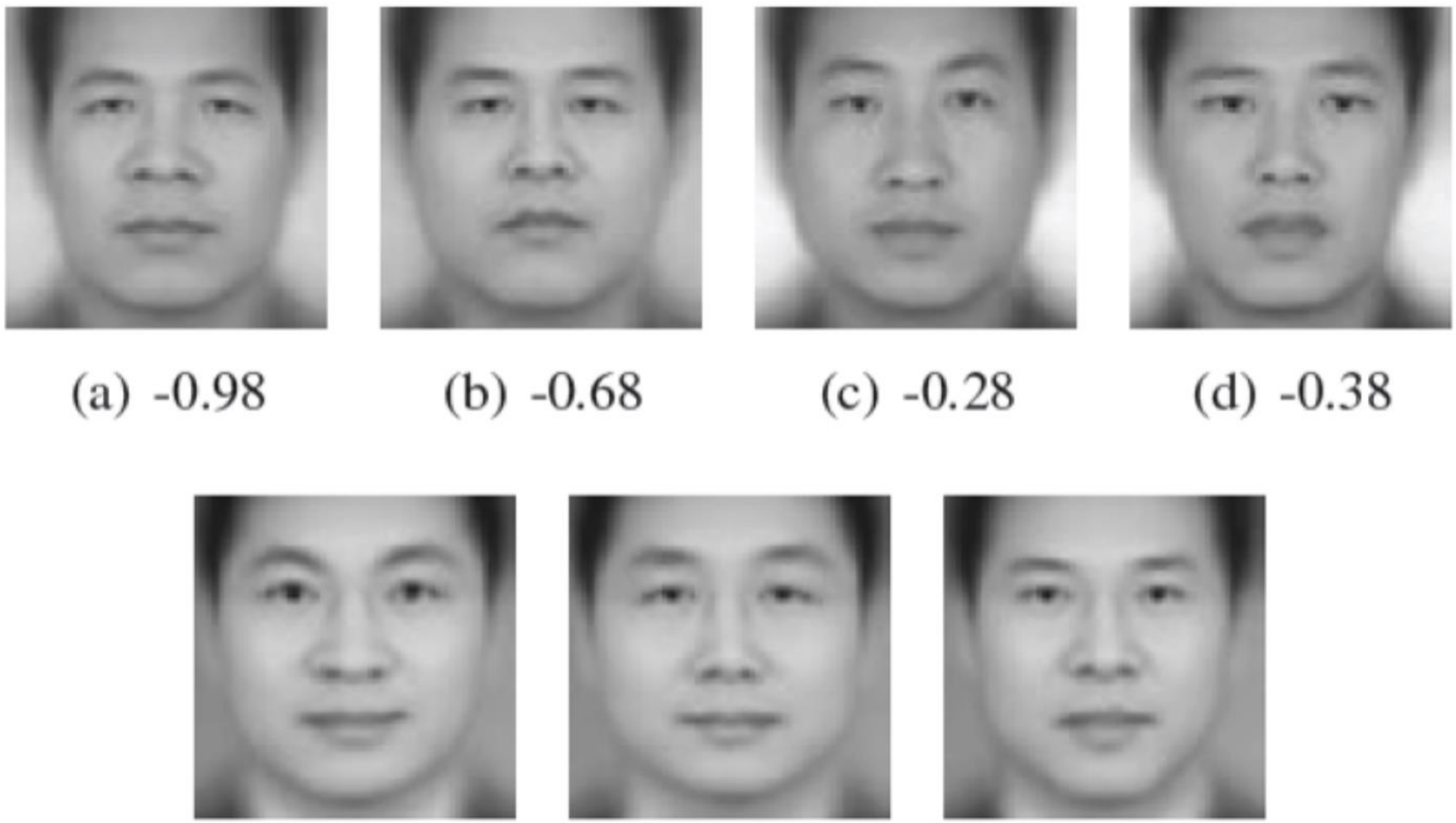
Criminal Machine Learning - Biased Training Set?

(a) Three samples in criminal ID photo set S_c.

(b) Three samples in non-criminal ID photo set S_n

https://www.callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

Criminal Machine Learning - Biased by Smile?



(a) -0.98 (b) -0.68 (c) -0.28 (d) -0.38

(e) 0.76 (f) 0.98 (g) 0.66

https://www.callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

Criminal Machine Learning

Responses to Critiques on Machine Learning of Criminality Perceptions (Addendum of arXiv:1611.04135)

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arXiv:1611.04135v3 [cs.CV] 26 May 2017

In November 2016 we submitted to arXiv our paper "Automated Inference on Criminality Using Face Images". It generated a great deal of discussions in the Internet and some media outlets. Our work is only intended for pure academic discussions; how it has become a media consumption is a total surprise to us.

Although in agreement with our critics on the need and importance of policing AI research for the general good of the society, we are deeply baffled by the ways some of them mispresented our work, in particular the motive and objective of our research.

1. Name calling

It should be abundantly clear, for anyone who reads our paper with a neutral mind setting, that our only motive is to know if machine learning has the potential of acquiring humanlike social perceptions of faces, despite the complexity and subtlety of such perceptions that are functions of both the observed and the observer. Our inquiry is to push the envelope and extend the research on automated face recognition from the biometric dimension (e.g., determining the race, gender, age, facial expression, etc.) to the sociopsychological dimension. We are merely interested in the distinct possibility of teaching machines to pass the Turing test on the task of duplicating humans in their first impressions (e.g., personality traits, mannerism, demeanor, etc.) of a stranger. The face perception of criminality was expediently (unfortunately to us in hindsight) chosen as an easy test case, at least in our intuition as explained in our paper:

> *"For validating the hypothesis on the correlations between the innate traits and social behaviors of a person and the physical characteristics of that persons face, it would be hard pushed to find a more convincing experiment than examining the success rates of discriminating between criminals and non-criminals with modern automatic classifiers. These two populations should be among the easiest to differentiate, if social attributes and facial features are correlated, because being a criminal requires a host of abnormal (outlier) personal traits. If the classification rate turns out low, then the validity of face-induced social inference can be safely negated."*

By a magical stretch of imagination, few of our critics intertwine the above passage into some of our honest observations and morph them into the following deduction of, they insist, ours:

> *"Those with more curved upper lips and eyes closer together are of a lower social order, prone to (as Wu and Zhang put it) "a host of abnormal (outlier) personal traits" ultimately leading to a legal diagnosis of "criminality" with high probability."*

We agree that the pungent word criminality should be put in quotation marks; a caveat about the possible biases in the input data should be issued. Taking a court conviction at its face value, i.e., as the "ground truth" for machine learning, was indeed a serious oversight on our part. However, throughout our paper we maintain a sober neutrality on whatever we might find; in the introduction, we declare

> *"In this paper we intend not to nor are we qualified to discuss or debate on societal stereotypes, rather we want to satisfy our curiosity in the accuracy of fully automated inference on criminality. At the onset of this study our gut feeling is that modern tools of machine learning and computer vision will refute the validity of physiognomy, although the outcomes turn out otherwise."*

Nowhere in our paper advocated the use of our method as a tool of law enforcement, nor did our discussions advance from correlation to causality. But still we got interpreted copiously by some with an insinuation of racism. This is not the way of academic exchanges we are used to.

https://arxiv.org/pdf/1611.04135.pdf 2017

medium.com/@kcimc/... Pausiert

How to recognize fake AI-generated images

Kyle McDonald Dec 5, 2018 · 7 min read

In 2014 machine learning researcher Ian Goodfellow introduced the idea of generative adversarial networks or GANs. “Generative” because they output things like images rather than predictions about input (like “hotdog or not”); “adversarial networks” because they use two neural networks competing with each other in a “cat-and-mouse game”, like a cashier and a counterfeiter: one trying to fool the other into thinking it can generate real examples, the other trying to distinguish real from fake.

The first GAN images were easy for humans to identify. Consider these faces from 2014.

medium.com/@kcimc/how-to-recognize-fake-ai-generated-images-4d1f6f9a2842 en.wikipedia.org/wiki/Data_science

Pausiert

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Data science

From Wikipedia, the free encyclopedia
(Redirected from Data Science)

Not to be confused with information science.

Data science is an inter-disciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from many structural and unstructured data.[1][2] Data science is related to data mining, machine learning and big data.

Data science is a "concept to unify statistics, data analysis and their related methods" in order to "understand and analyze actual phenomena" with data.[3] It uses techniques and theories drawn from many fields within the context of mathematics, statistics, computer science, domain knowledge and information science. Turing award winner Jim Gray imagined data science as a "fourth paradigm" of science (empirical, theoretical, computational and now data-driven) and asserted that "everything about science is changing because of the impact of information technology" and the data deluge.[4][5]

Contents [hide]

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Machine learning and data mining

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(**classification** • **regression**)
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Dimensionality reduction [show]
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V • T • E

Machine Learning & Data Driven Business (ML&DDB)

Prof. Dr. Michael Amberg

Was ist mit **Studienbeginn vor WS20/21?**

Alter Studienplan

Bachelor in **Wirtschaftsinformatik**		Semester					
		1	2	3	4	5	6
	ECTS	ECTS	ECTS	ECTS	ECTS	ECTS	ECTS
Pflichtbereich	40						
Übersicht/Welt des Unternehmens	**5**						
Buchführung (GOP)	5	5					
Wirtschaftsinformatik	**5**						
Business & Information Systems Engineering (GOP)	5	5					
Mathematik	**10**						
Analysis und Lineare Algebra (GOP)	5		5				
Finanzmathematik (GOP)	5		5				
Informatik	**20**						
Algorithmen und Datenstrukturen (für Medizintechnik) (GOP)	10	10					
Theoretische Informatik für Wirtschaftsinformatik	5				5		
Grundlagen der Logik in der Informatik	5			5			
Kernbereich	95						
BWL	**15**						
Unternehmer und Unternehmen	5	5					
Absatz	5		5				
Produktion, Logistik, Beschaffung	5			5			
Wirtschaftsinformatik	**45**		**5**	**10**	**10**	**15**	**5**
Data & Knowledge	15						
Digital Business	15						
Architectures & Development	15						
Informatik	**35**						
Konzeptionelle Modellierung	5	5					
Parallele und Funktionale Programmierung	5		5				
Systemprogrammierung	10		5	5			
Softwareentwicklung in Großprojekten	5			5			
Rechnerkommunikation	5				5		
Implementierung von Datenbanksystemen	5					5	
Schlüsselqualifikationen	10						
Seminar Wirtschaftsinformatik	5				5		
Forschungsmethodisches Seminar	5				5		
Vertiefungsbereich	35						
Fachliche Vertiefung	**35**						
Fachvertiefung	20					10	10
Bachelorarbeit	15						15
ECTS	**180**	**30**	**30**	**30**	**30**	**30**	**30**

Studierende der **Wirtschaftsinformatik** mit Studienbeginn **vor WS20/21** müssen die Veranstaltung „**Machine Learning & Data Driven Business**“ nicht belegen.

Webseite des Lehrstuhls:
www.it-management.rw.fau.de

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Machine Learning & Data Driven Business

Lehre

Hinweis

Die Veranstaltung *Machine Learning & Data Driven Business* ersetzt inhaltlich *IT und E-Business*. Studierende mit Studienbeginn **vor** WS2020 melden sich bitte für die Klausur bzw. Projektarbeit mit der *Prüfungs-Nr. 21521* bzw. *21522* an. Studierende mit Studienbeginn **ab** WS2020 melden sich bitte für die Klausur bzw. Projektarbeit mit der *Prüfungs-Nr. 21741, 21742* an.

Organisation

	Studienbeginn **vor** WS2020	Studienbeginn **ab** WS2020
Prüfungsnummer:	Klausur: *21521* Projektarbeit: *21522*	Klausur: *21741* Projektarbeit: *21742*
ECTS:	5	5
Turnus	WS	WS
Sprache	Deutsch	Deutsch

3. Schritt

Die erste Vorlesung findet virtuell im Rahmen der **Erstsemester-Einführungsveranstaltungen** am Montag, den 02.11.2020 um 14:00 Uhr statt. In den darauffolgenden Wochen findet die Vorlesung wie gewohnt am Mittwoch um 11:30 Uhr statt. Die Vorlesung wird von einem Tutorium zur Projektarbeit begleitet.

Weitere Informationen finden Sie in Kürze auf StudOn.

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Deutschland

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stefan.st.arnold@fau.de

Sprechzeiten

Nach Vereinbarung

Lehrveranstaltungen

- IT- und E-Business
- Data Driven Business
- IT-Management (Kaggle)

StudOn **Direktlink**: https://www.studon.fau.de/studon/goto.php?target=crs_3151257

StudOn (studon.fau.de) ist die **zentrale Informationsplattform – Navigation (8/8)**

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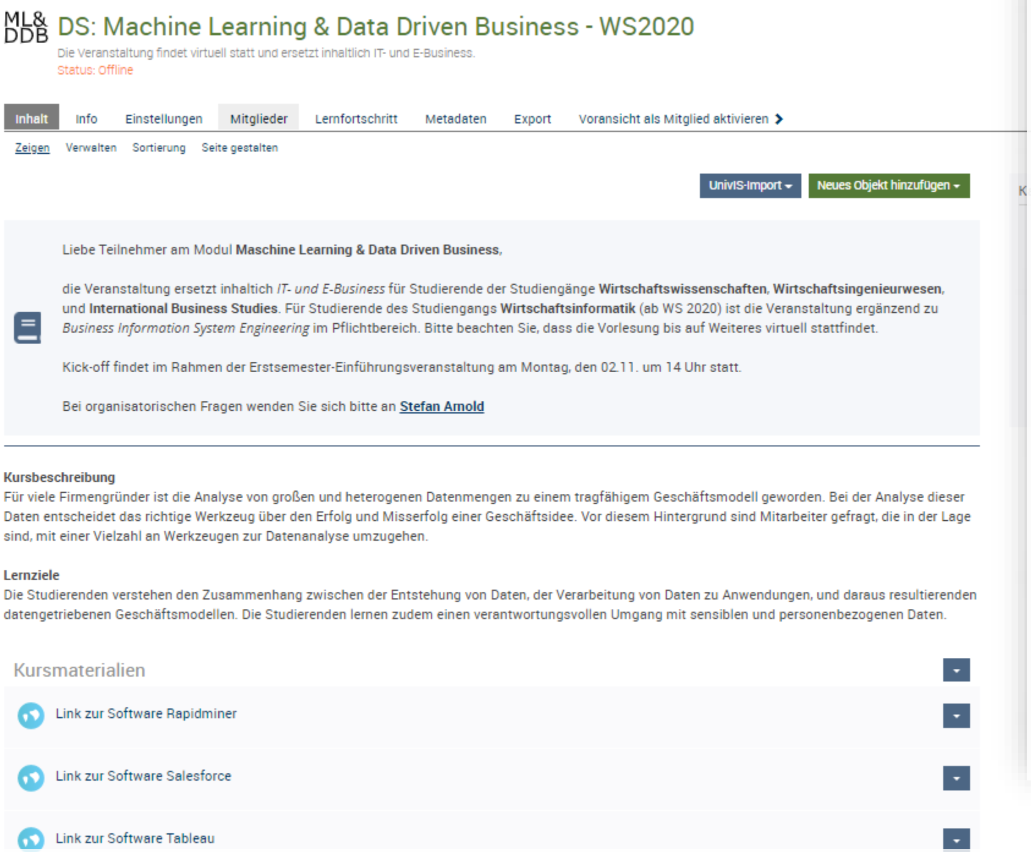

Bereitgestellte Inhalte:

- **Vorlesungsfolien**
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Machine Learning & **Data Driven Business**

Anwendungen und **Rahmenbedingungen** von **Data Science** und **Machine Learning** in **Unternehmen** und in einer **datengetriebenen Welt** kennen und einschätzen lernen.

Inhalte des Moduls

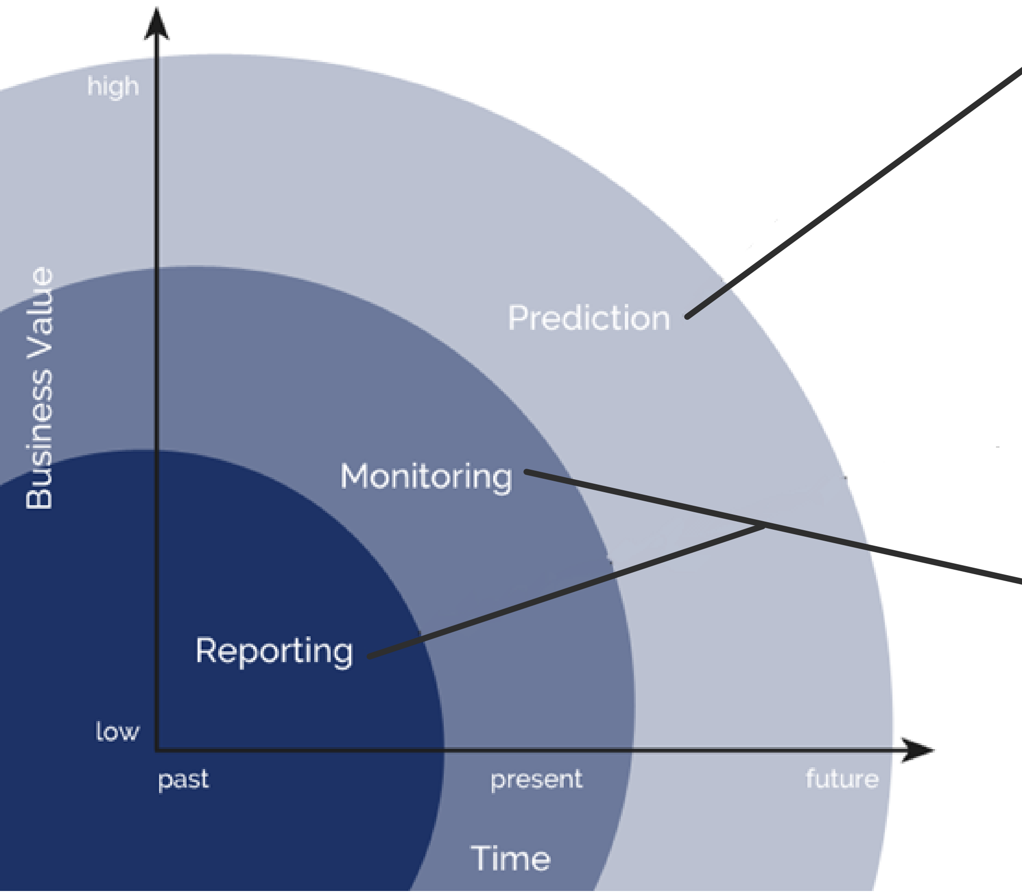
Vorlesung

Mittwoch, 11:30 Uhr über **Zoom**

Inhalte der Vorlesung:

- **Data Manipulation (Bullshit):** **The Art of Skepticism in a Data Driven World**
- **Data Handling:** **Handling of Data in different scenarios**
- **Data Privacy:** **Protecting the Privacy & Integrity of Data**
- **Data Driven Innovation:** **Innovative Business & Applications**
- **Project Management:** **Managing Projects successfully**
- **Business Systems:** **Relevant Enterprise Software Systems**
- **Emerging Technologies:** **Implications of selected Technologies**
- **Machine Learning I, II, III:** **Overview of ML Techniques & Methods**
- **ML & Robotics:** **Current Developments & Implications**

Machine Learning Software nutzt maschinelles Lernen für Datenanalysen.



Data Analytics & Machine Learning	
Technologies & Data Types	• mainly unstructured data • different types of sources • large data sets • dynamic • used for optimization and predictive modeling • predictive, prescriptive analysis
Common questions	• What if … ? • What will happen next? • Which trends can be predicted? • What is the optimal business scenario going to look like?

Business Intelligence	
Technologies & Data Types	• mainly structured data • traditional sources • managable data sets • static • used for reporting • retrospective, descriptive analysis
Common questions	• What happened in the last period? • Why did we (not) reach goal x? • Where is the problem?

WIKIPEDIA
The Free Encyclopedia

Business analytics

From Wikipedia, the free encyclopedia

Business analytics (**BA**) refers to the skills, technologies, practices for continuous iterative exploration and investigation of past business performance to gain insight and drive business planning.[1] Business analytics focuses on developing new insights and understanding of business performance based on data and statistical methods. In contrast, business intelligence traditionally focuses on using a consistent set of metrics to both measure past performance and guide business planning, which is also based on data and statistical methods.[citation needed]

Business analytics makes extensive use of analytical modeling and numerical analysis, including explanatory and predictive modeling,[2] and fact-based management to drive decision making. It is therefore closely related to management science. Analytics may be used as input for human decisions or may drive fully automated decisions. Business intelligence is querying, reporting, online analytical processing (OLAP), and "alerts."

In other words, querying, reporting, OLAP, it is alert tools can answer questions such as what happened, how many, how often, where the problem is, and what actions are needed. Business analytics can answer questions like why is this happening, what if these trends continue, what will happen next (predict), and what is the best outcome that can happen (optimize).[3]

Contents [hide]

Types of analytics [edit]

- Decision analytics: supports human decisions with visual analytics that the user models to reflect reasoning.[5]
- Descriptive analytics: gains insight from historical data with reporting, scorecards, clustering etc.
- Predictive analytics: employs predictive modelling using statistical and machine learning techniques
- Prescriptive analytics: recommends decisions using optimization, simulation, etc.

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Languages

Predictive analytics

From Wikipedia, the free encyclopedia

Predictive analytics encompasses a variety of statistical techniques from data mining, predictive modelling, and machine learning, that analyze current and historical facts to make predictions about future or otherwise unknown events.[1][2]

In business, predictive models exploit patterns found in historical and transactional data to identify risks and opportunities. Models capture relationships among many factors to allow assessment of risk or potential associated with a particular set of conditions, guiding decision-making for candidate transactions.[3]

The defining functional effect of these technical approaches is that predictive analytics provides a predictive score (probability) for each individual (customer, … nal unit) in order to determine, infor… as in marketing, credit risk asses… enforcement.

Predictive analytics is used … etail,[9] travel,[10] mobility,[11] healt… and other fields.

One of the best-known app… s a customer's credit history, lo… ng future credit payments on t…

Cont…

Definition [edit]

Predictive analytics is an area of statistics that deals with extracting information from data and using it to predict trends and behavior patterns. The enhancement of predictive web analytics calculates statistical probabilities of future events online. Predictive analytics statistical techniques include data modeling, machine learning, AI, deep learning algorithms and data mining.[18] Often the unknown event of interest is in the future, but predictive analytics can be applied to any type of unknown whether it be in the past, present or future. For example, identifying suspects after a crime has been committed, or credit card fraud as it occurs.[19] The core of predictive analytics relies on capturing relationships between explanatory variables and the predicted variables from past occurrences, and exploiting them to predict the unknown outcome. It is important to note, however, that the accuracy and usability of results will depend greatly on the level of data analysis and the quality of assumptions.

Gartner bewertet Software zur Datenanalyse

Figure 1. Magic Quadrant for Data Science and Machine Learning Platforms

Source: Gartner (February 2020)

Software und Plattformen für Unternehmen mit Fokus auf **Maschine Learning**, d.h. **prädiktive Analysen** zur Erstellung von **Prognosen**.

Beispiele:

- **Rapidminer**
- **IBM Watson**

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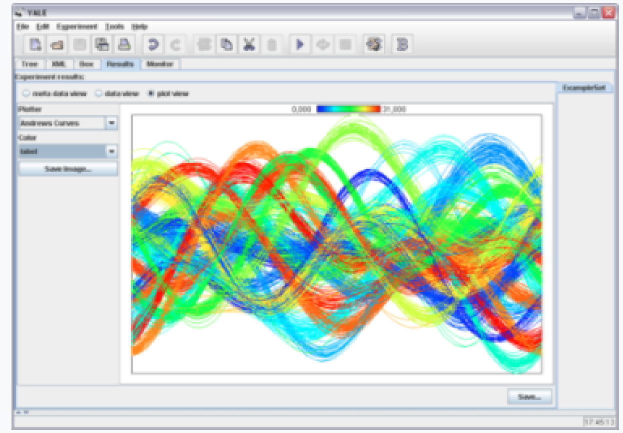
RapidMiner

From Wikipedia, the free encyclopedia

RapidMiner is a data science software platform developed by the company of the same name that provides an integrated environment for data preparation, machine learning, deep learning, text mining, and predictive analytics. It is used for business and commercial applications as well as for research, education, training, rapid prototyping, and application development and supports all steps of the machine learning process including data preparation, results visualization, model validation and optimization.[1] RapidMiner is developed on an open core model.

RapidMiner



Developer(s)	RapidMiner
Initial release	2006; 14 years ago
Stable release	9.6 / 2 March 2020; 7 months ago
Operating system	Cross-platform
Type	Data science, machine learning, predictive analytics
License	Professional and Enterprise Editions are Proprietary; Free Edition (10,000 rows and 1 logical processor limit) is available as AGPL
Website	rapidminer.com

Contents [hide]

History [edit]

RapidMiner, formerly known as YALE (Yet Another Learning Environment), was developed starting in 2001 by Ralf Klinkenberg, Ingo Mierswa, and Simon Fischer at the Artificial Intelligence Unit of

Inhalte des Moduls

Vorlesung

Mittwoch, 11:30 Uhr über **Zoom**

Inhalte der Vorlesung:

- **Data Manipulation (Bullshit)**
- **Data Handling**
- **Data Privacy**
- **Data Driven Innovation**
- **Project Management**
- **Business Systems**
- **Emerging Technologies**
- **Machine Learning I, II, III**
- **ML & Robotics**

Projektarbeit

Donnerstag, 13:15 Uhr über **Zoom**

Drei **toolgestützte Datenanalysen** selbständig unter Anleitung durchführen und in Form einer **wissenschaftlichen Arbeit toolgestützt** dokumentieren.

- **Selbstlernkurse** über *StudOn*
- **digitales Tutorium** über *Zoom*

salesforce

tableau

rapidminer

Machine Learning & Data Driven Business - Der zeitliche Ablauf im Überblick

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	04.11	11.11	18.11	25.11	02.12	09.12	16.12	23.12	30.12	06.01	13.02	20.20	27.20	03.20	10.02
Vorlesung	02.11 Einführungsveranstaltung							Weihnachtsferien	Weihnachtsferien	Weihnachtsferien					Klausurvorbereitung
	05.11			26.11			17.12				14.01			10.02	
Projektarbeit	Projektarbeit 1: Analyse mit Salesforce	Selbststudium	Selbststudium	Projektarbeit 2: Analyse mit Tableau			Projektarbeit 3: Analyse mit Rapidminer				Projektarbeit 4: wiss. Hausarbeit			Abgabe Projektarbeit (04.02.21, 00:00 Uhr)	

In KW45 finden zwei Vorlesungen statt:

- 02.11 14:00 Uhr
- 04.11 11:30 Uhr

Einbettung von „**Machine Learning & Data Driven Business**“ im **Studienverlauf**

Neue Studienplan

Bachelor in **Wirtschaftswissenschaften**		Semester					
		1	2	3	4	5	6
	ECTS	ECTS	ECTS	ECTS	ECTS	ECTS	ECTS
Pflichtbereich	**80**						
Übersicht/Welt des Unternehmens	**15**						
82031 Unternehmensplanspiel	5	5					
82021 Unternehmen, Märkte, Volkswirtschaften	5	5					
82011 Unternehmer und Unternehmen	5	5					
Data Science	**25**						
82174 Data Science: Machine Learning and Data Driven Business	5	5					
82179 Data Science: Datenauswertung	5	5					
82176 Data Science: Statistik	5	5					
82177 Data Science: Datenmanagement und -analyse	5		5				
82178 Data Science: Ökonometrie	5		5				
BWL/Unternehmen und ihr Geschäft	**15**						
82041 Absatz	5		5				
82051 Jahresabschluss	5				5		
82060 Produktion, Logistik, Beschaffung	5			5			
VWL/Unternehmen und ihr Umfeld	**15**						
82070 Makroökonomie	5		5				
82080 Mikroökonomie	5		5				
82091 Wirtschaft und Staat	5			5			
Recht	**10**						
82101 Grundlagen des öffentlichen Rechts und des Zivilrechts	5			5			
82111 Wirtschaftsprivatrecht	5				5		
Studium Integrale	**20**						
82162 Mathematik	5		5				
82141 Buchführung und Reporting	5			5			
81200 Sprachen	5			5			
83272 Schlüsselqualifikationsmodul	5				5		
Kernbereich des Schwerpunkts BWL	**20**						
82350 Kostenrechnung und Controlling	5			5			
82370 Internationale Unternehmensführung	5				5		
82360 Investition und Finanzierung	5				5		
84100 Integriertes Management	5						5
Vertiefungsbereich des Schwerpunkts BWL	**60**						
9 Vertiefungsmodule à 5 ECTS, davon mind. 5 aus dem Themenbereich BWL*	45				5	30	10
1997 Modul Bachelorarbeit (inkl. Seminar)	15						15
ECTS	**180**	**30**	**30**	**30**	**30**	**30**	**30**

Die Veranstaltung ist **Pflichtmodul** für alle Studierenden **ab WS20/21** mit den **Studiengängen**:

- **Wirtschaftswissenschaften**
- **Wirtschaftsinformatik**
- **Wirtschaftsingenieurwesen**

Einbettung von „**Machine Learning & Data Driven Business**“ im **Studienverlauf**

Neue Studienplan

Bachelor in **Wirtschaftsinformatik**		Semester					
		1	2	3	4	5	6
	ECTS	ECTS	ECTS	ECTS	ECTS	ECTS	ECTS
Wirtschaftswissenschaften	**20**						
Pflichtbereich Wirtschaftswissenschaften	**15**						
Unternehmer und Unternehmen (GOP)	5	5					
Absatz	5		5				
Produktion, Logistik, Beschaffung	5		5				
Wahlpflichtbereich Wirtschaftswissenschaften	**5**						
Wahlpflichtbereich Wirtschaftswissenschaften**	5			5			
Informatik	**50**						
Pflichtbereich Informatik	**30**						
Algorithmen & Datenstrukturen (für Medizintechnik) (GOP)*	10	10					
Konzeptionelle Modellierung*	5		5				
Grundlagen der Logik in der Informatik*	5			5			
Softwareentwicklung in Großprojekten*	5			5			
Theoretische Informatik für Wirtschaftsinformatik*	5				5		
Wahlpflichtbereich Informatik	**20**						
Wahlpflichtbereich Informatik*	20					10	10
Wirtschaftsinformatik	**65**						
Pflichtbereich Wirtschaftsinformatik	**30**						
WIN Projektwoche	5	5					
Business and Information System Engineering (GOP)	5	5					
DS: Machine Learning und Data-driven Business	5	5					
DS: Datenmanagement und -analyse (GOP)	5		5				
Business Process Management (GOP)	5		5				
Managing Projects Successfully	5		5				
Wahlpflichtbereich Wirtschaftsinformatik	**35**						
Data and Knowledge**	10				5	5	
Digital Business and Processes**	15			5	5	5	
Architectures and Development**	10				5		5
Methodische Grundlagen	**15**						
Pflichtbereich Methodische Grundlagen	**10**						
DS: Datenauswertung	5			5			
DS: Statistik	5			5			
Wahlpflichtbereich Methodische Grundlagen	**5**						
Wahlpflichtbereich Methodische Grundlagen**	5					5	
Seminare und Reflexion	**15**						
Projektseminar Wirtschaftsinformatik	10				10		
Forschungsmethodisches Seminar	5					5	
Bachelorarbeit	**15**						
Bachelorarbeit (inkl. Seminar)	15						15
ECTS	**180**	**30**	**30**	**30**	**30**	**30**	**30**

Die Veranstaltung ist **Pflichtmodul** für alle Studierenden **ab WS20/21** mit den **Studiengängen**:

- **Wirtschaftswissenschaften**
- **Wirtschaftsinformatik**
- **Wirtschaftsingenieurwesen**

Was ist mit **Studienbeginn vor WS20/21?**

Alter Studienplan

Bachelor in **International Business Studies**	ECTS	Semester 1 ECTS	2 ECTS	3 ECTS	4 ECTS	5 ECTS	6 ECTS
Pflichtbereich	**80**						
Übersicht/Welt des Unternehmens	**10**						
Unternehmensplanspiel	5	5					
Unternehmer und Unternehmen	5	5					
Methodische Grundlagen	**25**						
Buchführung	5	5					
IT und E-Business	5			5			
Intercultural competence	5	5					
Statistik	10	10					
Internationale Unternehmen und ihr Geschäft	**15**						
Absatz	5				5		
Jahresabschluss	5		5				
Produktion, Logistik, Beschaffung	5			5			
Internationale Unternehmen und ihre Umwelt	**20**						
Makroökonomie	5		5				
Mikroökonomie	5		5				
Global Governance	5				5		
International politics II	5				5		
Strategisches und internationales Management	**10**						
Strategisches und internationales Management I	5				5		
Strategisches und internationales Management II	5				5		
Schlüsselqualifikationen	**20**						
Sprachen IBS 1.1	5		5				
Sprachen IBS 1.2	5					5	
Case studies in international management	5			5			
Schlüsselqualifikationsmodul	5			5			
Kernbereich des Schwerpunkts IBS	**20**						
Internationale Wirtschaft	5			5			
Europäisches und internationales Recht	5				5		
Sprachen IBS 2	5		5				
Internationale Unternehmensführung	5		5				
Vertiefungsbereich des Schwerpunkts IBS	**60**						
5 Vertiefungsmodule à 5 ECTS*	25			5		5	15
Im Ausland zu belegende Veranstaltungen	20					20	
Modul Bachelorarbeit (inkl. Seminar)	15						15
ECTS	**180**	**30**	**30**	**30**	**30**	**30**	**30**

Für alle Studierenden **vor WS20/21** ersetzt die Veranstaltung „**Machine Learning & Data Driven Business**“ die Veranstaltung „**IT und E-Business**“.

Dies gilt für die **Studiengänge**:

- **Wirtschaftswissenschaften**
- **Wirtschaftsingenieurwesen**
- **International Business Studies**

Machine Learning &
Data Driven Business (ML&DDB)
Prof. Dr. Michael Amberg

Criminal Machine Learning

Automated Inference on Criminality using Face Images

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Abstract

We study, for the first time, automated inference on criminality based solely on still face images, which is free of any biases of subjective judgments of human observers. Via supervised machine learning, we build four classifiers (logistic regression, KNN, SVM, CNN) using facial images of 1856 real persons controlled for race, gender, age and facial expressions, nearly half of whom were convicted criminals, for discriminating between criminals and non-criminals. All four classifiers perform consistently well and empirically establish the validity of automated face-induced inference on criminality, despite the historical controversy surrounding this line of enquiry. Also, some discriminating structural features for predicting criminality have been found by machine learning. Above all, the most important discovery of this research is that criminal and non-criminal face images populate two quite distinctive manifolds. The variation among criminal faces is significantly greater than that of the non-criminal faces. The two manifolds consisting of criminal and non-criminal faces appear to be concentric, with the non-criminal manifold lying in the kernel with a smaller span, exhibiting a law of "normality" for faces of non-criminals. In other words, the faces of general law-biding public have a greater degree of resemblance compared with the faces of criminals, or criminals have a higher degree of dissimilarity in facial appearance than non-criminals.

management science, criminology, etc.

In all cultures and all periods of recorded human history, people share the belief that the face alone suffices to reveal innate traits of a person. Aristotle in his famous work Prior Analytics asserted, "It is possible to infer character from features, if it is granted that the body and the soul are changed together by the natural affections". Psychologists have known, for as long as a millennium, the human tendency of inferring innate traits and social attributes (e.g., the trustworthiness, dominance) of a person from his/her facial appearance, and a robust consensus of individuals' inferences . These are the facts found through numerous studies [3, 39, 5, 6, 10, 26, 27, 34, 32].

Independent of the validity of pedestrian belief in the (pseudo)science of physiognomy, a tantalizing question naturally arises: what facial features influence average Joes' impulsive and yet consensual judgments on social attributes of a non-acquaintance member of their own specie? Attempting to answer the question, Todorov and Oosterhof proposed a data-driven statistical modeling method to find visual determinants of social attributes by asking human subjects to score four percepts: dominance, attractiveness, trustworthiness, and extroversion, based on first impression of static face images [33]. This method can synthesize a representative (average) face image for a set of input face images scored closely on any of the four aforementioned social percepts. The ranking of these synthesized face images by subjective scores (e.g., from least to most trustwor-

https://arxiv.org/pdf/1611.04135.pdf 2016

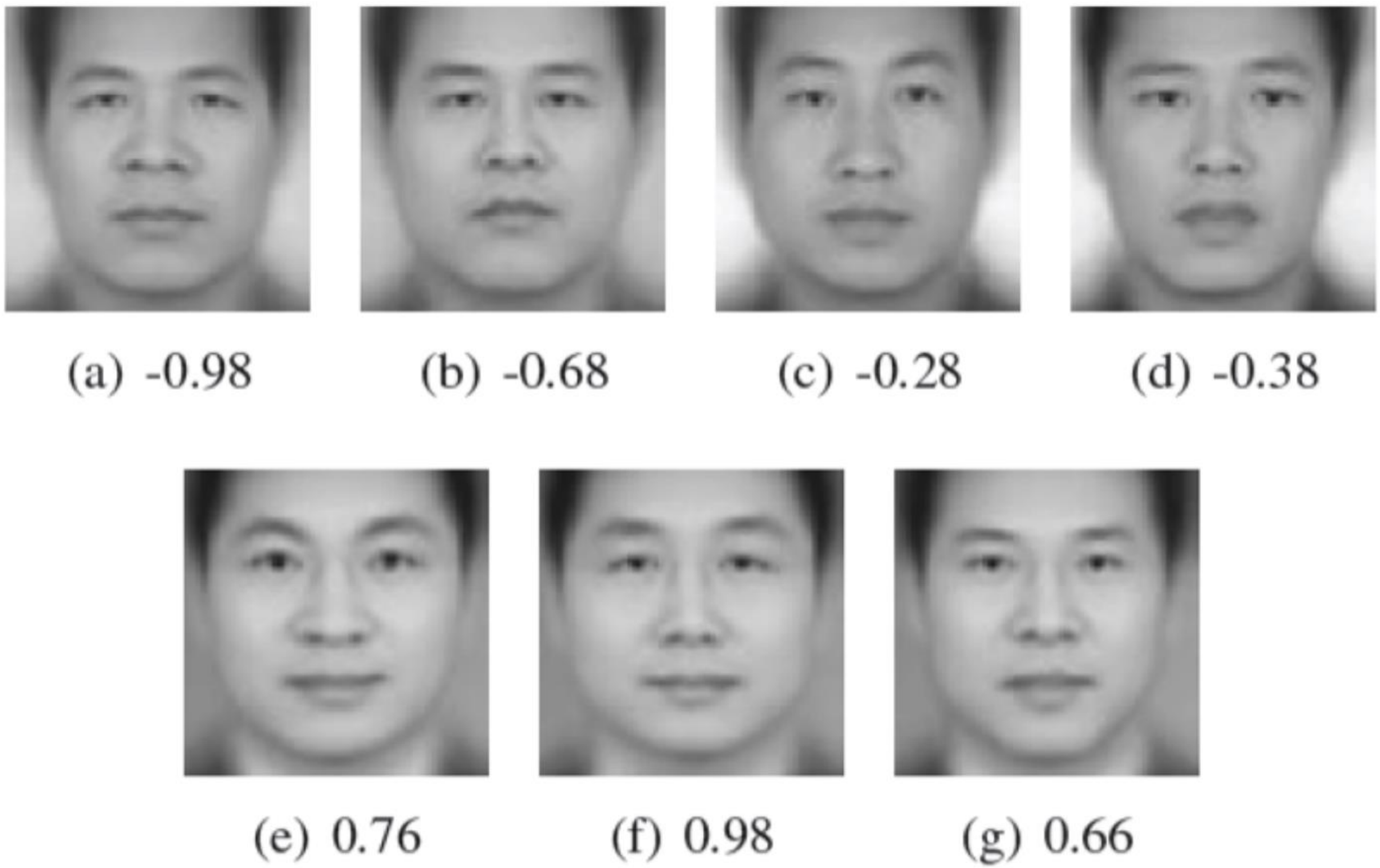
Criminal Machine Learning - Biased Training Set?

(a) Three samples in criminal ID photo set S_c.

(b) Three samples in non-criminal ID photo set S_n

https://www.callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

Criminal Machine Learning - Biased by Smile?



https://www.callingbullshit.org/case_studies/case_study_criminal_machine_learning.html

Criminal Machine Learning

Responses to Critiques on Machine Learning of Criminality Perceptions (Addendum of arXiv:1611.04135)

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Xi Zhang
Shanghai Jiao Tong University
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arXiv:1611.04135v3 [cs.CV] 26 May 2017

In November 2016 we submitted to arXiv our paper "Automated Inference on Criminality Using Face Images". It generated a great deal of discussions in the Internet and some media outlets. Our work is only intended for pure academic discussions; how it has become a media consumption is a total surprise to us.

Although in agreement with our critics on the need and importance of policing AI research for the general good of the society, we are deeply baffled by the ways some of them mispresented our work, in particular the motive and objective of our research.

1. Name calling

It should be abundantly clear, for anyone who reads our paper with a neutral mind setting, that our only motive is to know if machine learning has the potential of acquiring humanlike social perceptions of faces, despite the complexity and subtlety of such perceptions that are functions of both the observed and the observer. Our inquiry is to push the envelope and extend the research on automated face recognition from the biometric dimension (e.g., determining the race, gender, age, facial expression, etc.) to the sociopsychological dimension. We are merely interested in the distinct possibility of teaching machines to pass the Turing test on the task of duplicating humans in their first impressions (e.g., personality traits, mannerism, demeanor, etc.) of a stranger. The face perception of criminality was expediently (unfortunately to us in hindsight) chosen as an easy test case, at least in our intuition as explained in our paper:

> *"For validating the hypothesis on the correlations between the innate traits and social behaviors of a person and the physical characteristics of that persons face, it would be hard pushed to find a more convincing experiment than examining the success rates of discriminating between criminals and non-criminals with modern automatic classifiers. These two populations should be among the easiest to differentiate, if social attributes and facial features are correlated, because being a criminal requires a host of abnormal (outlier) personal traits. If the classification rate turns out low, then the validity of face-induced social inference can be safely negated."*

By a magical stretch of imagination, few of our critics intertwine the above passage into some of our honest observations and morph them into the following deduction of, they insist, ours:

> *"Those with more curved upper lips and eyes closer together are of a lower social order, prone to (as Wu and Zhang put it) "a host of abnormal (outlier) personal traits" ultimately leading to a legal diagnosis of "criminality" with high probability."*

We agree that the pungent word criminality should be put in quotation marks; a caveat about the possible biases in the input data should be issued. Taking a court conviction at its face value, i.e., as the "ground truth" for machine learning, was indeed a serious oversight on our part. However, throughout our paper we maintain a sober neutrality on whatever we might find; in the introduction, we declare

> *"In this paper we intend not to nor are we qualified to discuss or debate on societal stereotypes, rather we want to satisfy our curiosity in the accuracy of fully automated inference on criminality. At the onset of this study our gut feeling is that modern tools of machine learning and computer vision will refute the validity of physiognomy, although the outcomes turn out otherwise."*

Nowhere in our paper advocated the use of our method as a tool of law enforcement, nor did our discussions advance from correlation to causality. But still we got interpreted copiously by some with an insinuation of racism. This is not the way of academic exchanges we are used to.

https://arxiv.org/pdf/1611.04135.pdf 2017

medium.com/@kcimc/... Pausiert

How to recognize fake AI-generated images

Kyle McDonald Dec 5, 2018 · 7 min read

In 2014 machine learning researcher Ian Goodfellow introduced the idea of generative adversarial networks or GANs. "Generative" because they output things like images rather than predictions about input (like "hotdog or not"); "adversarial networks" because they use two neural networks competing with each other in a "cat-and-mouse game", like a cashier and a counterfeiter: one trying to fool the other into thinking it can generate real examples, the other trying to distinguish real from fake.

The first GAN images were easy for humans to identify. Consider these faces from 2014.

medium.com/@kcimc/how-to-recognize-fake-ai-generated-images-4d1f6f9a2842 en.wikipedia.org/wiki/Data_science

Pausiert

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Special pages
Permanent link
Page information
Cite this page
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Wikimedia Commons

Data science

From Wikipedia, the free encyclopedia
(Redirected from Data Science)

Not to be confused with information science.

Data science is an inter-disciplinary field that uses scientific methods, processes, algorithms and systems to extract knowledge and insights from many structural and unstructured data.[1][2] Data science is related to data mining, machine learning and big data.

Data science is a "concept to unify statistics, data analysis and their related methods" in order to "understand and analyze actual phenomena" with data.[3] It uses techniques and theories drawn from many fields within the context of mathematics, statistics, computer science, domain knowledge and information science. Turing award winner Jim Gray imagined data science as a "fourth paradigm" of science (empirical, theoretical, computational and now data-driven) and asserted that "everything about science is changing because of the impact of information technology" and the data deluge.[4][5]

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

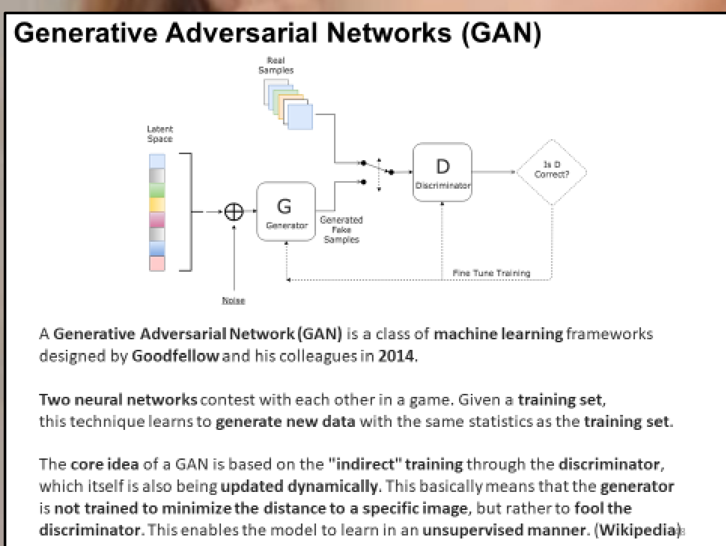
Contents [hide]

Machine Learning & Data Driven Business (ML&DDB)

Prof. Dr. Michael Amberg

8 Machine Learning III
- Specialized Areas in Machine Learning
(3) Autoencoder

8 Machine Learning III
- Specialized Areas in Machine Learning
(4) 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**)

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

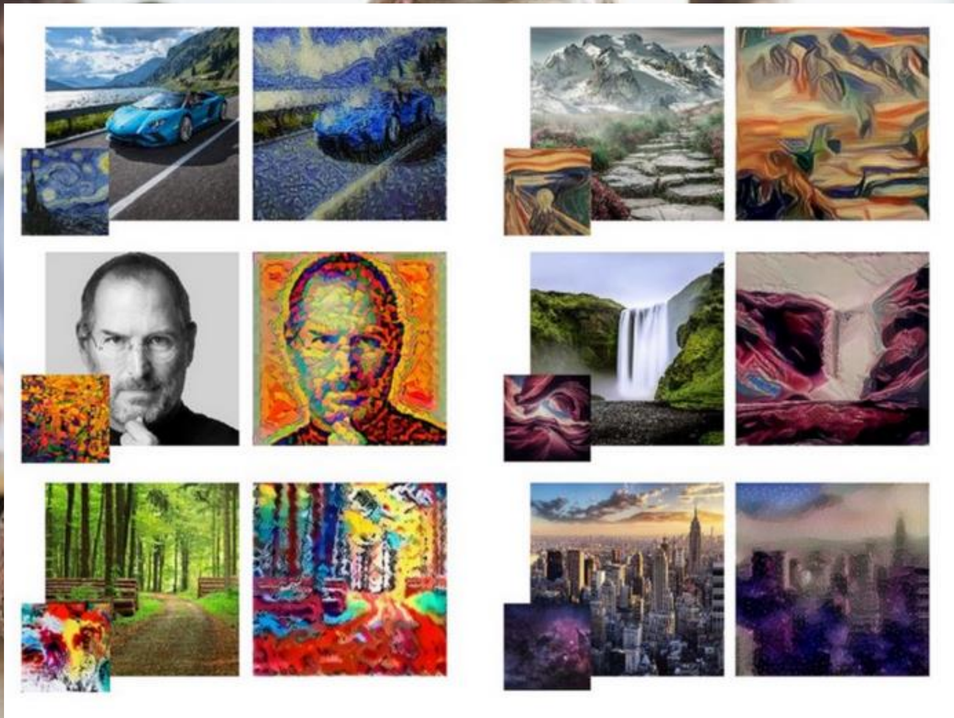
8 Machine Learning III
- Specialized Areas in Machine Learning

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**

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

Art des Wissens / Schwierig-keitsgrad	Abfragewissen (Vorlesung)	Anwendungswissen (Literatur)
Einfach		
Mittel		
Schwierig		



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

8 Machine Learning III
- Specialized Areas in Machine Learning
(6) Reinforcement Learning

Fill in the Blank.

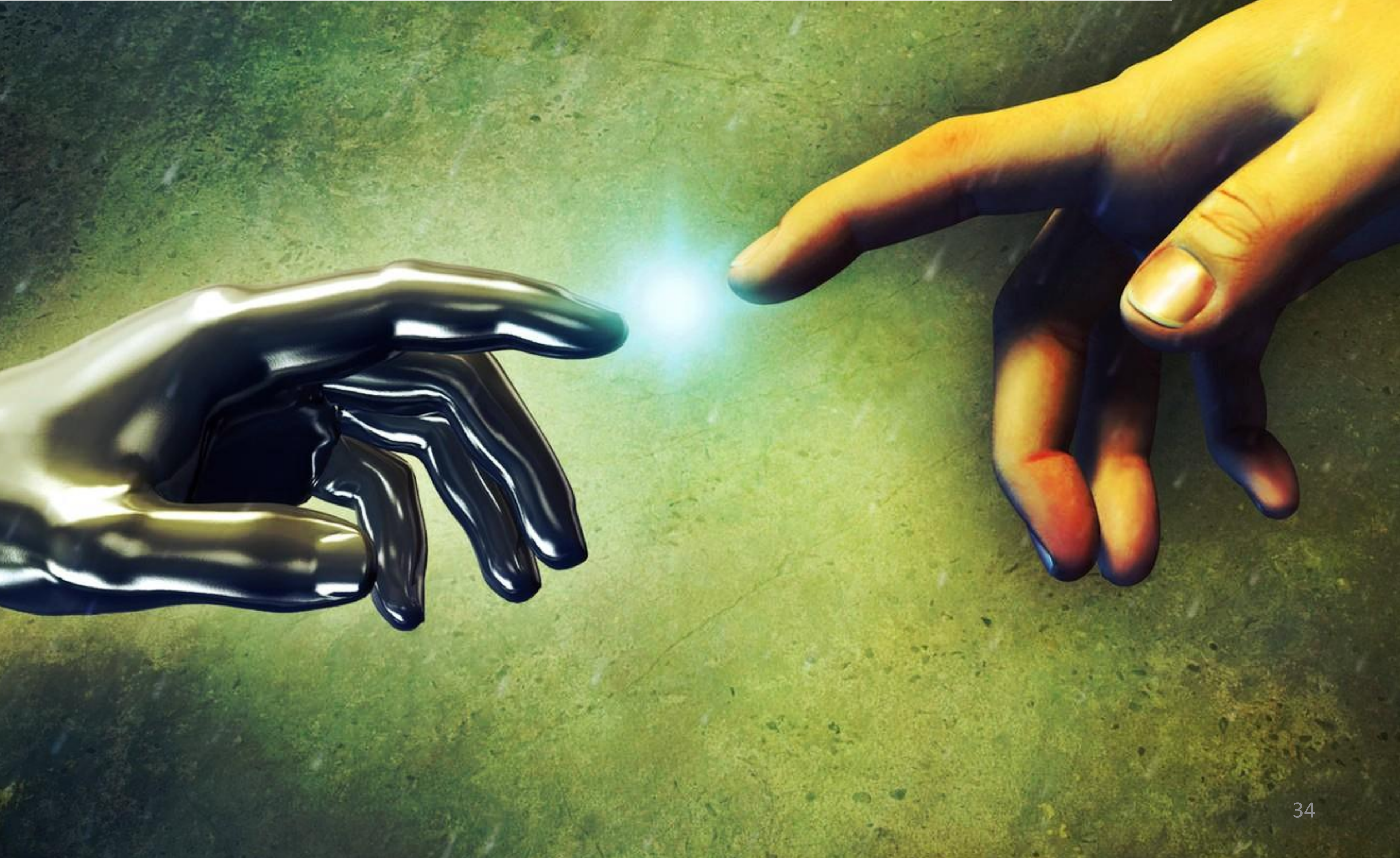
Art des Wissens / Schwierigkeitsgrad	Abfragewissen (Vorlesung)	Anwendungswissen (Literatur)
Einfach		
Mittel		
Schwierig		

1 is an area of machine learning concerned with **how intelligent agents** ought to **take actions** in 2 in order to 3 the notion of cumulative 4

1 is one of three basic Machine Learning Paradigms, alongside **Supervised Learning** and **Unsupervised Learning**. (Wikipedia)

a) **Reinforcement learning| environment| maximize | mistakes**
b) **Reinforcement learning| environment| minimize | rewards**
c) **Reinforcement learning | process| generate | loss**
d) **Reinforcement learning | process| minimize | loss**
e) **Reinforcement learning| environment| maximize | rewards**

8 Machine Learning III
- Specialized Areas in Machine Learning
(6) The Human Role in Machine Learning ?



Automated Machine Learning (AutoML)

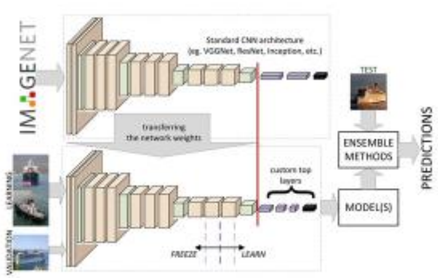
Wikipedia: **Automated machine learning (AutoML)** is the **process of automating the process** of **applying machine learning to real-world problems**. **AutoML** covers the **complete pipeline** from the **raw dataset** to the deployable **machine learning model**.

AutoML was proposed as an **artificial intelligence-based solution** to the **ever-growing challenge of applying machine learning**.

Automating the process of applying machine learning end-to-end additionally offers the **advantages** of **producing simpler solutions**, **faster creation** of those solutions, and models that often **outperform hand-designed models**.

8 Machine Learning III
- Specialized Areas in Machine Learning
(1) Transfer Learning

Transfer Learning: When to apply

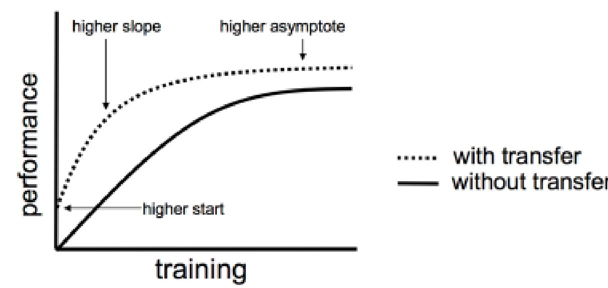


When to **apply Transfer Learning**:

- **Data:** When there is **huge amount of similar Data** in another Domain, but **less Data in current Domain.**
- **Process:** Have **enough Data** for Training, but don't have enough **Computational Resources** to train it.

Deep Learning - using ResNets for Transfer Learning, 2019
madhuramiah.medium.com/deep-learning-using-resnets-for-transfer-learning-d7f4799fa863

Transfer Learning: Benefits



Benefits from **Transfer Learning**:

- Related to **Data: Train** with **smaller amount of Data**.
- Related to **Process: Faster training progress** (higher start, slope, asymptote).

A Gentle Introduction to Transfer Learning for Deep Learning
machinelearningmastery.com/transfer-learning-for-deep-learning/

ARTIFICIAL INTELLIGENCE

Google's Artificial Intelligence Built an AI That Outperforms Any Made by Humans

It's more accurate and more efficient than any other system.

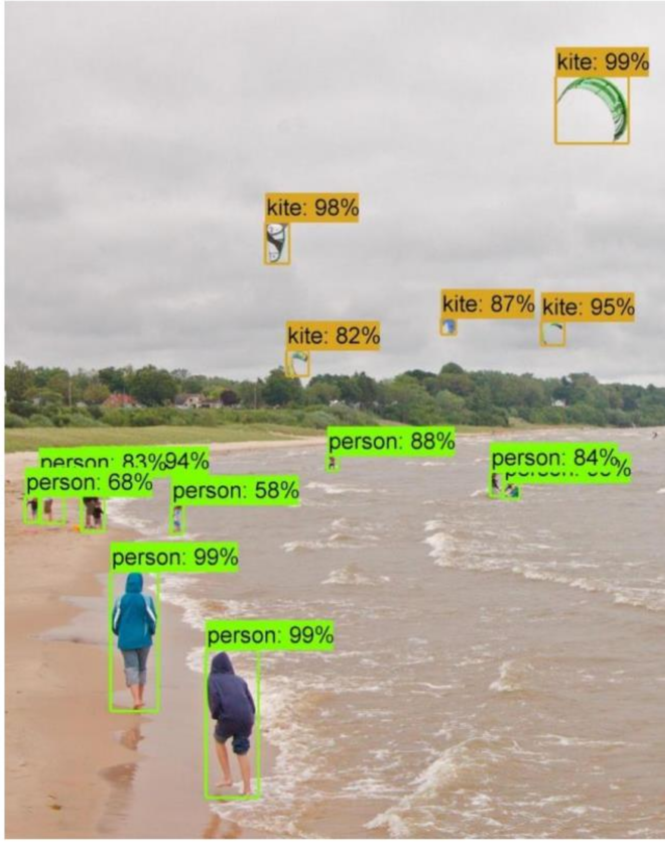
DOM GALEON | DECEMBER 1ST 2017

An AI That Can Build AI

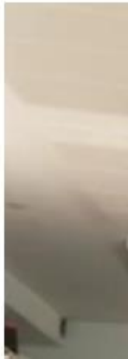
In May 2017, researchers at Google Brain announced the creation of AutoML, an artificial intelligence (AI) that's capable of generating its own AIs. More recently, they decided to present AutoML with its biggest challenge to date, and the AI that can build AI created a "child" that outperformed all of its human-made counterparts.

The Google researchers automated the design of machine learning models using an approach called reinforcement learning. AutoML acts as a controller neural network that develops a child AI network for a specific task. For this particular child AI, which the researchers called NASNet, the task was recognizing objects — people, cars, traffic lights, handbags, backpacks, etc. — in a video in real-time.

According to the researchers, NASNet was 82.7 percent accurate at predicting images on ImageNet's validation set. This is 1.2 percent better than any previously published results, and the system is also 4 percent more efficient, with a 43.1 percent mean Average Precision (mAP). Additionally, a less computationally demanding version of NASNet outperformed the best similarly sized models for mobile platforms by 3.1 percent.



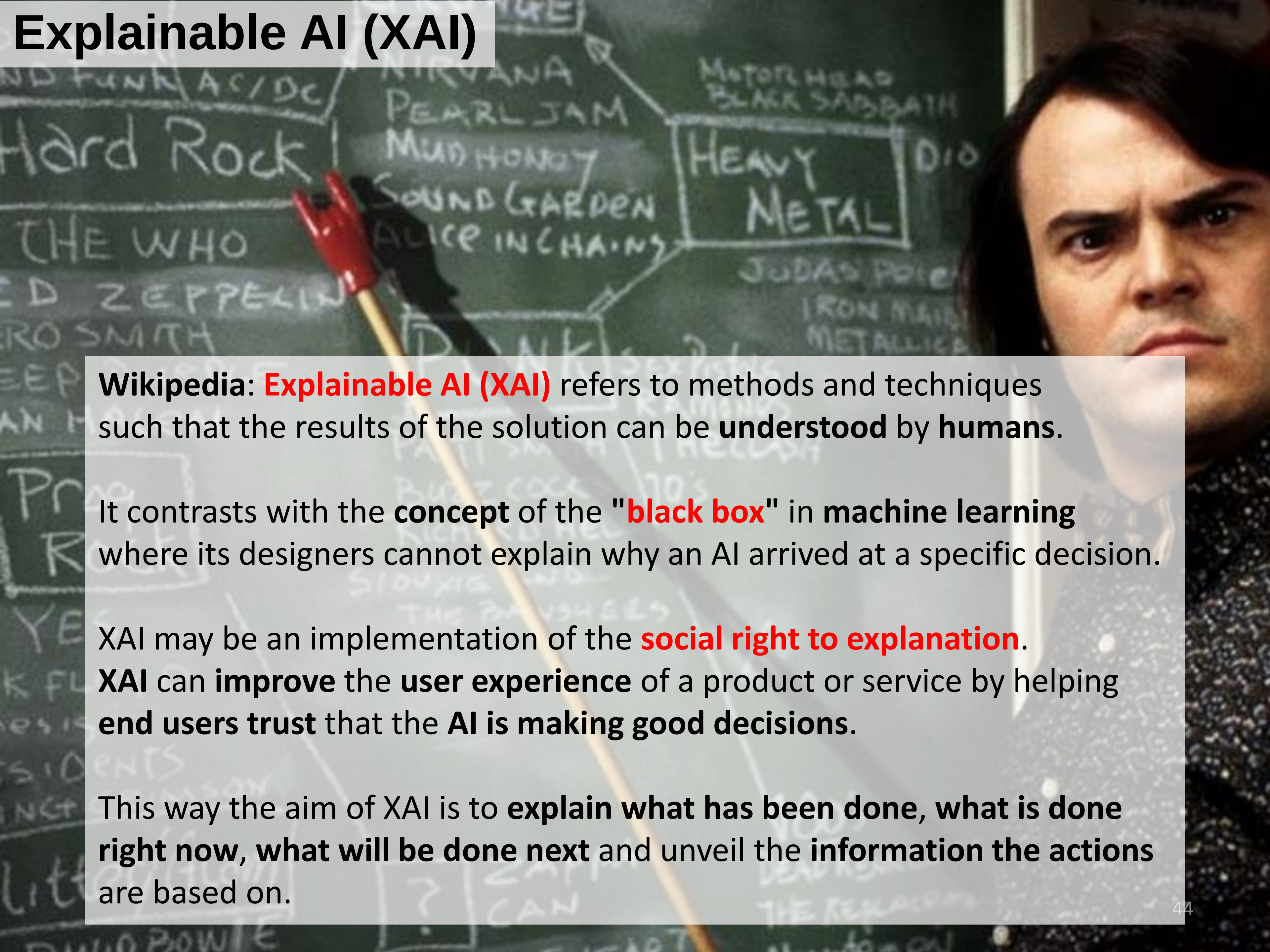
People Don't Trust AI--Here's How



On the other hand, if Watson generated a recommendation that contradicted the experts' opinion, doctors would typically conclude that Watson wasn't competent. And the machine wouldn't be able to explain why its treatment was plausible because its machine learning algorithms were simply too complex to be fully understood by humans. Consequently, this has caused even more mistrust and disbelief, leading many doctors to ignore the seemingly outlandish AI recommendations and stick to their own expertise.

As a result, IBM Watson's premier medical partner, the MD Anderson Cancer Center, recently announced it was dropping the programme. Similarly, a Danish hospital reportedly abandoned the AI

Explainable AI (XAI)



Wikipedia: **Explainable AI (XAI)** refers to methods and techniques such that the results of the solution can be **understood** by **humans**.

It contrasts with the **concept** of the **"black box"** in **machine learning** where its designers cannot explain why an AI arrived at a specific decision.

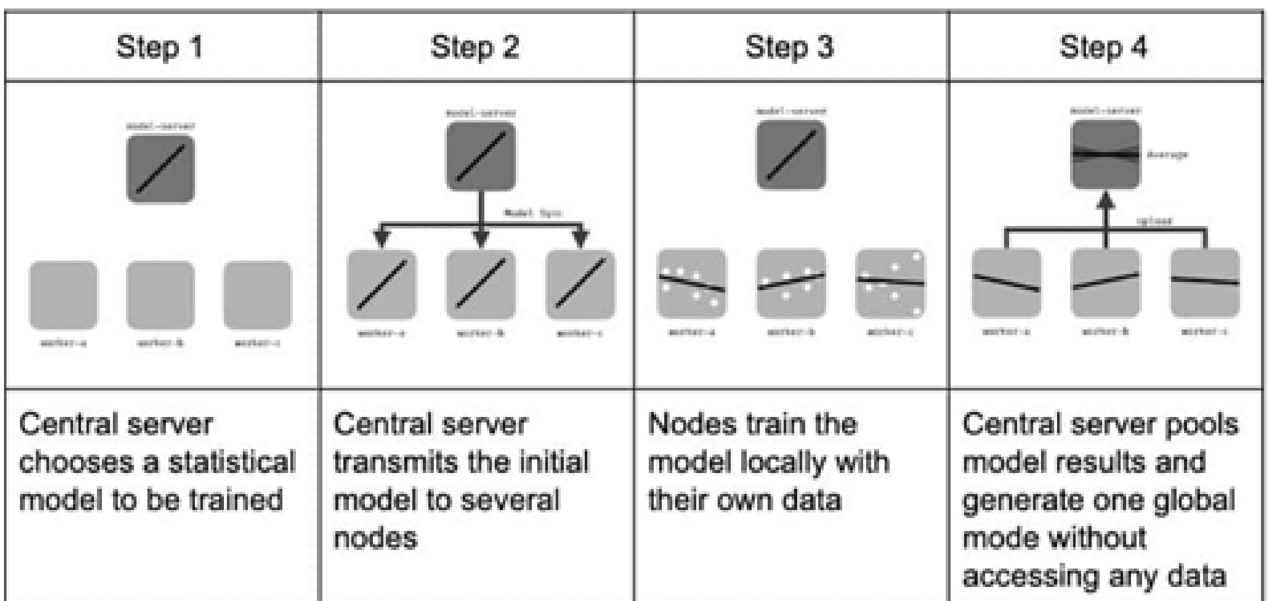
XAI may be an implementation of the **social right to explanation**.
XAI can **improve** the **user experience** of a product or service by helping **end users trust** that the **AI is making good decisions**.

This way the aim of XAI is to **explain what has been done**, **what is done right now**, **what will be done next** and unveil the **information the actions** are based on.

Privacy Preserving AI & Federated Learning

Wikipedia: Federated learning is a machine learning technique that **trains** an **algorithm** across **multiple decentralized servers** holding **local data** samples, **without exchanging the data**.

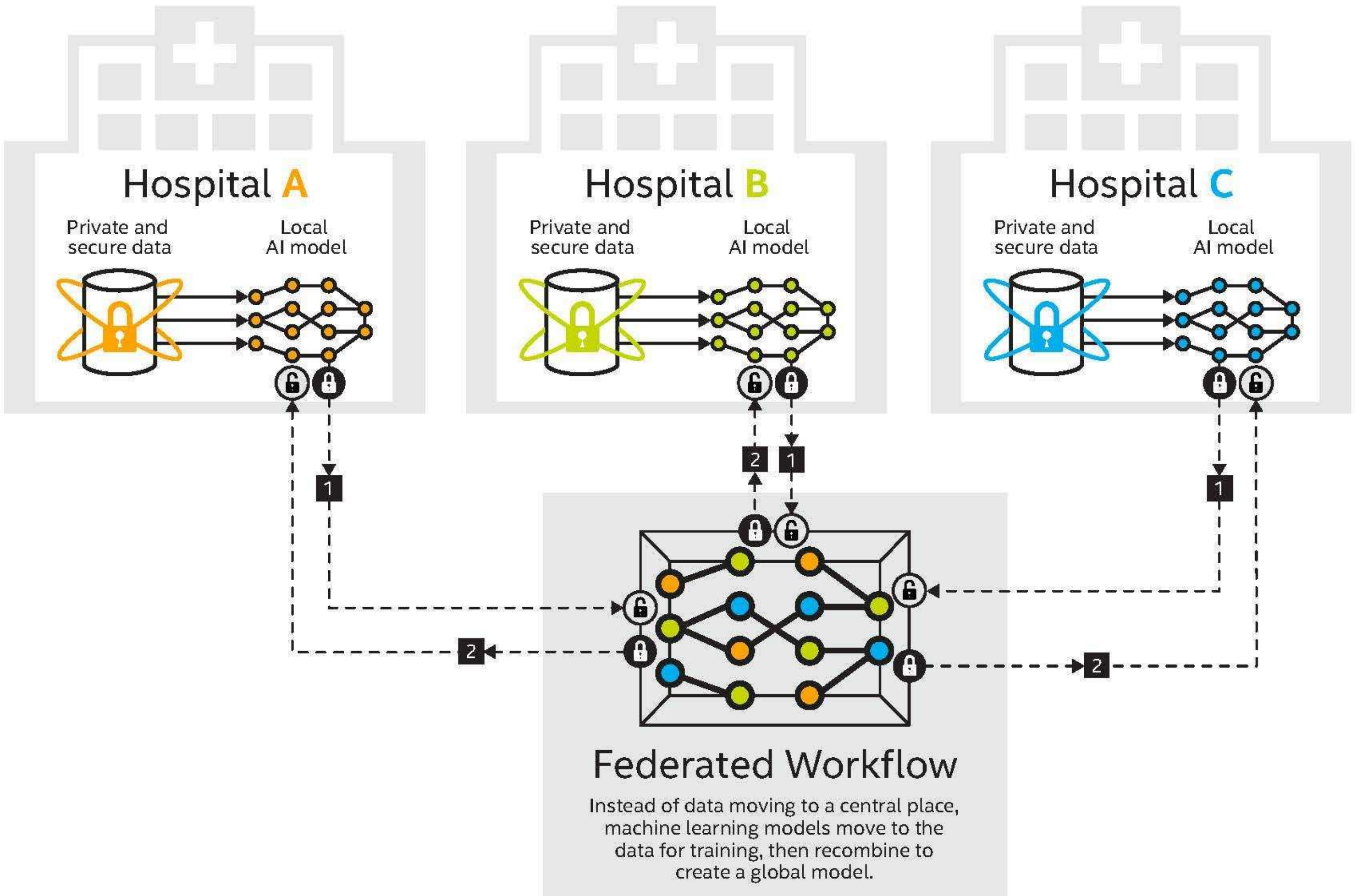
Federated learning enables **multiple actors** to build a **common, robust machine learning model without sharing data**, thus allowing to address **critical issues** such as **data privacy**, **data security**, **data access rights** and **access to heterogeneous data**.



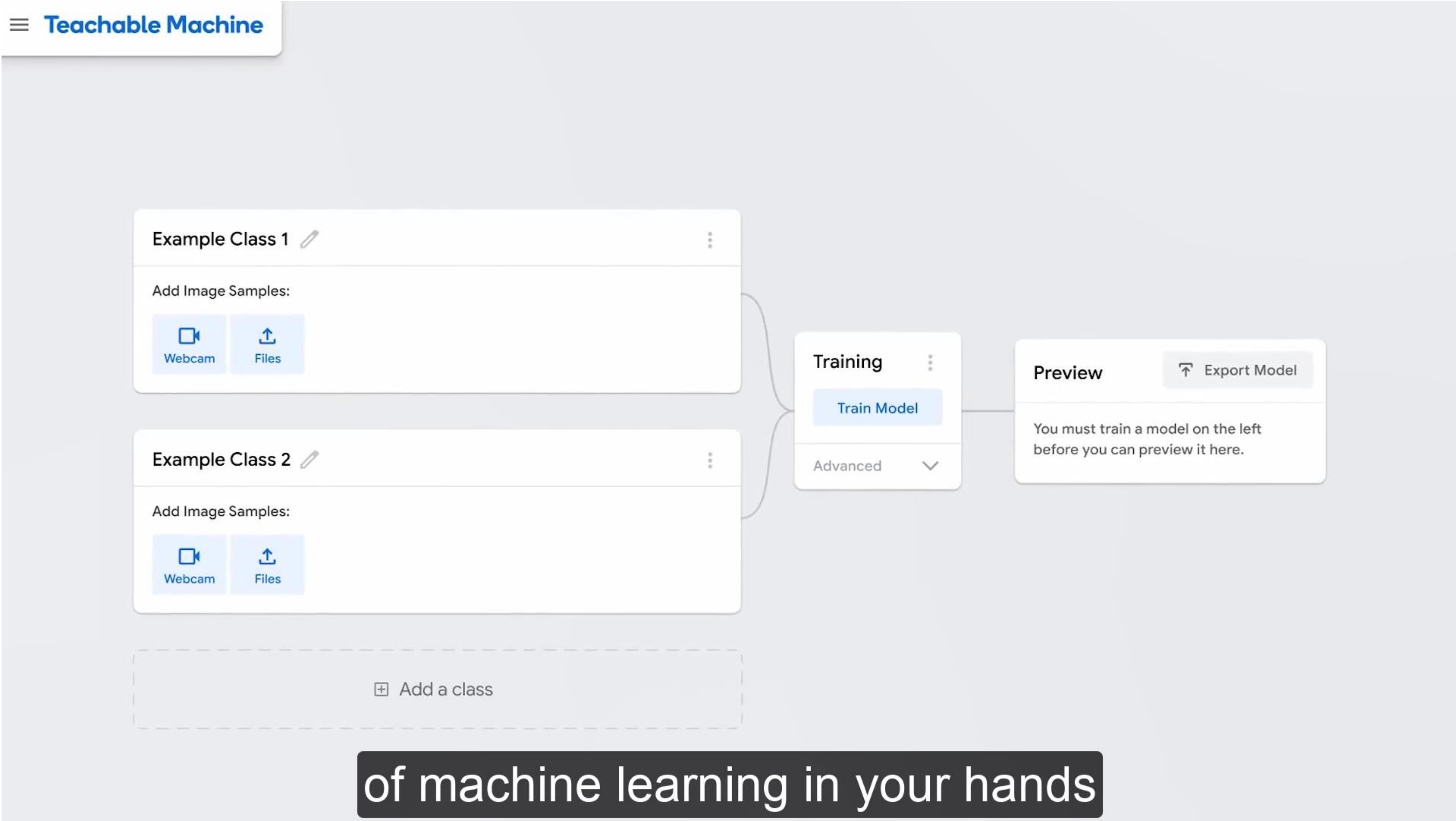
Federated Learning Architecture

Federated learning is a distributed machine learning approach that enables organizations to collaborate on machine learning projects without sharing sensitive data such as patient records.

KEY: 1 Local model sharing 2 Global model sharing updates

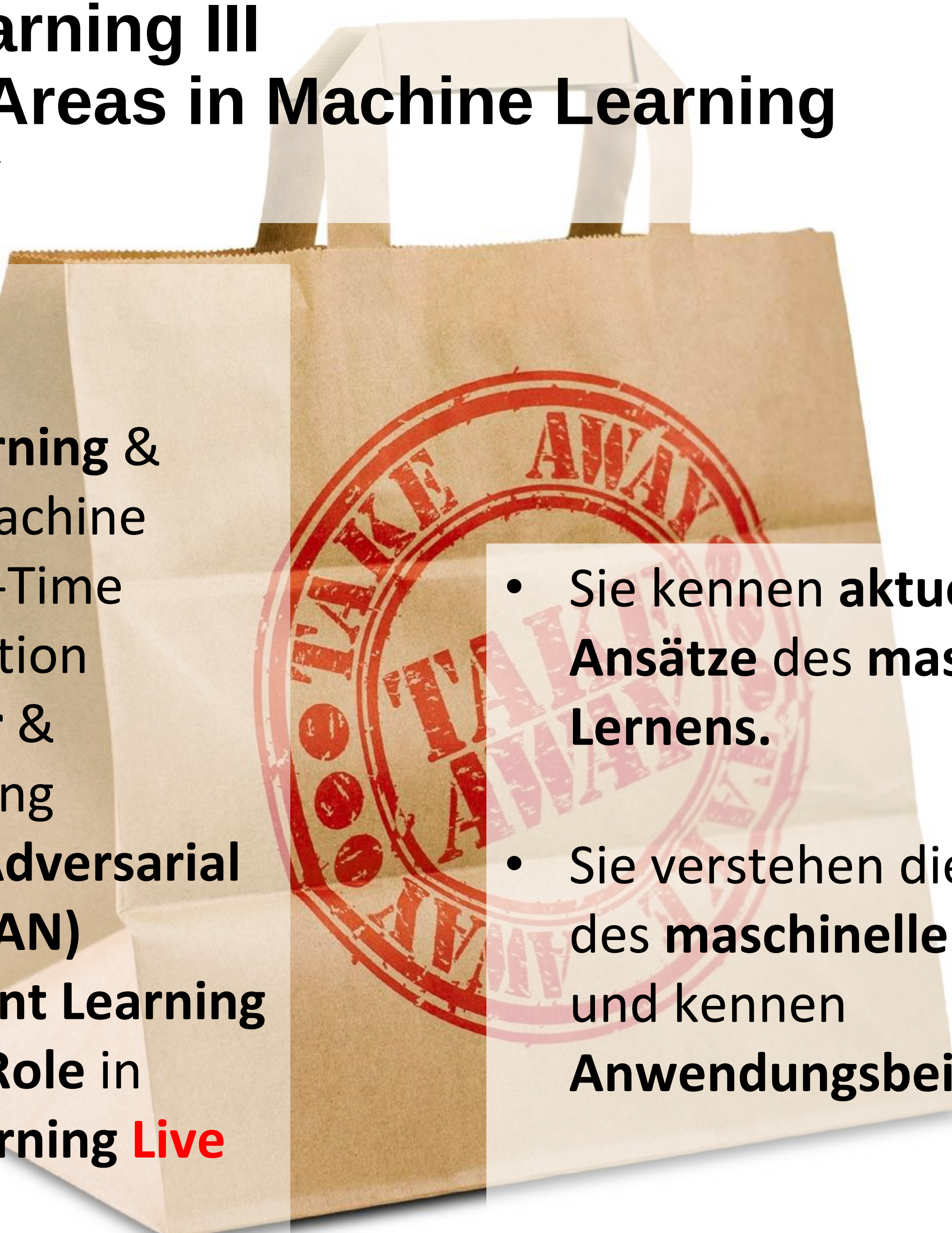


8 Machine Learning III
- Specialized Areas in Machine Learning
(1b) Teachable Machine



teachablemachine.withgoogle.com

8 Machine Learning III
- Specialized Areas in Machine Learning
(7) Summary



Content:

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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**.

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Machine Learning for Lead Management

Theory and a Practical Case Study

Chinmay Kakatkar
Jan 20 · 16 min read ★

Painless Introduction to Applied Bayesian Inference using (Py)Stan

Applied Bayesian regression in PyStan

Sergio E. Betancourt
Jan 20 · 13 min read ★

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- SCHOOL OF Cloud Computing
- SCHOOL OF Business

Your path to the right job

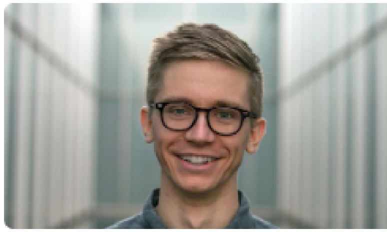
- Machine Learning Engineer
- Deep Learning Engineer
- Artificial Intelligence Specialist

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.

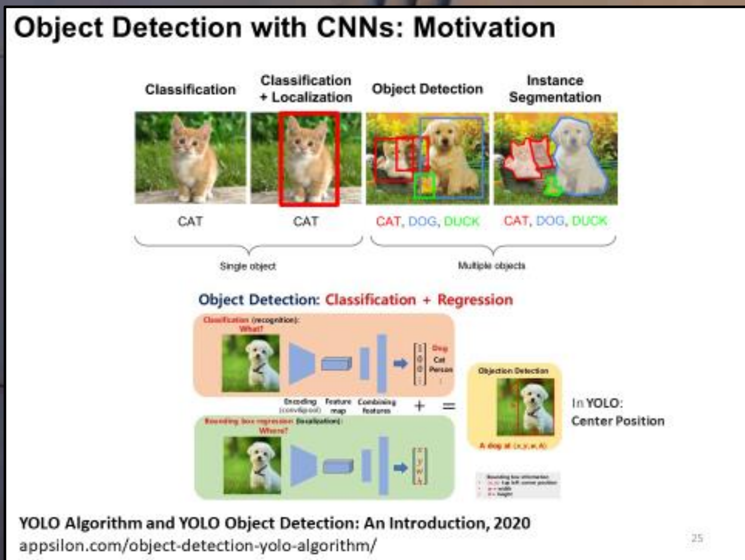
RECOMMENDED PROGRAMS

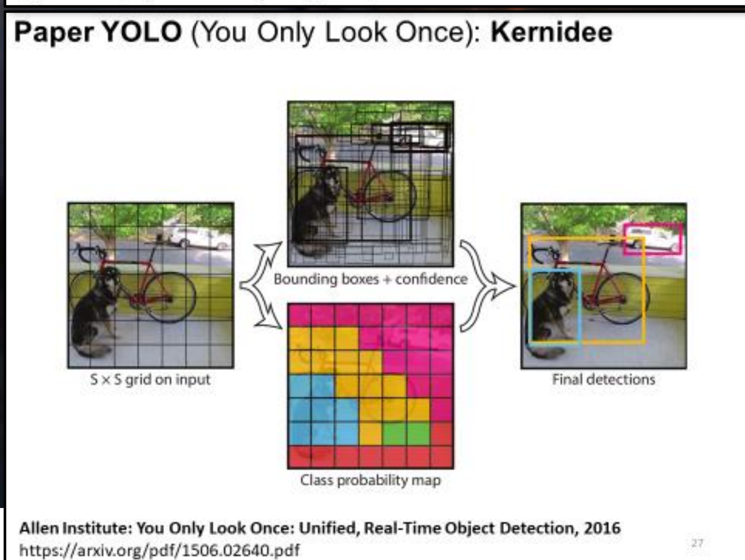
ALUMNI SUCCESS

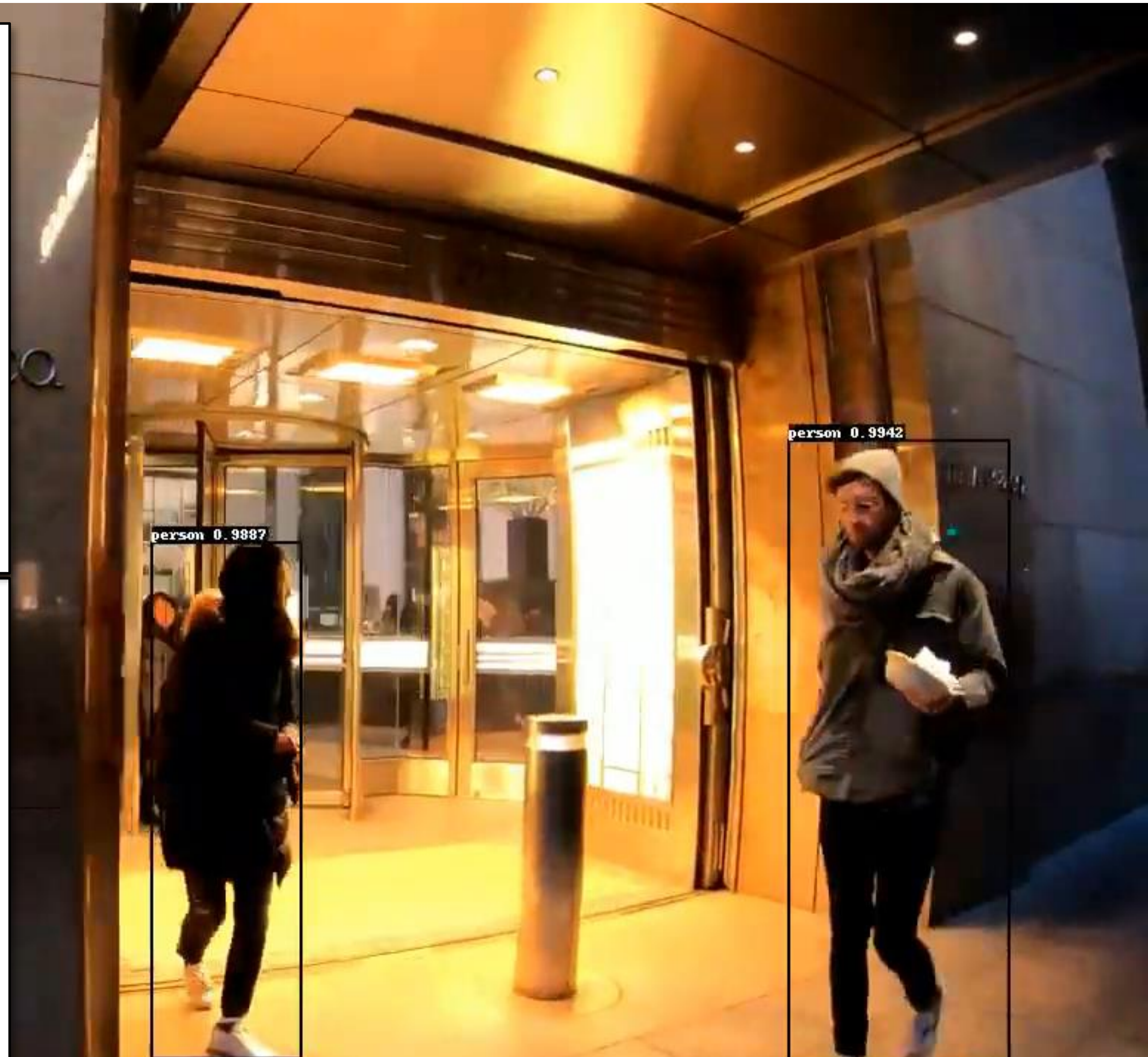


Jeremy Jordan

8 Machine Learning III
- Specialized Areas in Machine Learning
(2) YOLO & Object Detection in Real-Time







Machine Learning & Data Driven Business (ML&DDB)

Prof. Dr. Michael Amberg

Machine Learning III – Specialized Areas

Original s/w, 1896

4K, 60 FPS s/w, 2020

4K, 60 FPS Farbe, 2020

KI-Upscaling: So sieht ein Video von 1896 in 4K, 60 FPS und Farbe aus, 2020
mixed.de/ki-upscaling-so-sieht-ein-video-von-1896-in-4k-60-fps-und-farbe-aus/

Michael Amberg

Todays Content:

1. **Transfer Learning** & Teachable Machine
2. **YOLO** & Real-Time Object Detection
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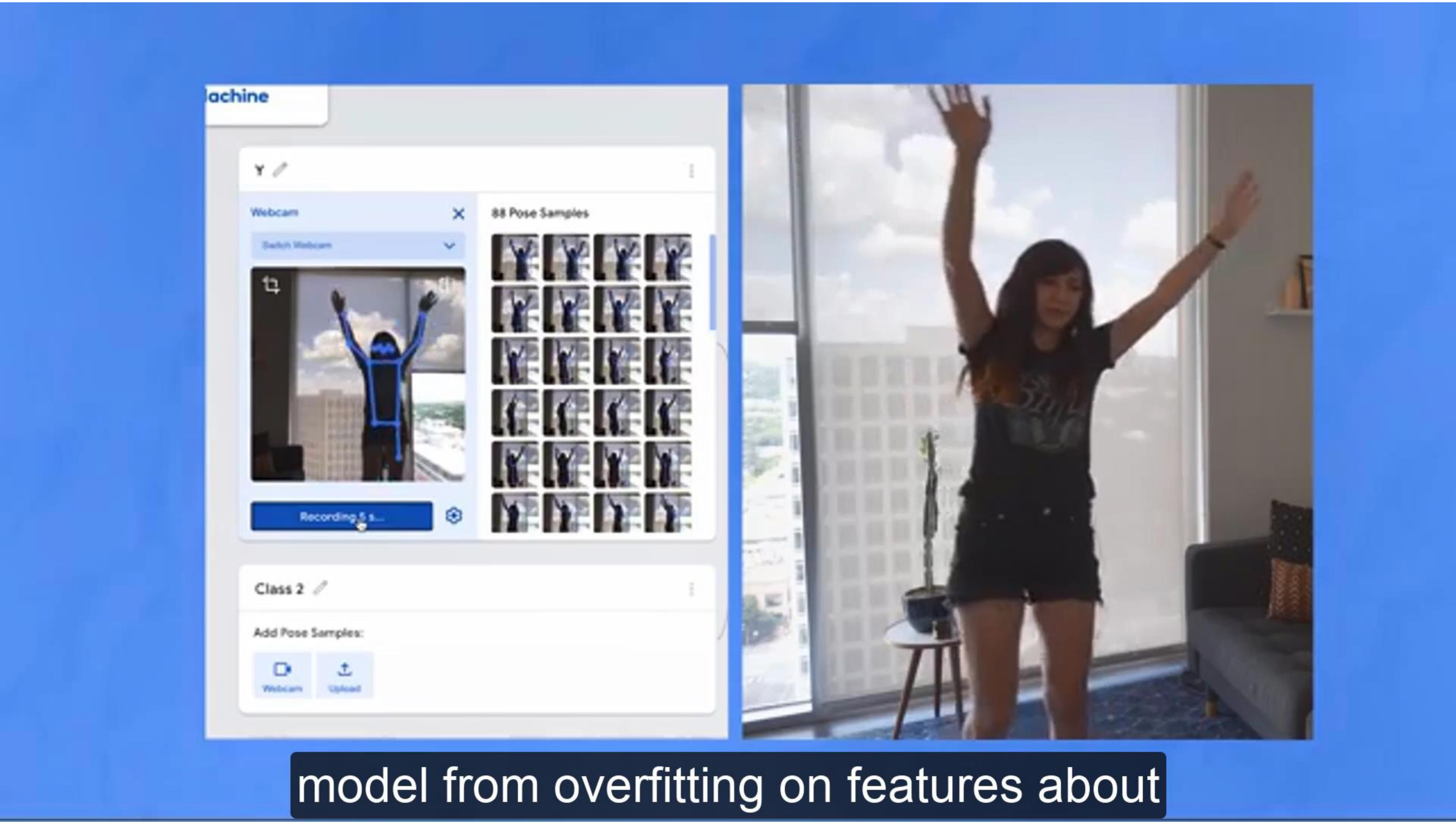
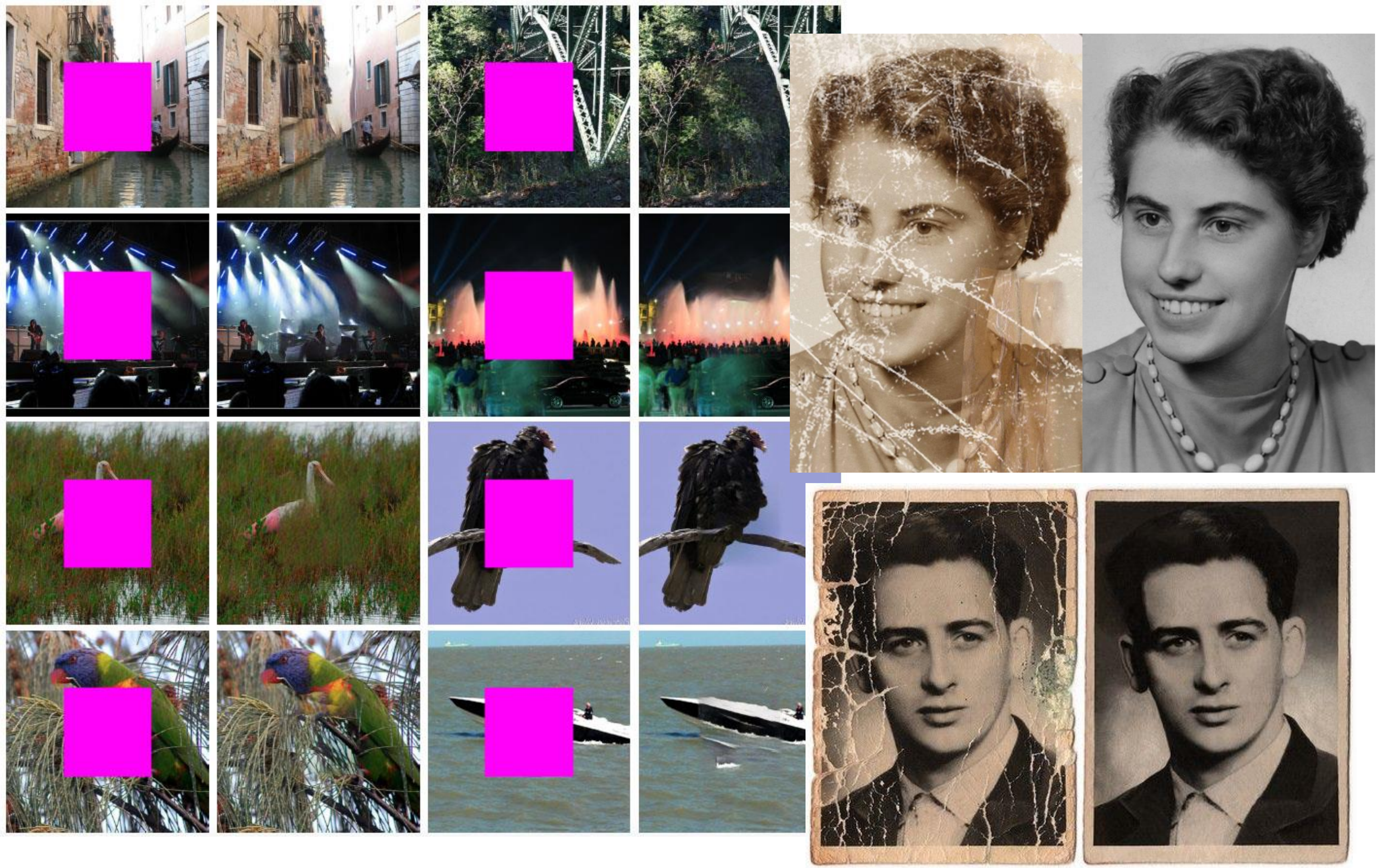
5. **Reinforcement Learning**
6. **The Human Role** in **Machine Learning** **Live**
7. **Summary**

Google Teachable Machine: An Example



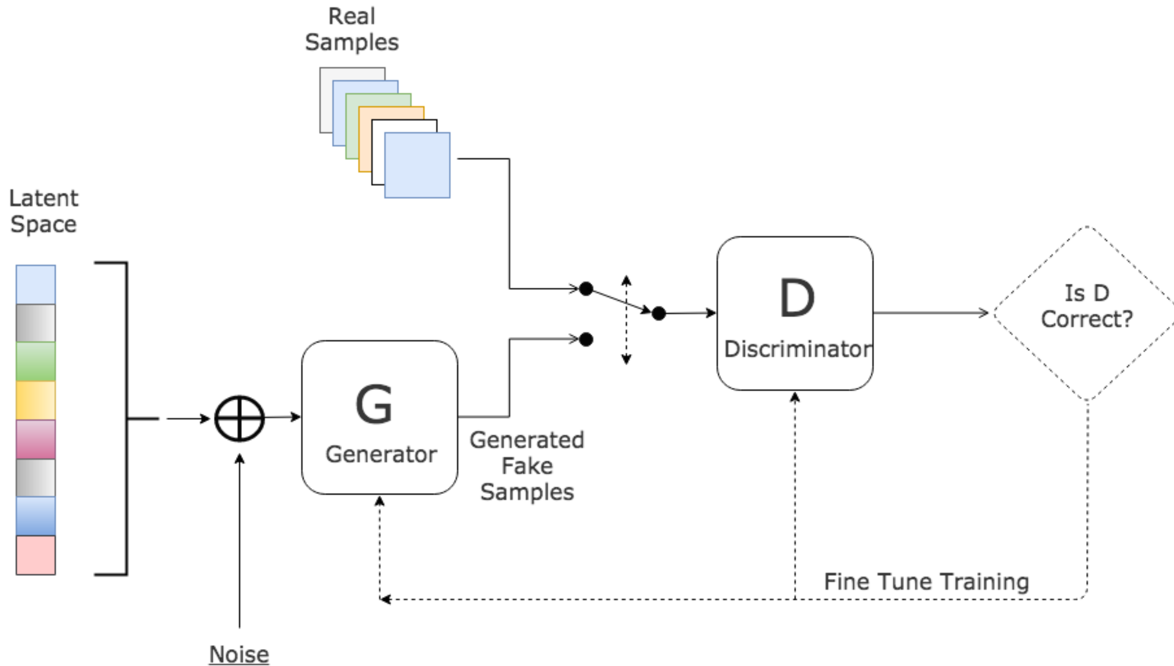
Machine learning without code in the browser, 2020 2min
www.youtube.com/watch?v=i9tjzr1KME0

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...

Generative Adversarial Networks (GAN)

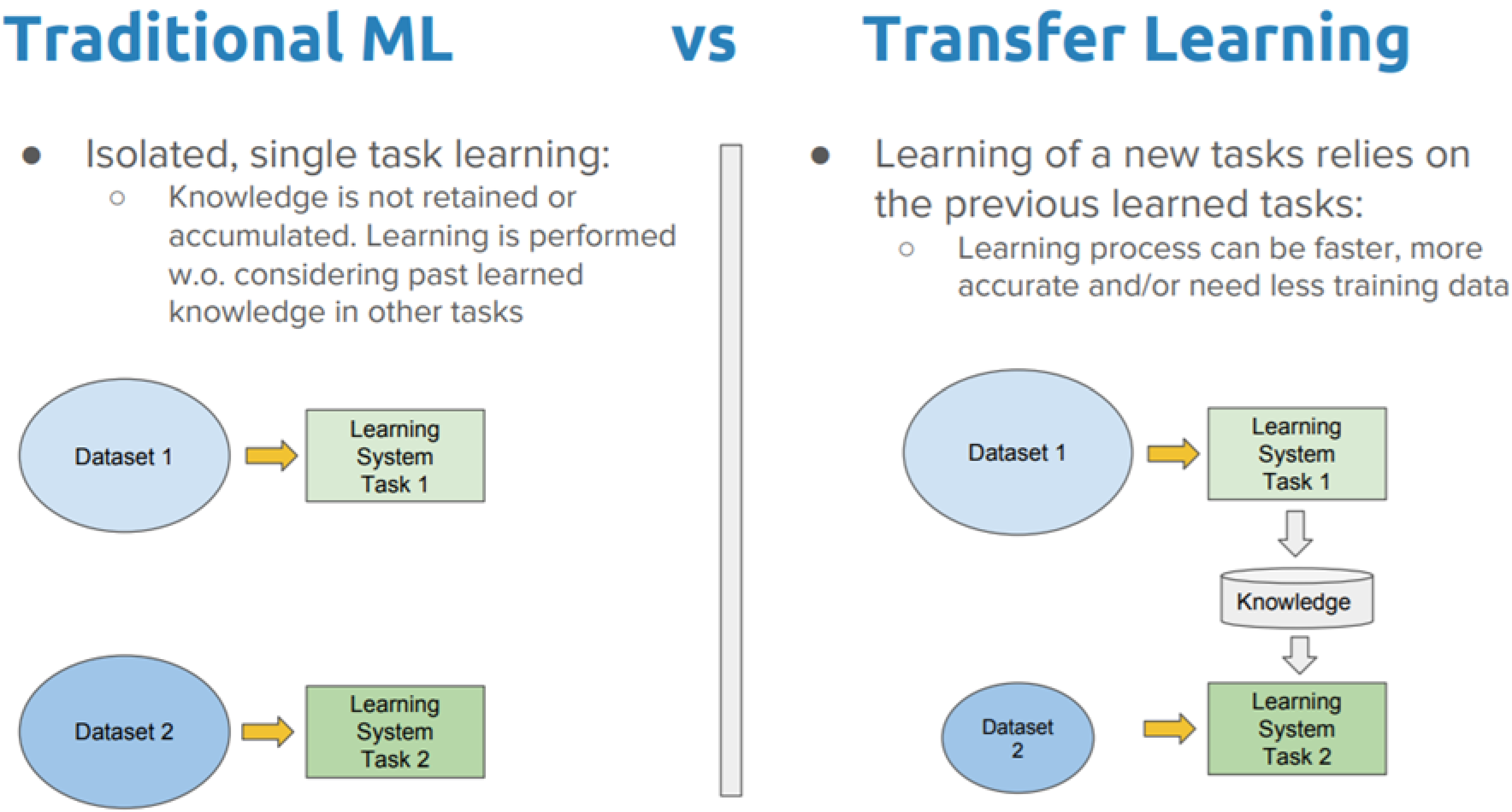


A **Generative Adversarial Network (GAN)** is a class of **machine learning** frameworks designed by **Goodfellow** and his colleagues in **2014**.

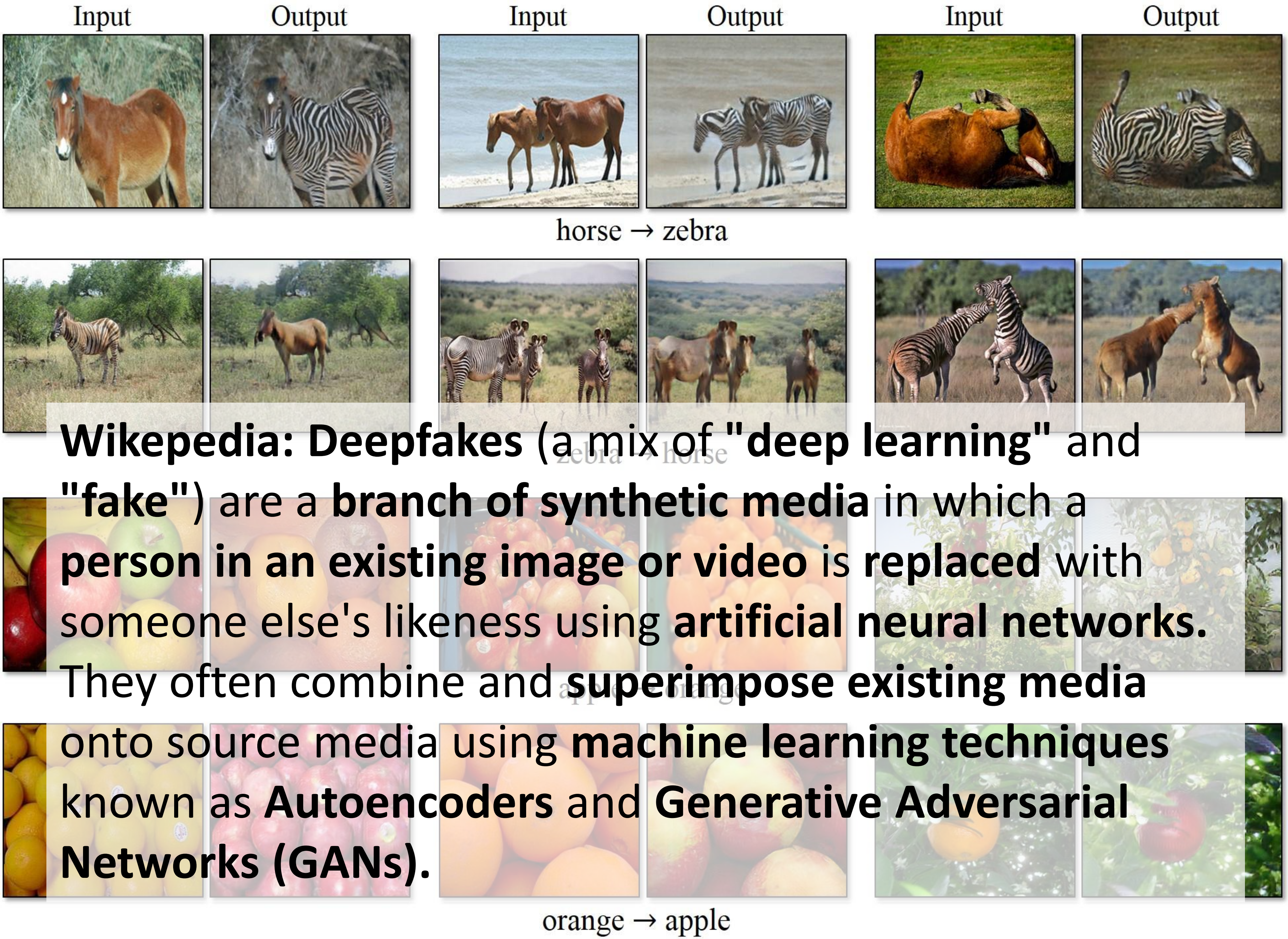
Two neural networks contest with each other in a game. Given a **training set**, this technique learns to **generate new data** with the same statistics as the **training set**.

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**)

Transfer Learning vs Traditional Machine Learning

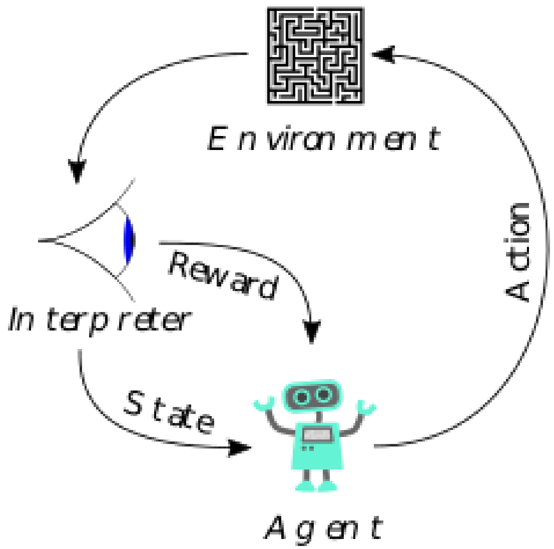


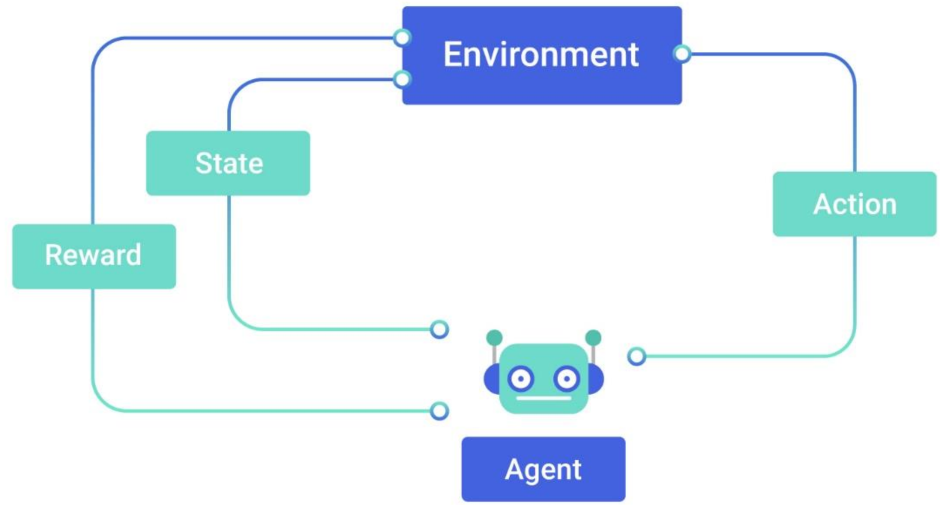
A Comprehensive Hands-on Guide to Transfer Learning with Real-World Applications, 2018
towardsdatascience.com/a-comprehensive-hands-on-guide-to-transfer-learning-with…



Wikepedia: Deepfakes (a mix of **"deep learning"** and **"fake"**) are a **branch of synthetic media** in which a **person in an existing image or video** is **replaced** with someone else's likeness using **artificial neural networks.** They often combine and **superimpose existing media** onto source media using **machine learning techniques** known as **Autoencoders** and **Generative Adversarial Networks (GANs).**

Reinforcement Learning (RL)





Reinforcement Learning (RL) is an area of machine learning concerned with **how intelligent agents** ought to **take actions** in an **environment** in order to **maximize** the notion of cumulative **reward (learn from mistakes / experience)**.

Reinforcement Learning is one of three basic Machine Learning Paradigms, alongside **Supervised Learning** and **Unsupervised Learning**. (Wikipedia)

Machine Learning & Data Driven Business (ML&DDB)

Prof. Dr. Michael Amberg

Anwendungen und **Rahmenbedingungen** von **Data Science** und **Machine Learning** in **Unternehmen** und in einer **datengetriebenen Welt** kennen und einschätzen lernen.

1. **Bullshit with Data:** **The Art of Skepticism in a Data Driven World**
2. **Personal Data Handling:** **Handling of Data in Different Scenarios**
3. **Protect Data:** **Protecting the Privacy & Integrity of Data**
4. **Data Driven Innovation:** **Innovative Business & Applications**
5. **Project Management:** **Managing Projects successfully**
6. **Business Systems:** **Relevant Enterprise Software Systems**
7. **Emerging Technologies:** **Implications of selected Technologies**
8. **Machine Learning I, II, III:** **Overview of ML Techniques & Methods**
9. **ML & Robotics:** **Current Developments & Implications**

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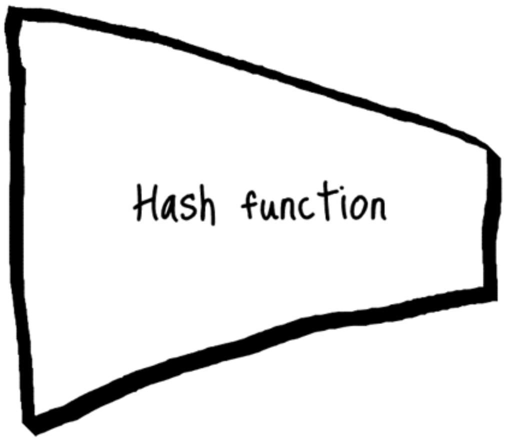
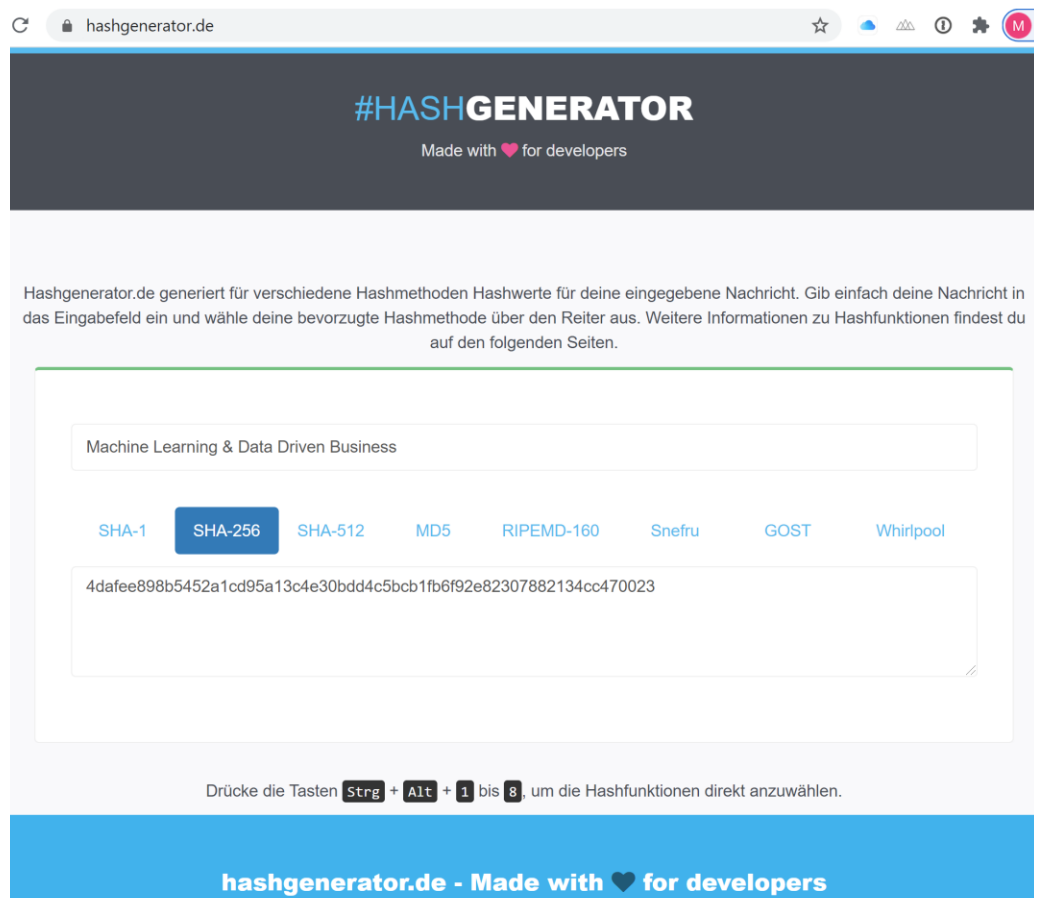
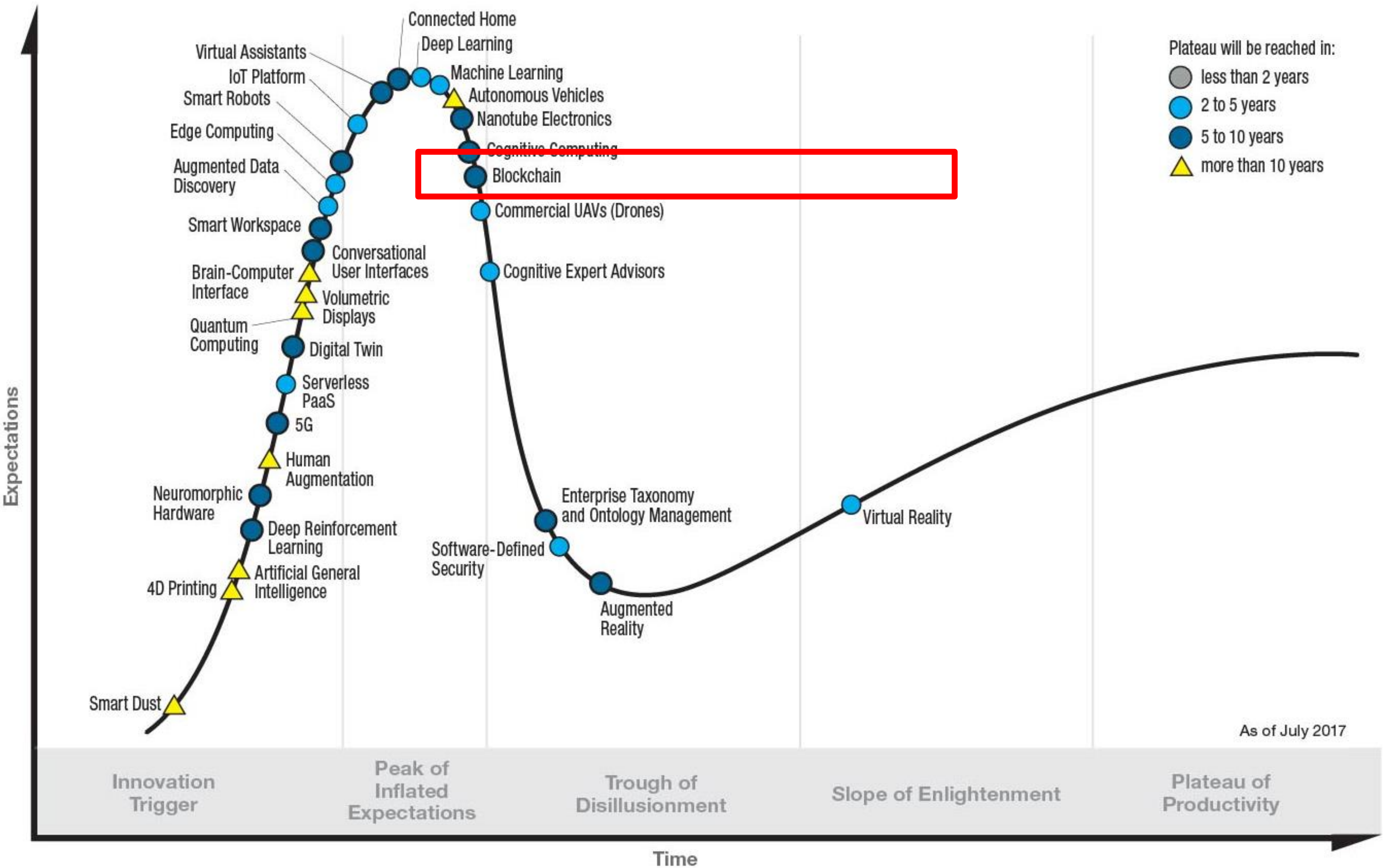
SHA-256 Hash Generator





Hashgenerator.de

Gartner Hype Cycle for Emerging Technologies, 2017



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Machine Learning & Data Driven Business (ML&DDB)

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Evaluation der Veranstaltung

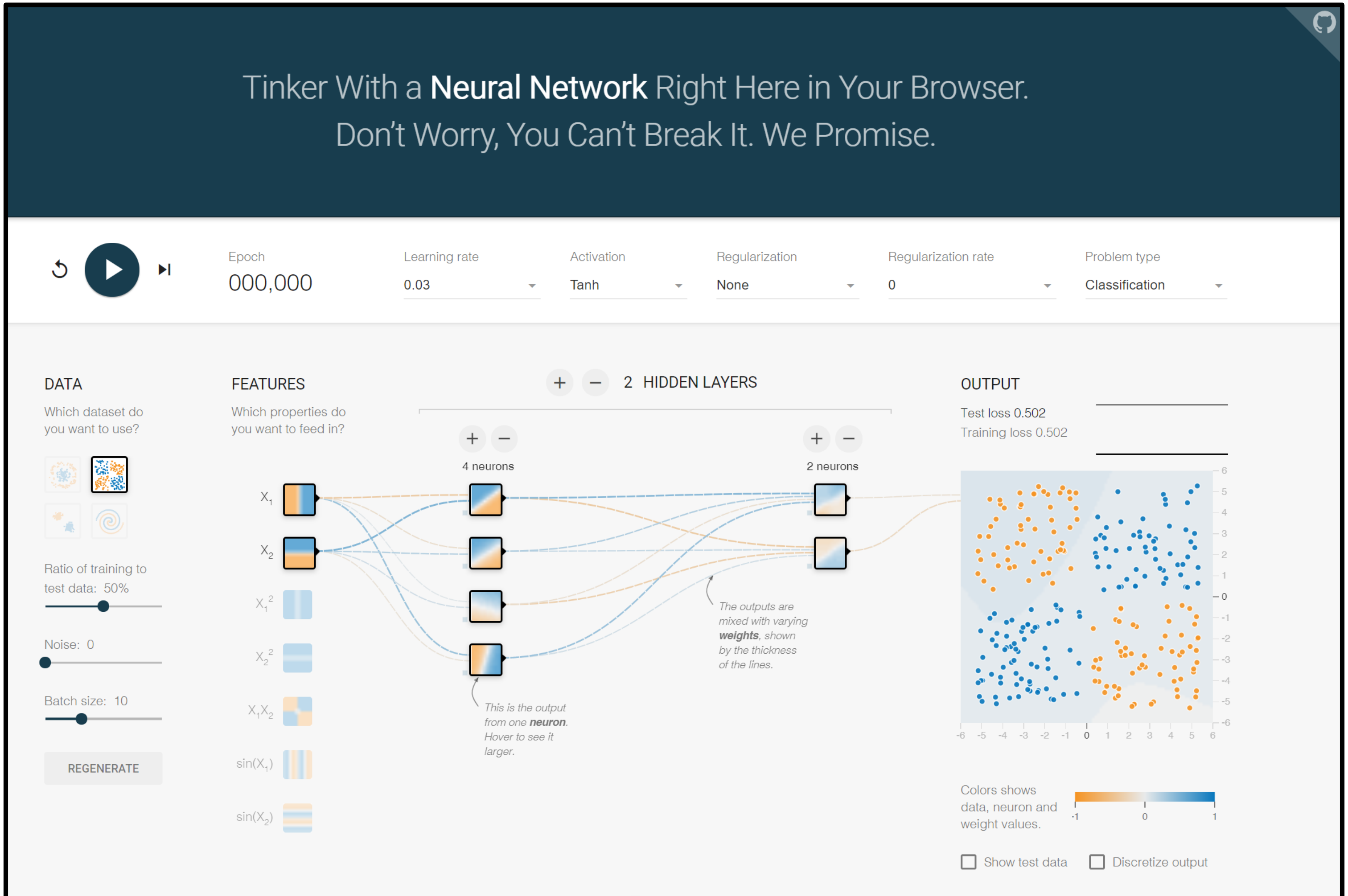
Machine Learning & Data Driven Business

Bitte nehmen Sie über den QR Code oder folgendenden Link an der Evaluation teil:

https://www.eva.fau.de

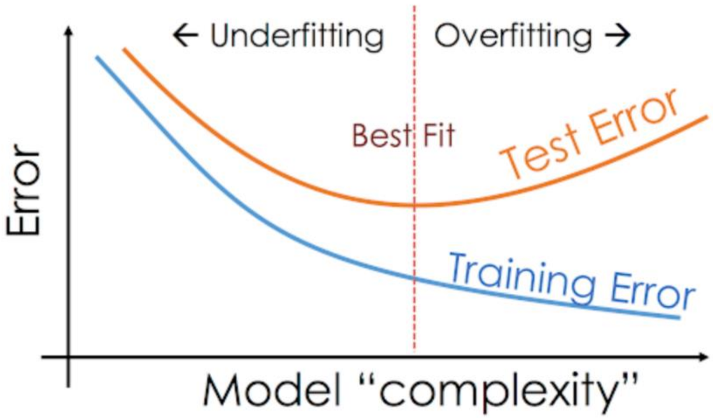
Losung: USMDM

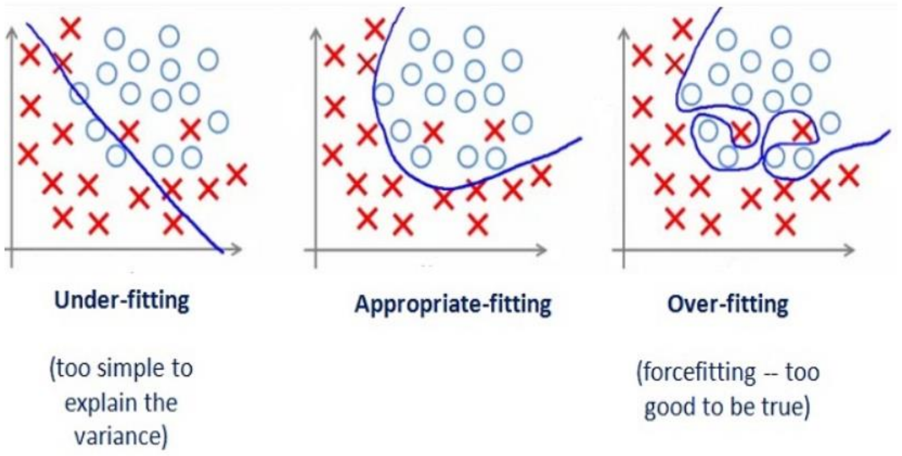
8 Machine Learning I
- Neural Networks & Deep Learning
(3) **TensorFlow Playground**



playground.tensorflow.org

NN: **Underfitting** und **Overfitting** beachten



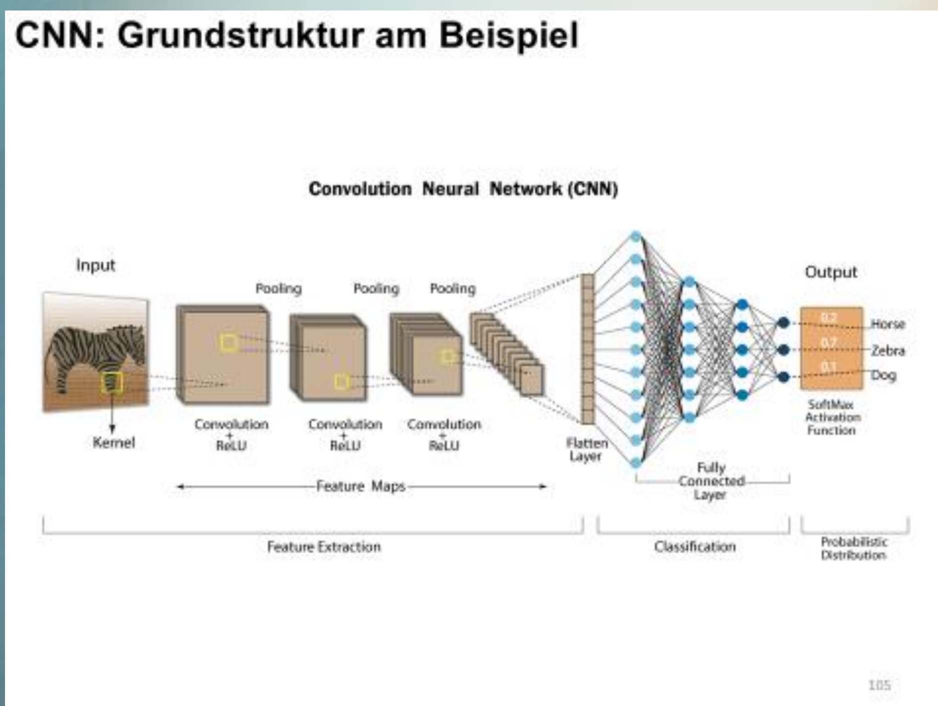


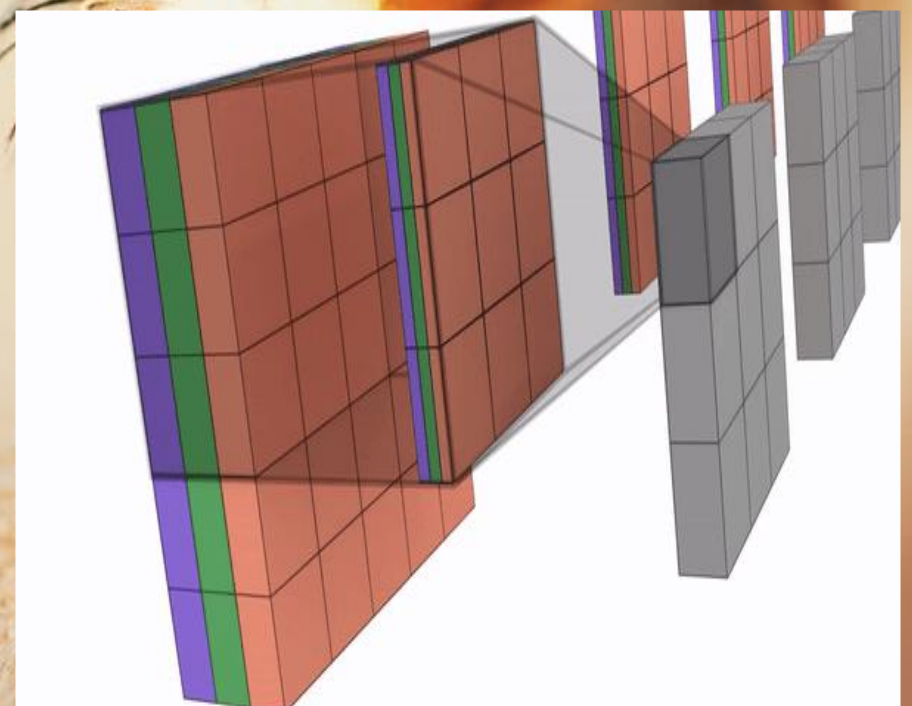
Mit der **Fehlerrate** beim **Trainieren** (oben: **Training Error**) und beim **Testen** (oben: **Test Error**) kann man beurteilen, wie gut eine **Neuronales Netz** das gewählte **Problem** löst.

Das **Neuronale Netz** sollte so gestaltet sein, dass **Underfitting** (Struktur zu einfach) und **Overfitting** (Struktur zu komplex) vermieden wird.

What is underfitting and overfitting in machine learning and how to deal with it
medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning...

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





JAMES | Journal of Advances in Modeling Earth Systems

RESEARCH ARTICLE
10.1029/2020MS002301

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 microphy
Advance
12, e202
10.1029/

Received
Accepte
Accepte

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

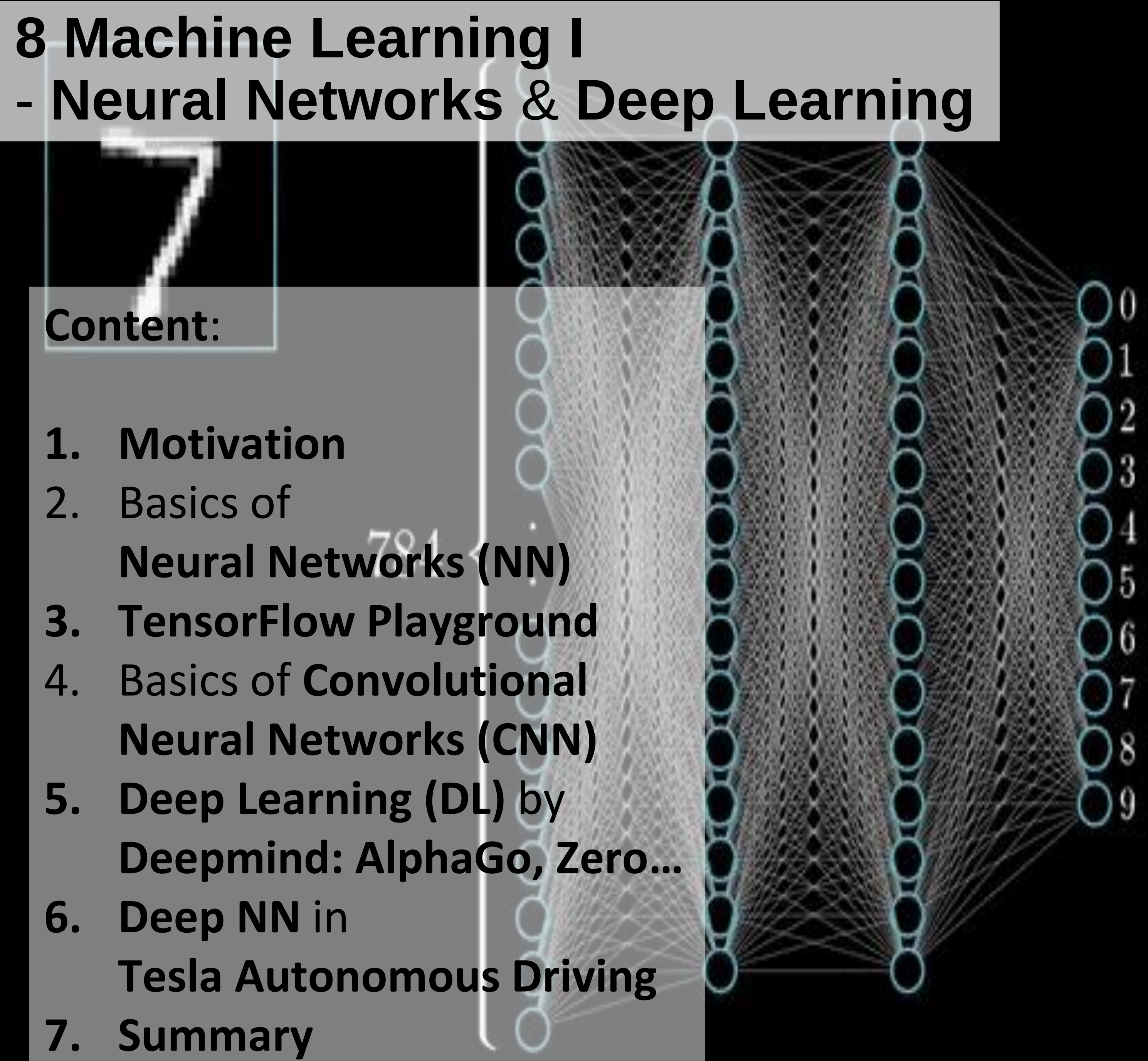
Axel Seifert[1] and Stephan Rasp[2]

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

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.

8 Machine Learning I
- 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**

CNN: Eine Beispielanwendung

EXPERT REVIEW OF PRECISION MEDICINE AND DRUG DEVELOPMENT
https://doi.org/10.1080/23808993.2019.1585805

Taylor & Francis
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REVIEW

OPEN ACCESS Check for updates

Deep learning and radiomics in precision medicine

Vishwa S. Parekh[a,b] and Michael A. Jacobs[a,c]

[a]The Russell H. Morgan Department of Radiology and Radiological Sciences, John Hopkins University, School of Medicine, Baltimore, MD, USA; [b]Department of Computer Science, The Johns Hopkins University, Baltimore, MD, USA; [c]Sidney Kimmel Comprehensive Cancer Center, The Johns Hopkins University School of Medicine, Baltimore, MD, USA

ABSTRACT

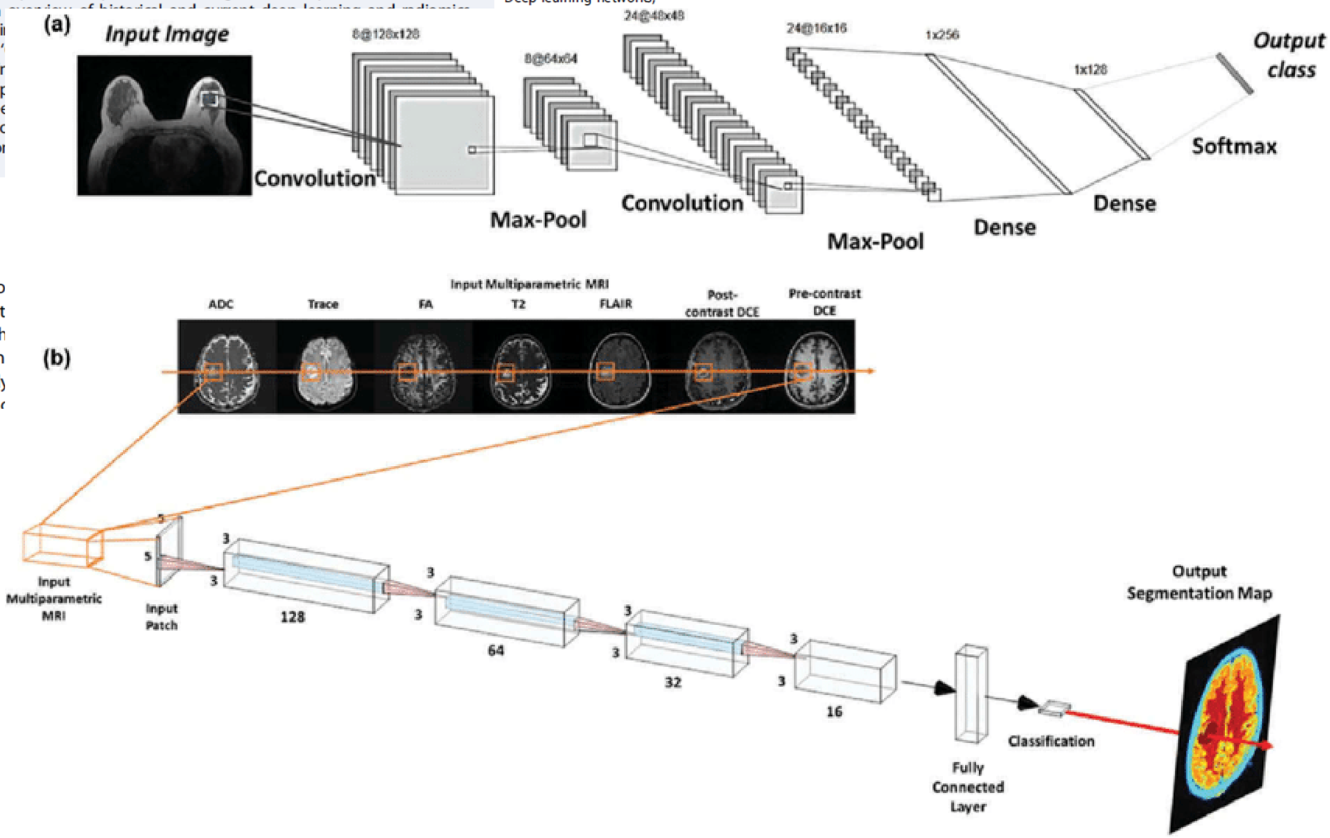
Introduction: The radiological reading room is undergoing a paradigm shift to a symbiosis of computer science and radiology using artificial intelligence integrated with machine and deep learning with radiomics to better define tissue characteristics. The goal is to use integrated deep learning and radiomics with radiological parameters to produce a personalized diagnosis for a patient.

Areas covered: This review provides an
methods in the context of precision medici
'Machine learning', 'Artificial Intelligence', '
'Autoencoders', Deep Belief Networks", Rei
PubMed, ArXiv, Scopus, CVPR, SPIE, IEEE X

Expert opinion: In conclusion, both de
ogies that will unite in the future to pr
with a potential to completely revolutio

ARTICLE HISTORY
Received 5 December 2018
Accepted 19 February 2019

KEYWORDS
Deep learning networks;



1. Introduction

Radiological imaging methods are used to
regions of body for detection and charact
abnormal pathology and aid diagnosis. Th
ging procedures can produce large volum
imaging data from regional or whole-body
make "reading and interpreting" the imag

Wikipedia zu DeepMind

DeepMind

From Wikipedia, the free encyclopedia

DeepMind Technologies Limited is a British artificial intelligence company founded in September 2010.

Acquired by Google in 2014, the company has created a neural network that learns how to play video games in a fashion similar to that of humans,[4] as well as a Neural Turing machine,[5] or a neural network that may be able to access an external memory like a conventional Turing machine, resulting in a computer that mimics the short-term memory of the human brain.[6][7]

The company made headlines in 2016 after its AlphaGo program beat a human professional Go player for the first time in October 2015[8] and again when AlphaGo beat Lee Sedol the world champion in a five-game match, which was the subject of a documentary film.[9]

A more generic program, AlphaZero, beat the most powerful programs playing go, chess and shogi (Japanese chess) after a few hours of play against itself using reinforcement learning.[10]

Contents [hide]

DeepMind Technologies Limit

DeepMin

Type of business	Subsidiary
Founded	23 September 2010; 7 yea ago [1]
Headquarters	6 Pancras Square,[2] London N1C 4AG, UK
Founder(s)	Demis Hassabis, Shane Legg, Mustafa Suleyman
CEO	Demis Hassabis
Industry	Artificial Intelligence
Employees	400 [3]
Parent	Independent (2010–2014) Google Inc. (2014–preser Alphabet Inc. (2015–prese
Website	www.deepmind.com

Wikipedia zu AlphaGo

AlphaGo

From Wikipedia, the free encyclopedia

AlphaGo logo

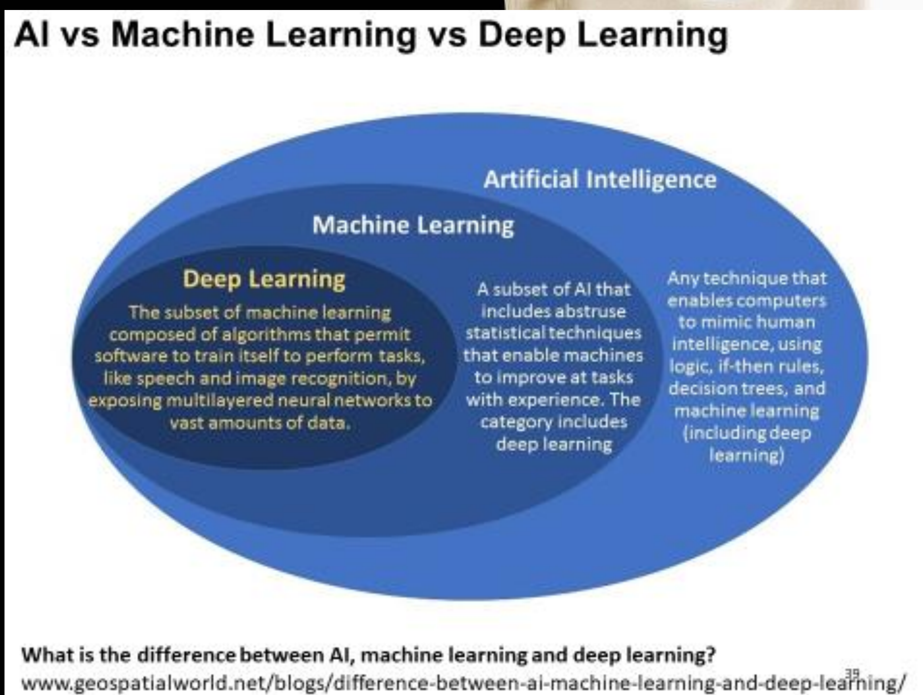
AlphaGo is a computer program that plays the board game Go.[1] It was developed by Alphabet Inc.'s Google DeepMind in London.

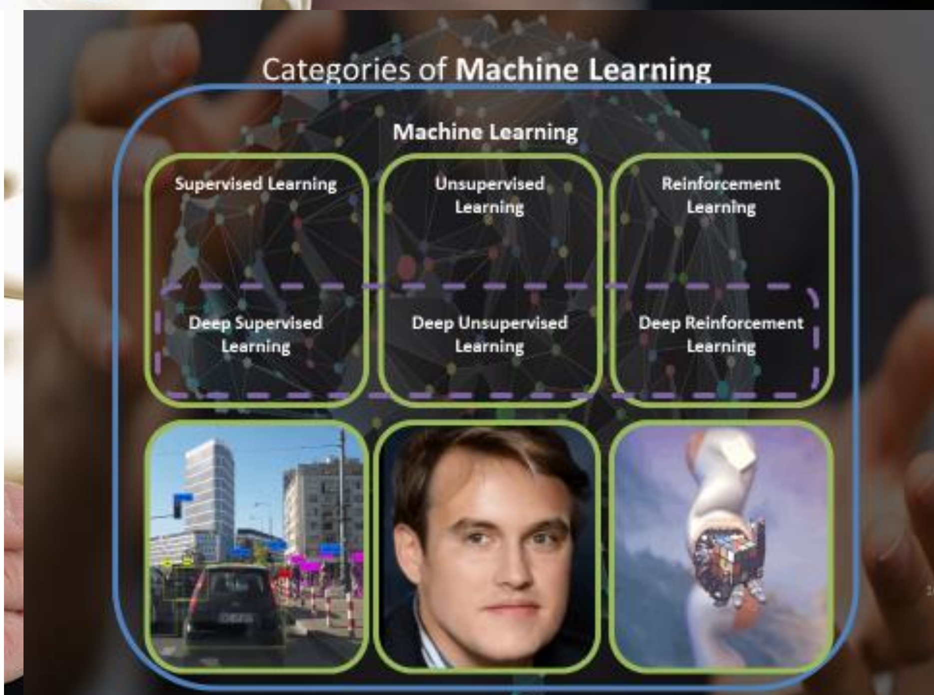
In October 2015, AlphaGo became the first computer Go program to beat a human professional Go player without handicaps on a full-sized 19×19 board.[2][3] In March 2016, it beat Lee Sedol in a five-game match, the first time a computer Go program has beaten a 9-dan professional without handicaps.[4] Although it lost to Lee Sedol in the fourth game, Lee resigned the final game, giving a final score of 4 games to 1 in favour of AlphaGo. In recognition of the victory, AlphaGo was awarded an honorary 9-dan by the Korea Baduk Association.[5] The lead up and the challenge match with Lee Sedol were documented in a documentary film also titled *AlphaGo*,[6] directed by Greg Kohs. It was chosen by *Science* as one of the Breakthrough of the Year runners-up on 22 December 2016.[7]

At the 2017 Future of Go Summit, AlphaGo beat Ke Jie, the world No.1 ranked player at the time, in a three-game match. After this, AlphaGo was awarded professional 9-dan by the Chinese Weiqi Association.[8] After the match between AlphaGo and Ke Jie, AlphaGo retired while DeepMind continues AI research in other areas.[9]

AlphaGo uses a Monte Carlo tree search algorithm to find its moves based on knowledge previously "learned" by machine learning, specifically by an artificial neural network (a deep learning method) by extensive training, both from human and computer play.[10]

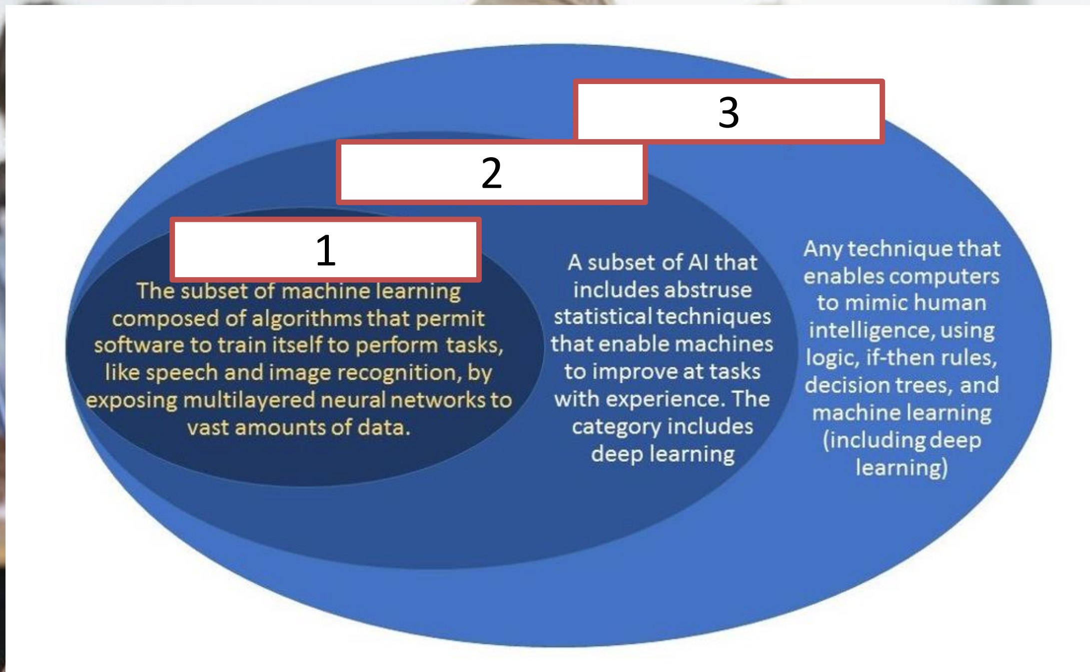
8 Machine Learning I
- Neural Networks & Deep Learning
(1) **Motivation** & Intro **Machine Learning**





Fill in the blank

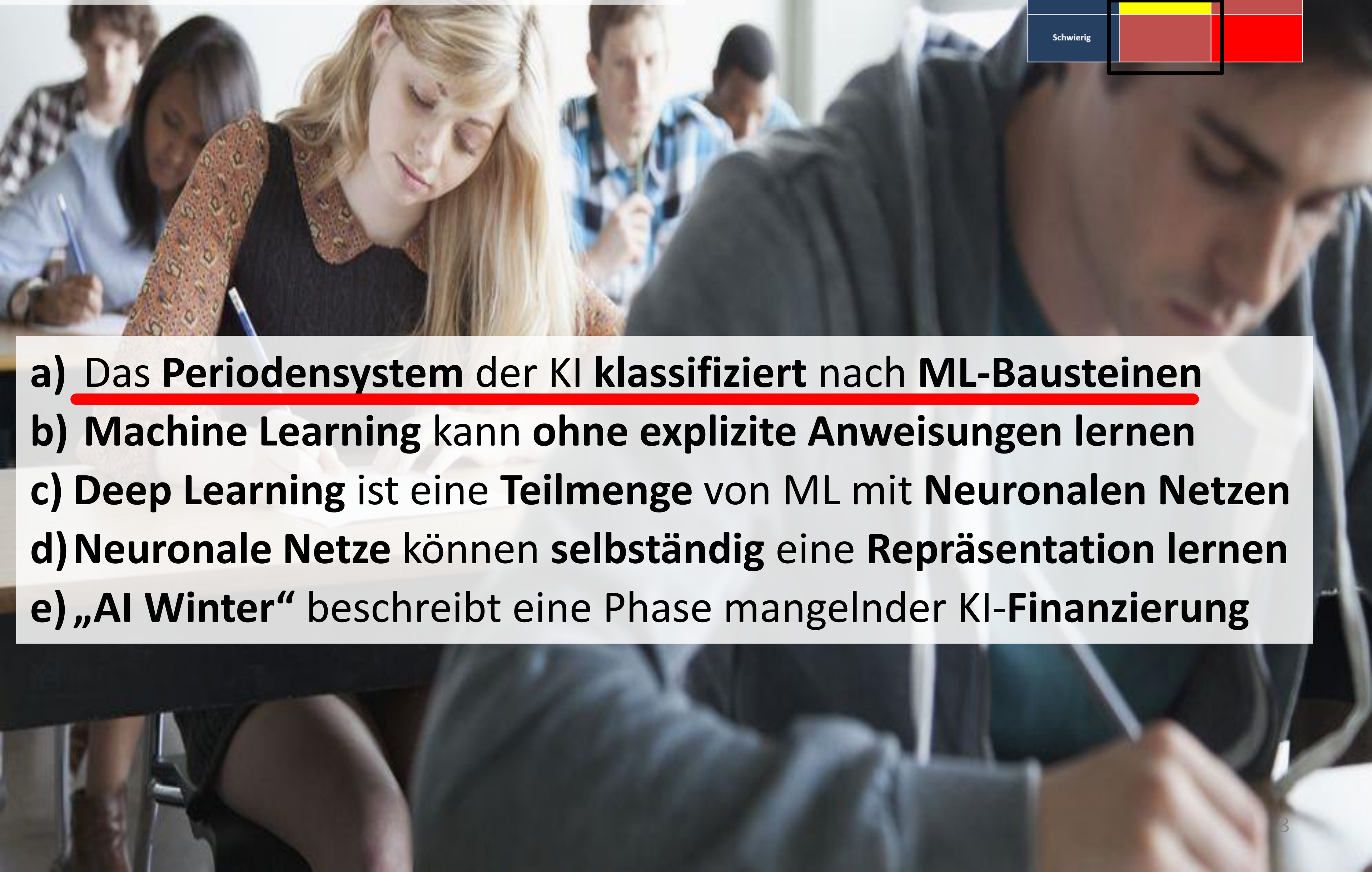
Art des Wissens / Schwierigkeitsgrad	Abfragewissen (Vorlesung)	Anwendungswissen (Literatur)
Einfach		
Mittel		
Schwierig		



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**

Welche Aussage zu AI/ML/DL ist FALSCH?

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



a) Das **Periodensystem** der KI **klassifiziert** nach **ML-Bausteinen**
b) **Machine Learning** kann **ohne explizite Anweisungen lernen**
c) **Deep Learning** ist eine **Teilmenge** von ML mit **Neuronalen Netzen**
d) **Neuronale Netze** können **selbständig** eine **Repräsentation lernen**
e) **„AI Winter“** beschreibt eine Phase mangelnder KI-**Finanzierung**

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

Content:

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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**

- 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.

Machine Learning & Data Driven Business (ML&DDB)

Prof. Dr. Michael Amberg

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Liverpool partner with SkillCorner for AI-powered analysis

Machine learning platform to measure player performance.

Posted: October 11 2019 | By: Tom Bassam

Getty Images

English soccer giants Liverpool have secured a multi-year partnership with SkillCorner, a Paris-based start-up specialising in artificial intelligence (AI) tracking.

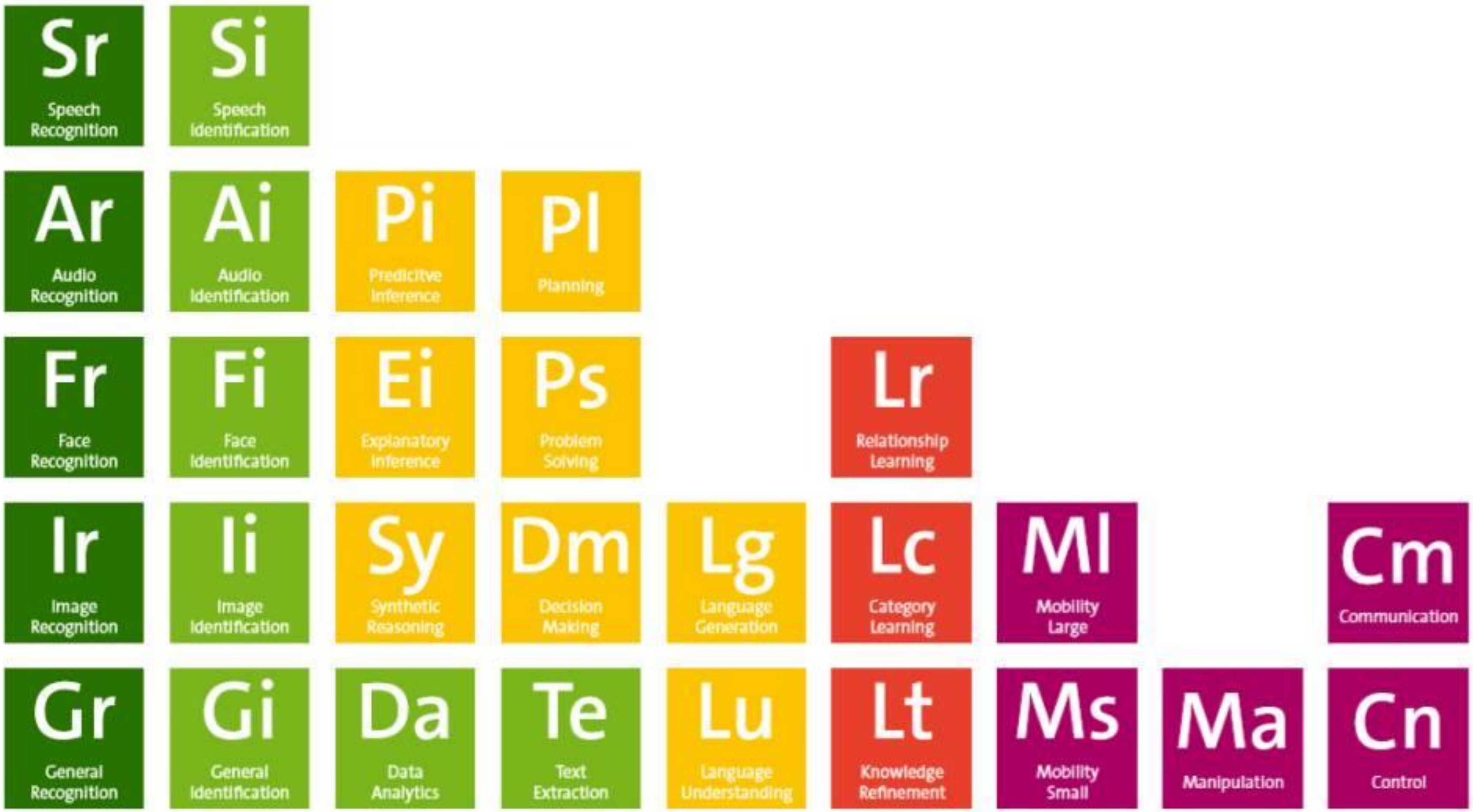
Einführung in Machine Learning & Deep Learning

Wie kann man **Machine Learning (ML)** sinnvoll unterteilen bzw. strukturieren?

Leider gibt es **kein einheitliches Gesamtverständnis (z.B. als Taxanomie) und viele unklare Interpretationen**.

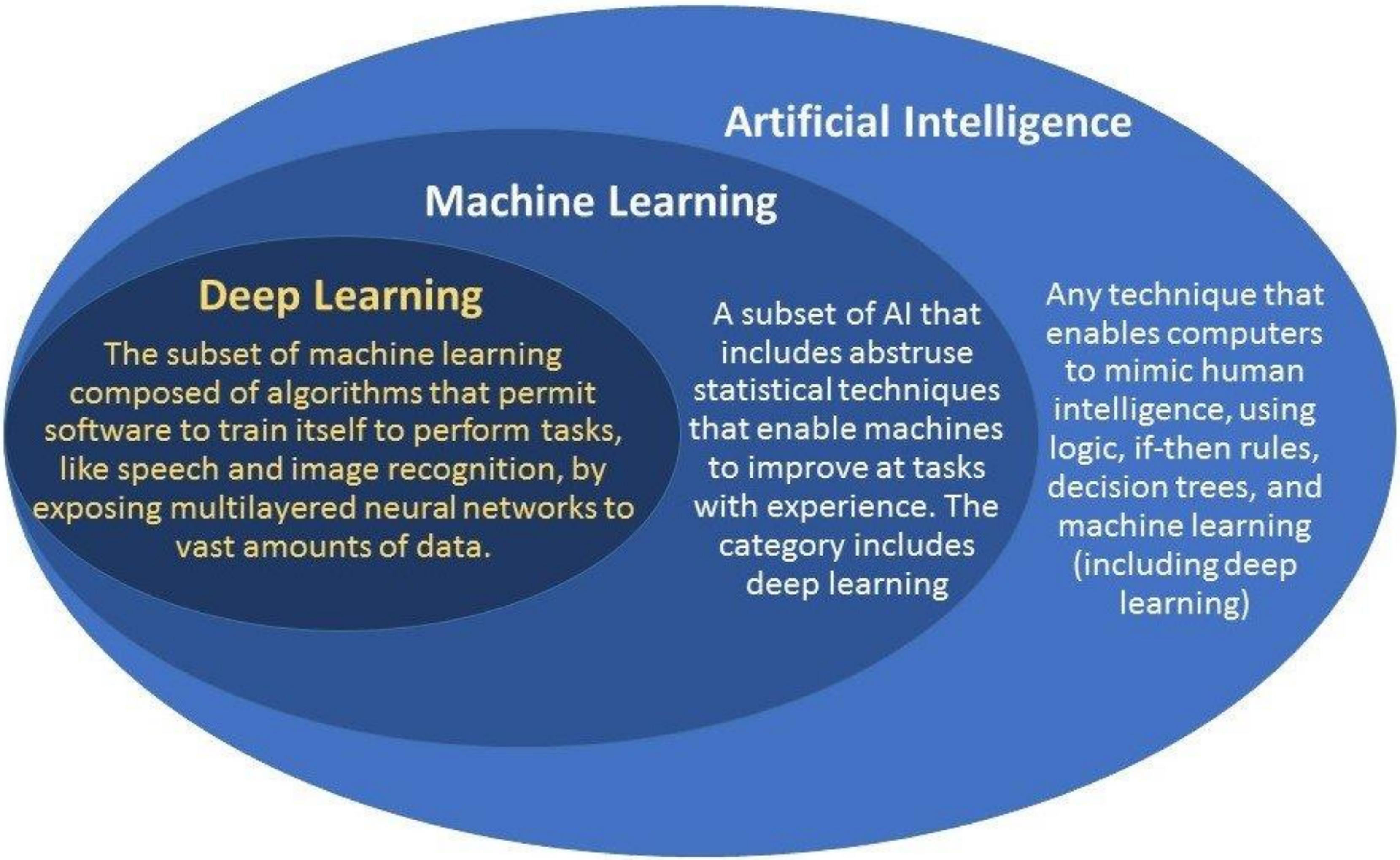
Der **Versuch** eines ersten **Überblicks** folgt.

Das **„Periodensystem der KI“ klassifiziert Einsatzszenarien** des Machine Learning



https://periodensystem-ki.de/Mit-Legosteinen-die-Kuenstliche-Intelligenz-bauen

AI vs Machine Learning vs Deep Learning



What is the difference between AI, machine learning and deep learning?
www.geospatialworld.net/blogs/difference-between-ai-machine-learning-and-deep-learning/

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 s**tatistical 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]

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.

Part of a series on
Artificial intelligence

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Machine learning

From Wikipedia, the free encyclopedia

Machine learning (**ML**) is the study of computer algorithms that improve automatically through experience.[1] It is seen as a subset of artificial intelligence. Machine learning algorithms build a model based on sample data, known as "training data", in order to make predictions or decisions without being explicitly programmed to do so.[2] Machine learning algorithms are used in a wide variety of applications, such as email filtering and computer vision, where it is difficult or unfeasible to develop conventional algorithms to perform the needed tasks.

A subset of machine learning is closely related to computational statistics, which focuses on making predictions using computers; but not all machine learning is statistical learning. The study of mathematical optimization delivers methods, theory and application domains to the field of machine learning. Data mining is a related field of study, focusing on exploratory data analysis through unsupervised learning.[4][5] In its application across business problems, machine learning is also referred to as predictive analytics.

Part of a series on
Machine learning and data mining

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Structured prediction	[show]
Anomaly detection	[show]
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Deep learning

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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

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Supervised learning (classification • regression)	[show]
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Artificial intelligence

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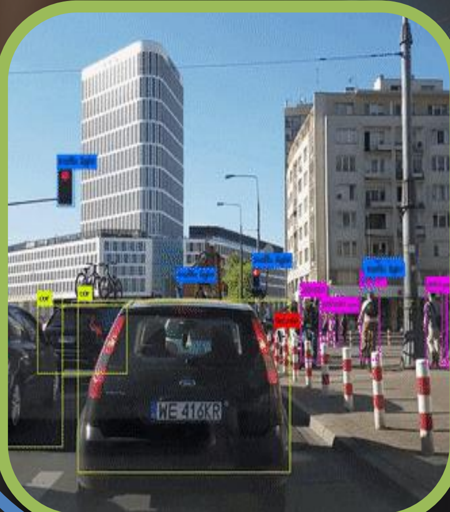
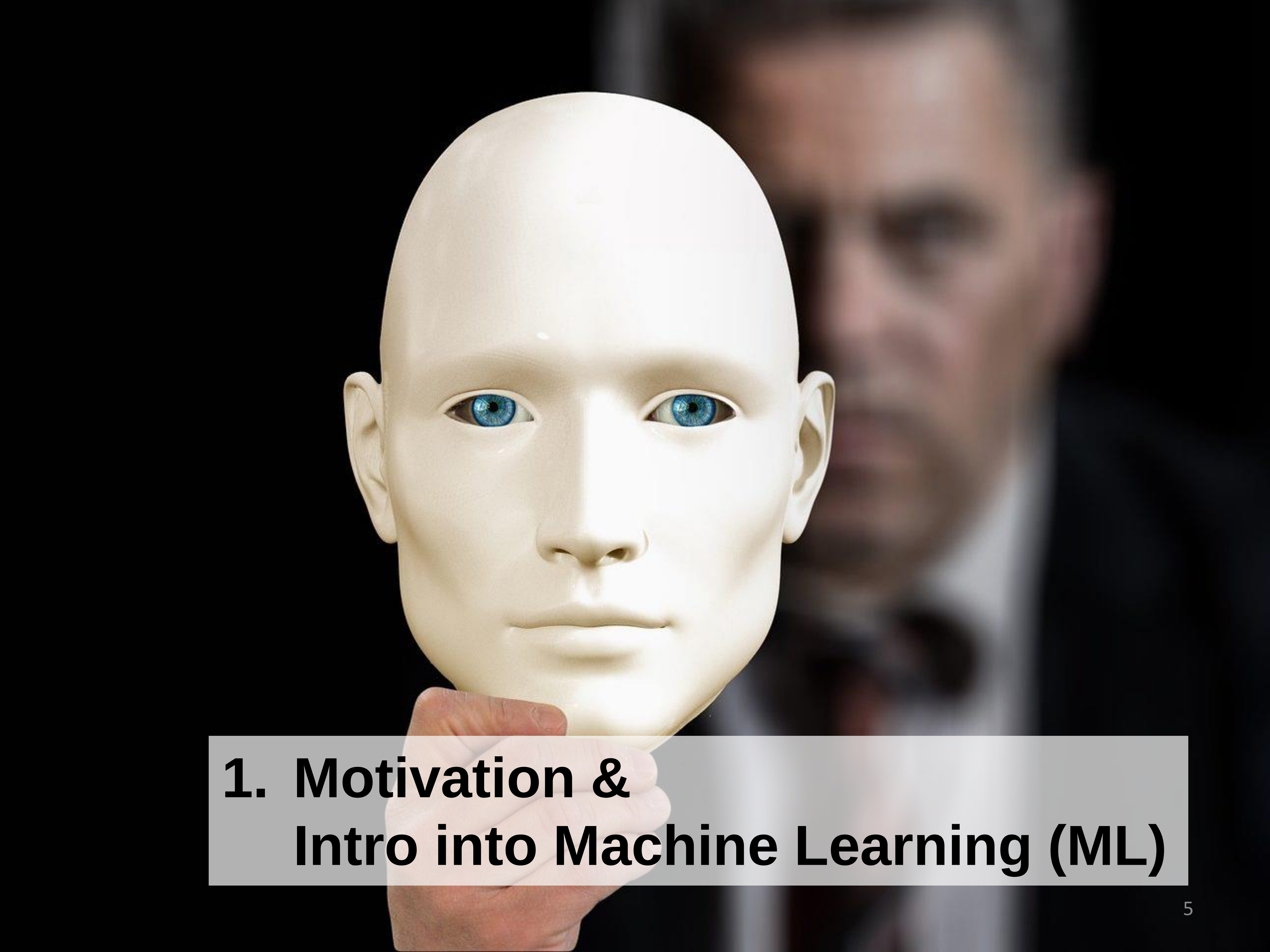
Categories of **Machine Learning**

Machine Learning

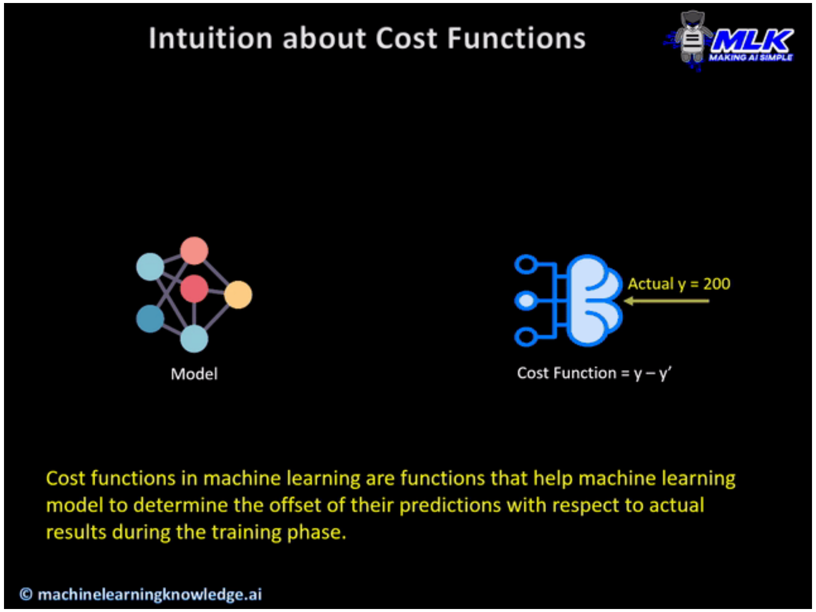
Supervised Learning	Unsupervised Learning	Reinforcement Learning
Deep Supervised Learning	Deep Unsupervised Learning	Deep Reinforcement Learning

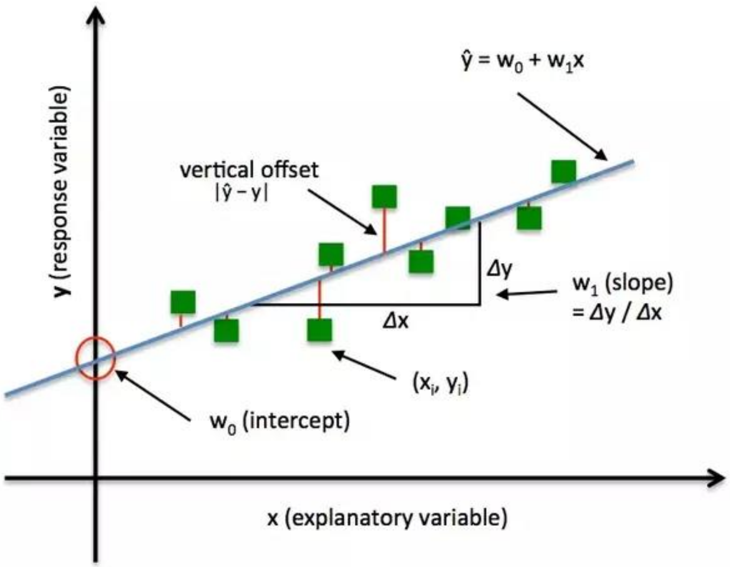




1. Motivation & Intro into Machine Learning (ML)

NN: **Verlustfunktion (Lost / Cost Function)**



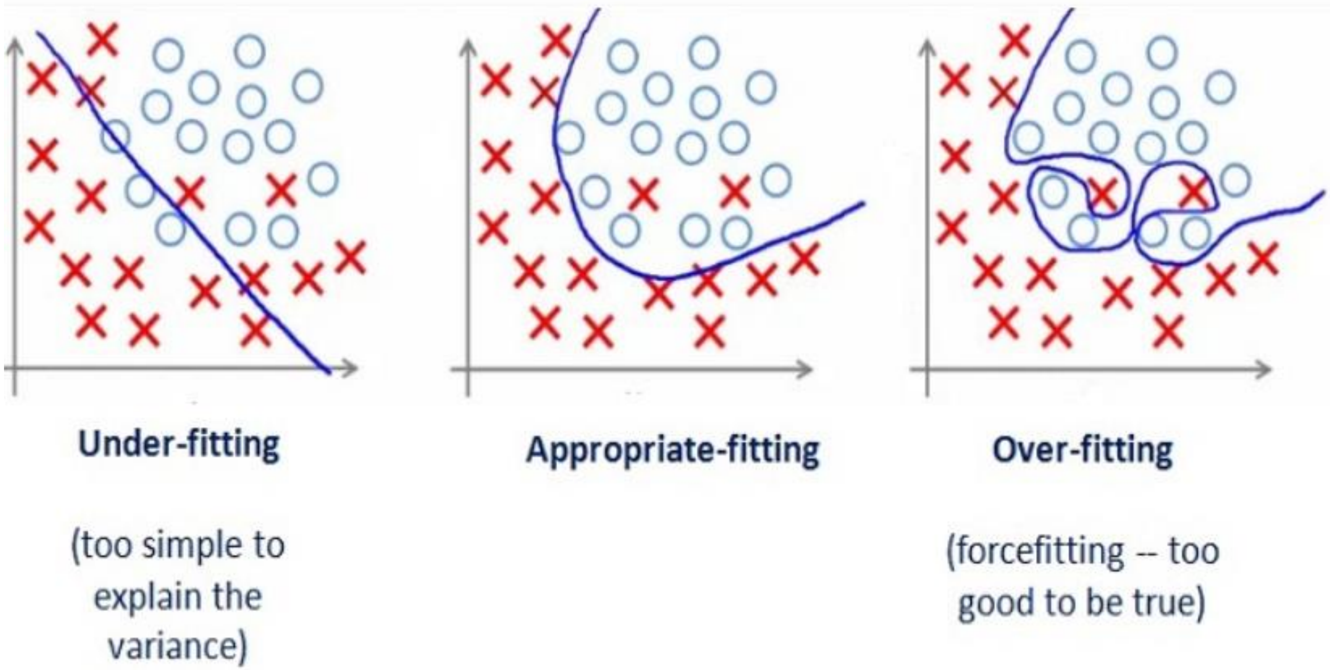


Eine **Verlustfunktion** ist erforderlich, um zu **quantifizieren**, **wie weit die Ausgabe** des aktuellen Modells von der **korrekten Ausgabe entfernt** ist.
Beim Training des Modells besteht das Ziel darin, die **Verlustfunktion über alle Trainingsdaten hinweg zu minimieren** und die **Ausgabe** schrittweise (**Gradient Descent, Lernrate**) so nah wie möglich an den **korrekten Wert** heranzuführen.

Gängige **Verlustfunktion** sind **Root Mean Squared Error** und **Cross Entropy**.

Dummies guide to Cost Functions in Machine Learning [with Animation]
https://machinelearningknowledge.ai/cost-functions-in-machine-learning/

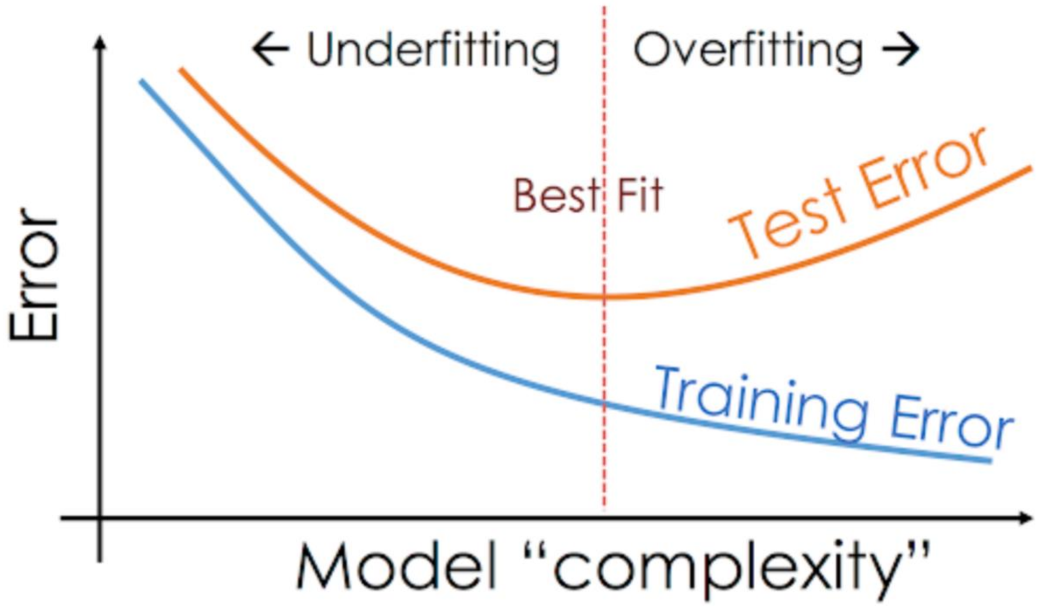
NN: **Underfitting** und **Overfitting** beachten



Das **Neuronale Netz** sollte so gestaltet sein, dass
Underfitting (Struktur zu einfach) und
Overfitting (Struktur zu komplex) vermieden wird.

What is underfitting and overfitting in machine learning and how to deal with it
medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning…

NN: **Underfitting** und **Overfitting** beachten



Mit der **Fehlerrate** beim **Trainieren** (oben: **Training Error**) und
beim **Testen** (oben: **Test Error**) kann man beurteilen,
wie gut eine **Neuronales Netz** das gewählte **Problem** löst.

What is underfitting and overfitting in machine learning and how to deal with it
medium.com/greyatom/what-is-underfitting-and-overfitting-in-machine-learning...

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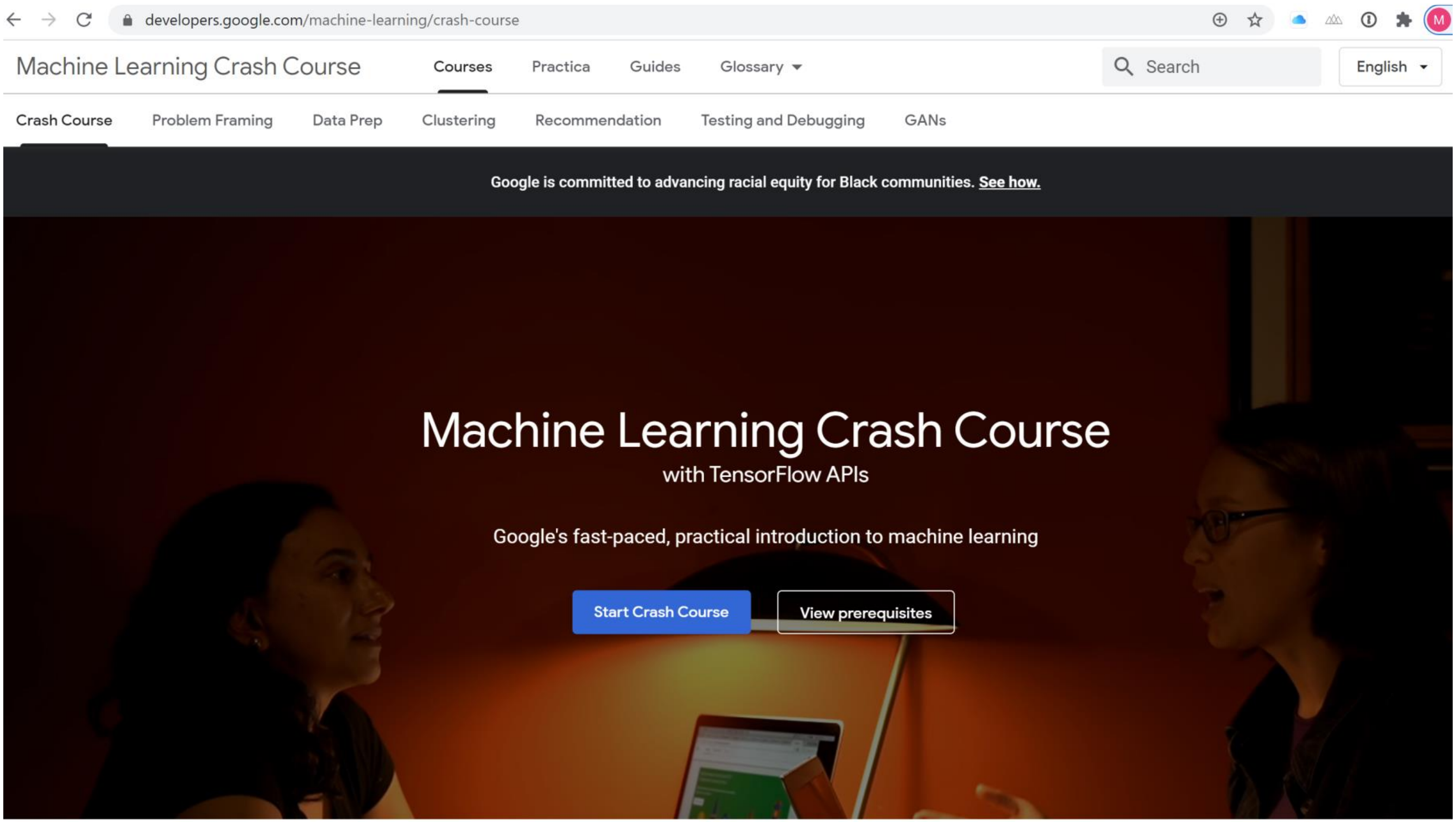
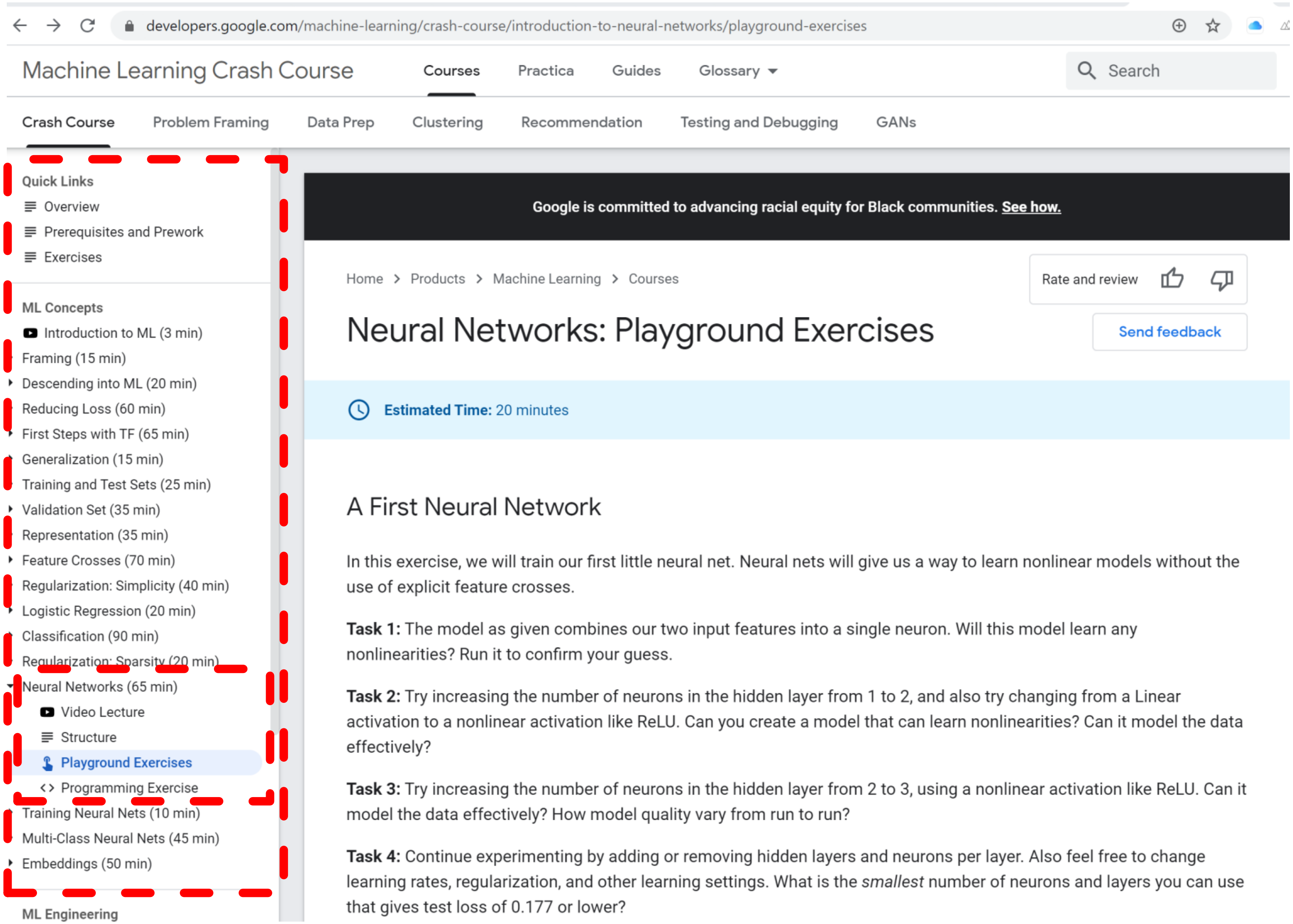


A self-study guide for aspiring machine learning practitioners

developers.google.com/machine-learning/crash-course

Machine Learning Crash Course – A self-study Guide



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- Prerequisites and Prework
- Exercises

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- Framing (15 min)
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- Reducing Loss (60 min)
- First Steps with TF (65 min)
- Generalization (15 min)
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  - Video Lecture
  - Structure
  - Playground Exercises
  - Programming Exercise
- Training Neural Nets (10 min)
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- Embeddings (50 min)

ML Engineering

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Neural Networks: Playground Exercises

Estimated Time: 20 minutes

A First Neural Network

In this exercise, we will train our first little neural net. Neural nets will give us a way to learn nonlinear models without the use of explicit feature crosses.

Task 1: The model as given combines our two input features into a single neuron. Will this model learn any nonlinearities? Run it to confirm your guess.

Task 2: Try increasing the number of neurons in the hidden layer from 1 to 2, and also try changing from a Linear activation to a nonlinear activation like ReLU. Can you create a model that can learn nonlinearities? Can it model the data effectively?

Task 3: Try increasing the number of neurons in the hidden layer from 2 to 3, using a nonlinear activation like ReLU. Can it model the data effectively? How model quality vary from run to run?

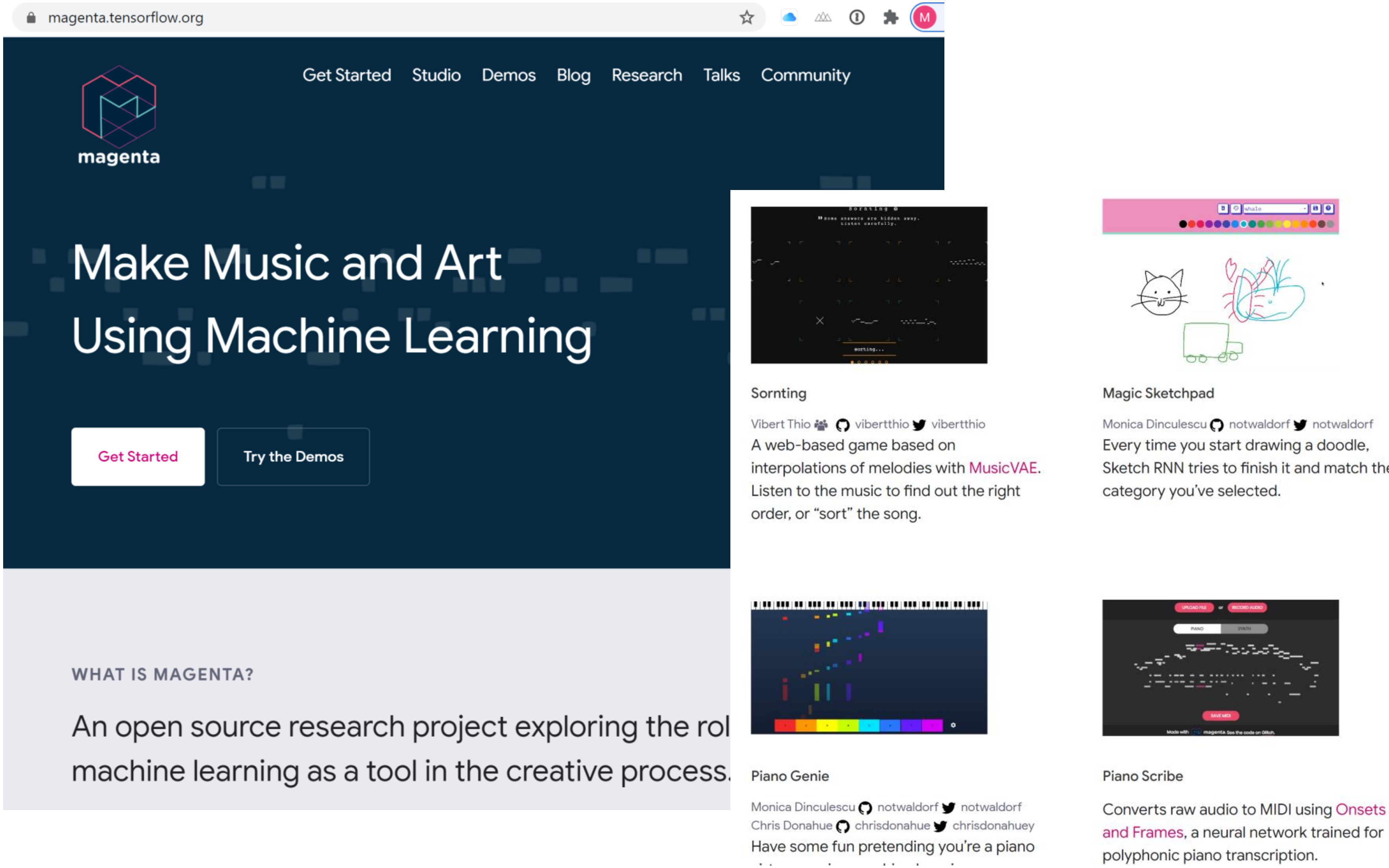
Task 4: Continue experimenting by adding or removing hidden layers and neurons per layer. Also feel free to change learning rates, regularization, and other learning settings. What is the *smallest* number of neurons and layers you can use that gives test loss of 0.177 or lower?

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

Machine Learning & Data Driven Business (ML&DDB)

Prof. Dr. Michael Amberg

Experimente & Demos mit Machine Learning



Make Music and Art Using Machine Learning
magenta.tensorflow.org/demos/web/

8 Machine Learning II
- ML in Natural Language Processing (NLP)

Content:

1. **Motivation**
2. **IBM Watson**
3. **RNN & LSTM Networks**
4. **Transformer Models**
5. **Transformer BERT**
6. **Transformer GPT-3**
7. **Summary**

8 Machine Learning II
- ML in Natural Language Processing (NLP)
(5) Transformer BERT, Google

8 Machine Learning II
- ML in Natural Language Processing (NLP)
(1) **Motivation** & Intro **NLP**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Facebook is reportedly building a tool called 'TLDR' that will read and summarize news articles for you

Isobel Asher Hamilton Dec 16, 2020, 1:50 PM

Facebook's CEO Mark Zuckerberg Charles Platiau/Reuters

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Data to assembly lines, QA, shipping products, tracking orders and stocking shelves because fulfilling the world's every need is Everything.

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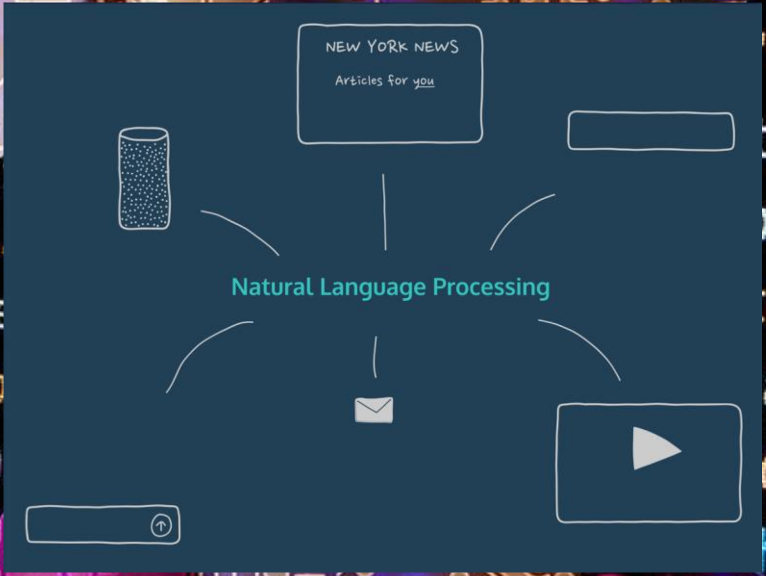
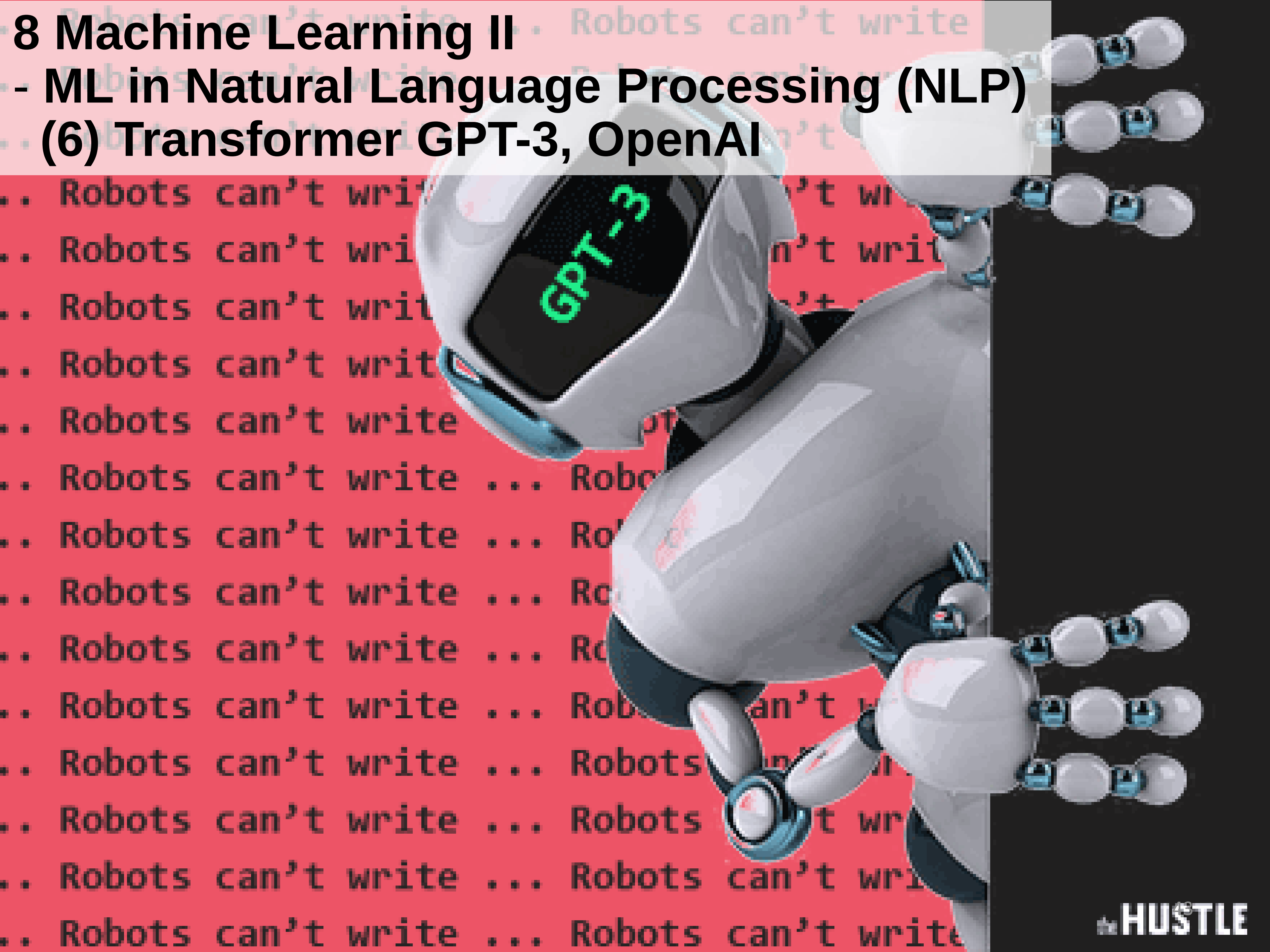
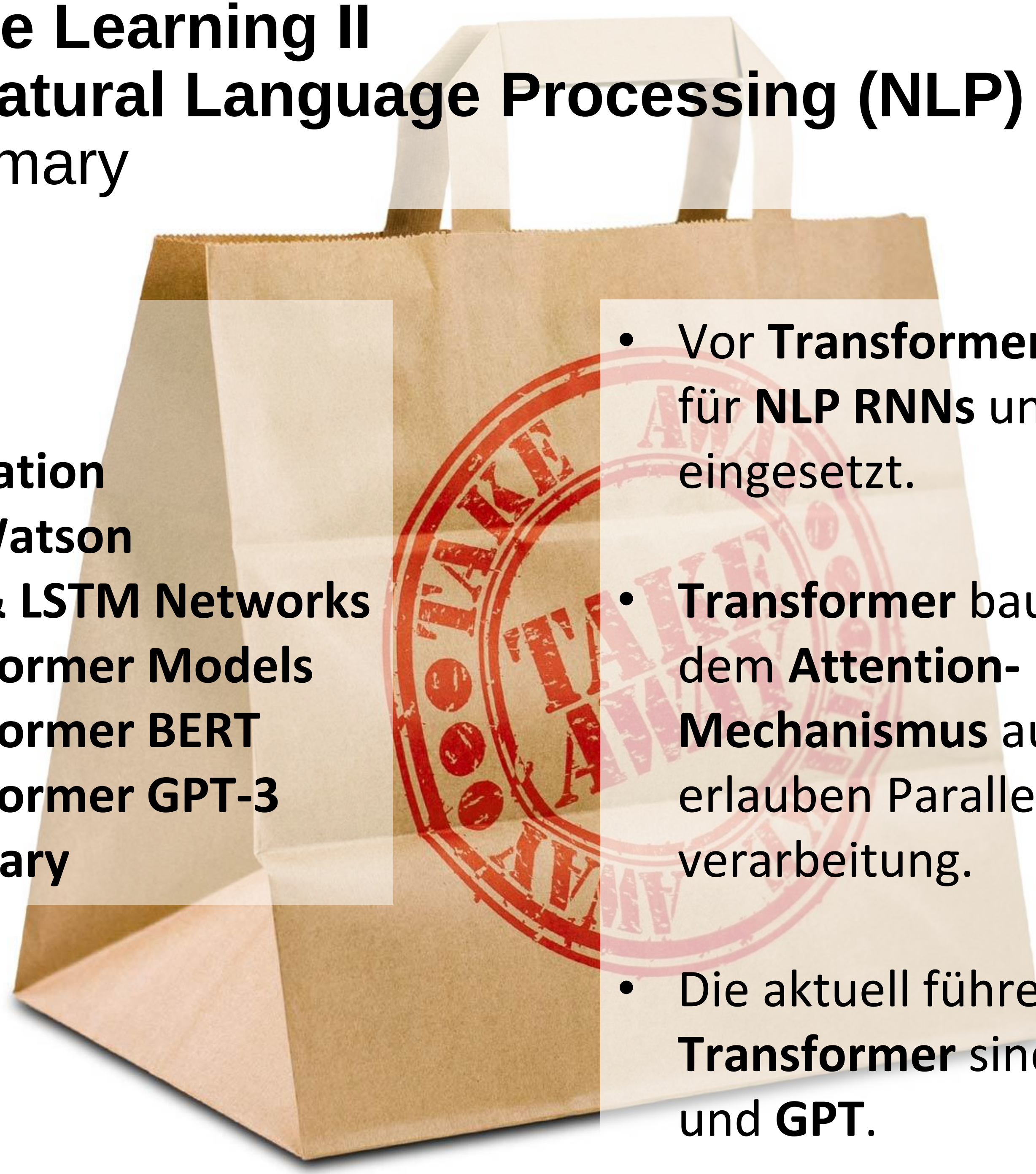


8 Machine Learning II
- ML in Natural Language Processing (NLP)
(6) Transformer GPT-3, OpenAI



8 Machine Learning II
- ML in Natural Language Processing (NLP)
(7) Summary



Content:

1. **Motivation**
2. **IBM Watson**
3. **RNN & LSTM Networks**
4. **Transformer Models**
5. **Transformer BERT**
6. **Transformer GPT-3**
7. **Summary**

- Vor **Transformer** wurden für **NLP RNNs** und **LSTMs** eingesetzt.
- **Transformer** bauen auf dem **Attention-Mechanismus** auf und erlauben Parallel-verarbeitung.
- Die aktuell führenden **Transformer** sind **BERT** und **GPT**.

8 Machine Learning II
- ML in Natural Language Processing (NLP)
(2) IBM Watson Supercomputer

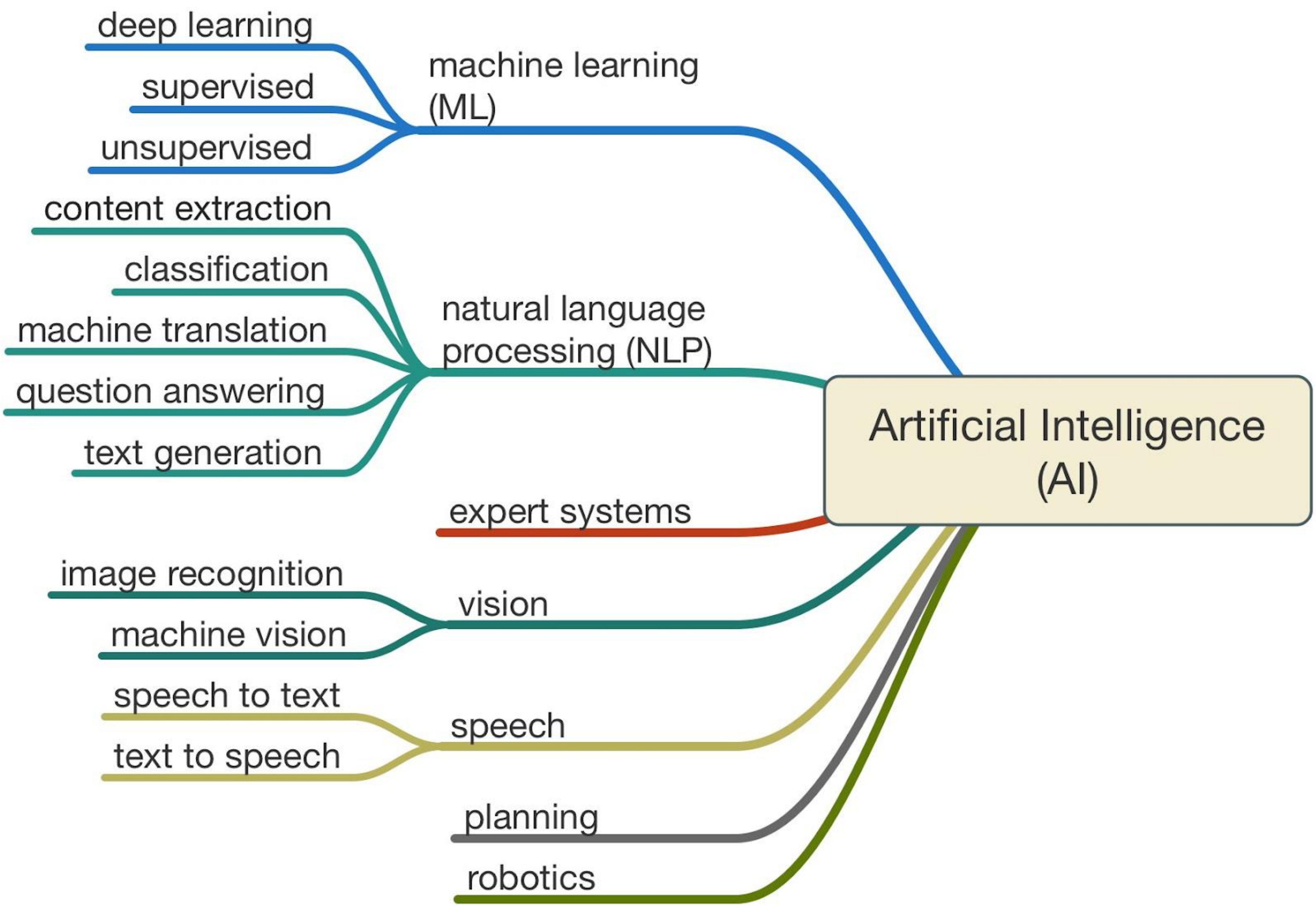
Machine Learning & Data Driven Business (ML&DDB)

Prof. Dr. Michael Amberg

Anwendungen und **Rahmenbedingungen** von **Data Science** und **Machine Learning** in **Unternehmen** und in einer **datengetriebenen Welt** kennen und einschätzen lernen.

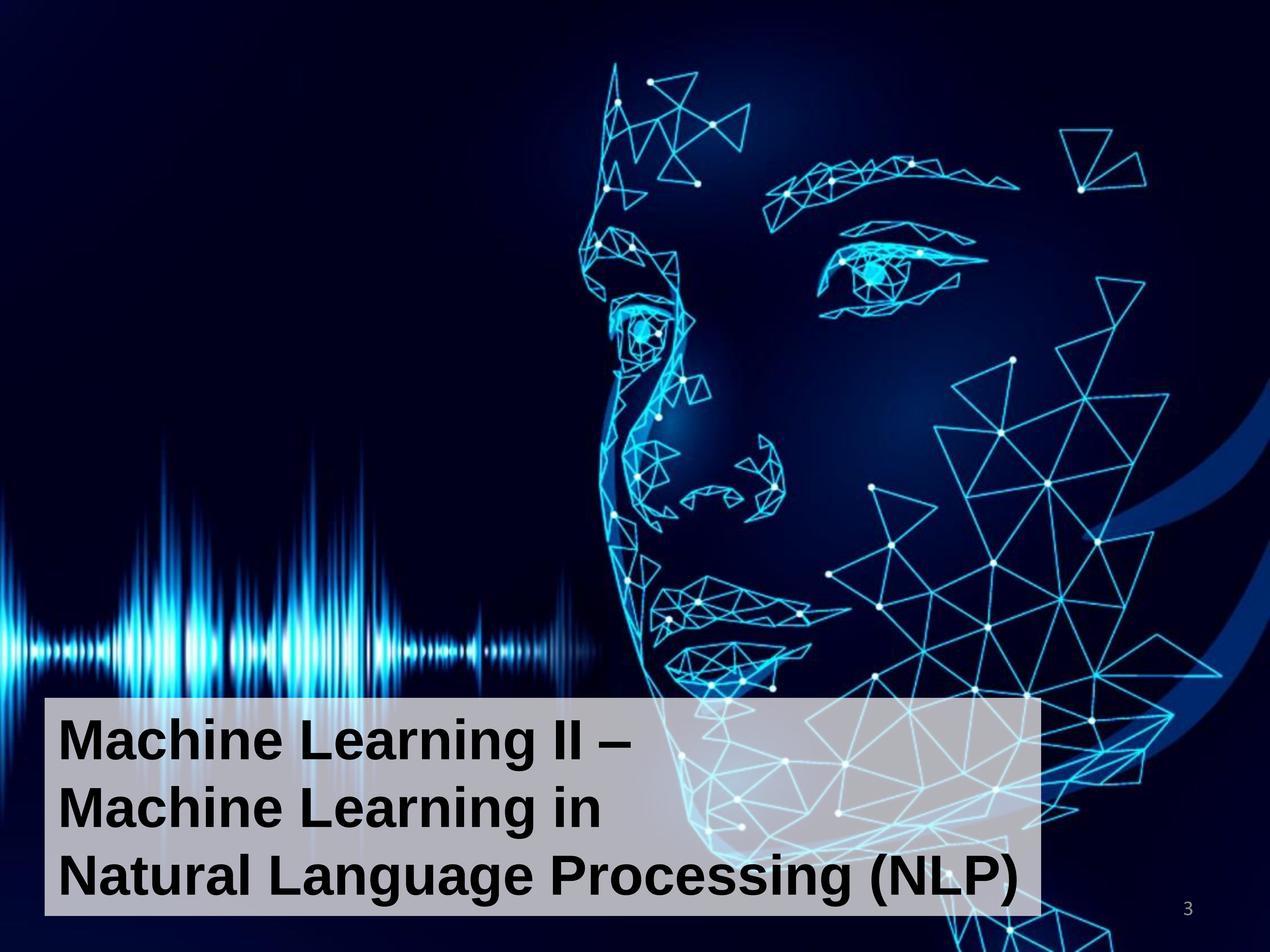
1. **Bullshit with Data:** **The Art of Skepticism in a Data Driven World**
2. **Personal Data Handling:** **Handling of Data in Different Scenarios**
3. **Protect Data:** **Protecting the Security & Integrity of Data**
4. **Data Driven Innovation:** **Innovative Business & Applications**
5. **Project Management:** **Managing Projects successfully**
6. **Business Systems:** **Relevant Enterprise Software Systems**
7. **Emerging Technologies:** **Business Implications of Technologies**
8. **Machine Learning I, II, III:** **Overview of ML Techniques & Methods**
9. **ML & Robotics:** **Current Developments & Implications**

Overview **Natural Language Processing**



The Complete Roadmap for AI, Data Scientist Aspirants, 2020

tekrajawasthi15.medium.com/the-complete-roadmap-to-be-a-data-scientist-9a07721b88fd



Machine Learning II – Machine Learning in Natural Language Processing (NLP)

IBM Watson Supercomputer

Watson is an **IBM supercomputer** that combines **artificial intelligence** (AI) and sophisticated **analytical software** for performance as a **“question answering” machine**.

The Watson supercomputer processes at a **rate of 80 teraflops** (trillion floating-point operations per second). Watson accesses **90 servers** with a combined **data store of over 200 million pages of information**, which it processes against **six million logic rules**.
The device and its data are **self-contained** in a **space** that could accommodate **10 refrigerators**.

Watson's key components include:

- **Apache UIMA** (Unstructured Information Management Architecture) frameworks, infrastructure and other elements required for the **analysis of unstructured data**.
- **Apache's Hadoop**, a free, Java-based programming framework that supports the **processing of large data sets in a distributed computing environment**.
- **SUSE Enterprise Linux Server 11**, the fastest available **Power7 processor operating system**.
- **2,880 processor cores**.
- **15 terabytes of RAM**.
- **500 gigabytes** of **preprocessed information**.
- **IBM'sDeepQA software**, which is designed for information retrieval that incorporates **natural language processing** and **machine learning**.

Quelle: http://whatis.techtarget.com/definition/IBM-Watson-supercomputer

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]

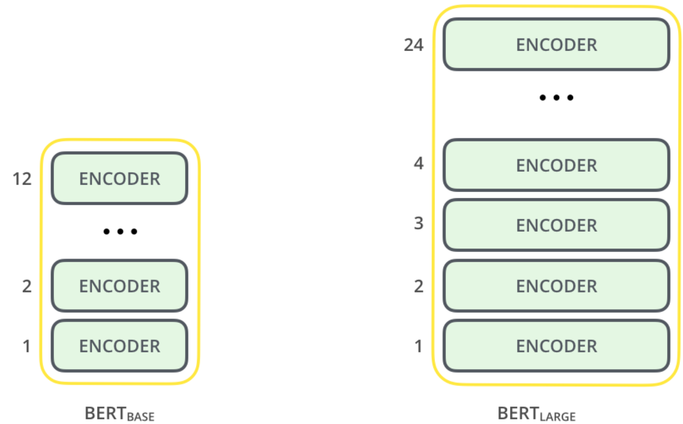
BERT Transformer, Google 2018

BERT (language model)

From Wikipedia, the free encyclopedia

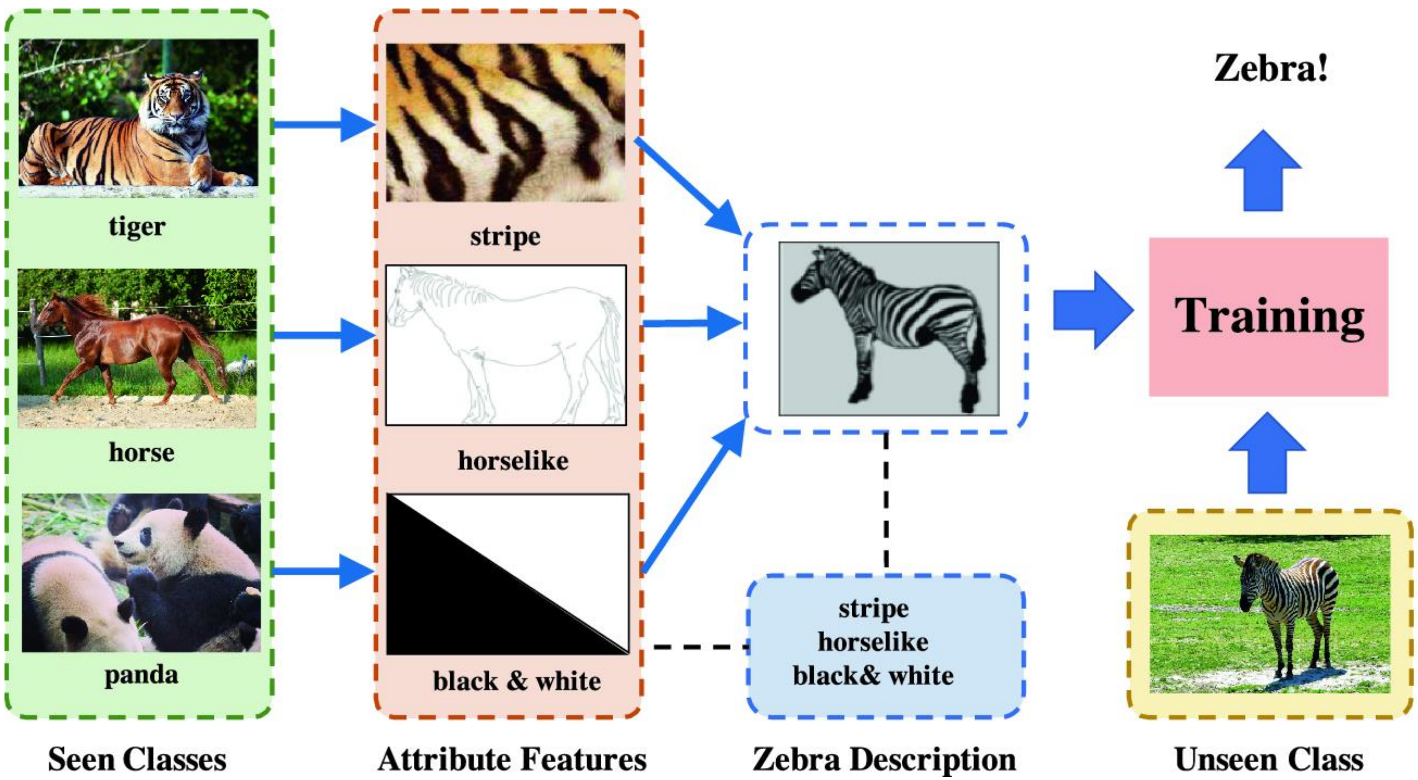
Bidirectional Encoder Representations from Transformers (**BERT**) is a Transformer-based machine learning technique for natural language processing (NLP) pre-training developed by Google. BERT was created and published in 2018 by Jacob Devlin and his colleagues from Google.[1][2] As of 2019, Google has been leveraging BERT to better understand user searches.[3]

The original English-language BERT model comes with two pre-trained general types:[1] (1) the $\mathrm{BERT}_{\mathrm{BASE}}$ model, a 12-layer, 768-hidden, 12-heads, 110M parameter neural network architecture, and (2) the $\mathrm{BERT}_{\mathrm{LARGE}}$ model, a 24-layer, 1024-hidden, 16-heads, 340M parameter neural network architecture; both of which were trained on the BooksCorpus[4] with 800M words, and a version of the English Wikipedia with 2,500M words.



Zero-Shot Learning (Kernidee)

In **Machine Learning, Zero-Shot Learning** is a **problem setup** where, **at test stage**, a learner **recognizes object from classes not previously seen at training stage**. This problem is widely studied in **computer vision**, **natural language processing** and **machine perception**.



en.wikipedia.org/wiki/Zero-shot_learning
deepai.org/publication/zero-shot-learning-by-generating-pseudo-feature-representations

GPT-3 Transformer, OpenAI 2020

GPT-3

From Wikipedia, the free encyclopedia

Generative Pre-trained Transformer 3 (**GPT-3**) is an autoregressive language model that uses deep learning to produce human-like text. It is the third-generation language prediction model in the GPT-n series (and the successor to GPT-2) created by OpenAI, a San Francisco-based artificial intelligence research laboratory.[2] GPT-3's full version has a capacity of 175 billion machine learning parameters. GPT-3, which was introduced in May 2020, and was in beta testing as of July 2020,[3] is part of a trend in natural language processing (NLP) systems of pre-trained language representations.[1] Before the release of GPT-3, the largest language model was Microsoft's Turing NLG, introduced in February 2020, with a capacity of 17 billion parameters or less a tenth of GPT-3s.[4]

The quality of the text generated by GPT-3 is so high that it is difficult to distinguish from that written by a human, which has both benefits and risks.[4] Thirty-one OpenAI researchers and engineers presented the original May 28, 2020 paper introducing GPT-3. In their paper, they warned of GPT-3's potential dangers and called for research to mitigate risk.[1]:34 David Chalmers, an Australian philosopher, described GPT-3 as "one of the most interesting and important AI systems ever produced."[5]

Microsoft announced on September 22, 2020 that it had licensed "exclusive" use of GPT-3; others can still use the public API to receive output, but only Microsoft has control of the source code.[6]