



CS283: Robotics Fall 2019: DL & Ethics

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DEEP LEARNING IN ROBOTICS

End-to-End Deep Learning



Deep Learning

- Very hot trend in Machine Learning / AI
- Traditional approaches: Hand tuned features, e.g.:
 - Feature extraction (Computer Vision);
 Hidden Markov Models & Statistics (Natural Language Processing)
- Deep Learning approach:
 - Learning of parameters for Artificial Neural Network (ANN) based on training data
- Recent success based on:
 - Huge amounts of (training) data
 - Lots of computing power
 - Better DL architectures



Image Source: Matthew Mayo

Traditional Pattern Recognition: Fixed/Handcrafted Feature Extractor



Mainstream Pattern Recognition 9until recently)



Deep Learning: Multiple stages/layers trained end to end



Multiple Layers: Levels of Abstraction

Source: NIPS'2015 Tutorial Geoff Hinton, Yoshua Bengio & Yann LeCun



Amazon Picking Challenge

- Robot stow and take (pick) products from shelves
- Challenges in: Computer vision (find object and its pose [position & orientation]) and Manipulation (planning, grasping)
- Since 2015 now co-located with RoboCup
- Winner 2016: Team Delft
 - Suction gripper (easy!)
 - 100 items per hour (human: 400)
 - Failure rate: 16.7 %
 - Deep learning to find objects:
 - Stereo camera for 3D
 - ROS Industrial

https://www.theverge.com/2016/7/5/12095788 /amazon-picking-robot-challenge-2016



End-to-End Deep Reinforcement Learning

- From sensors to actuation: one layered or recurrent neural network! =>
 - NOT classical general control scheme (Perception, SLAM, Cognition & Planning, Navigation)
- Needs reward signal: sparse, noisy, delayed!
- Take time into account: input frames are related!
- Gained interest 2013 again with:
 - Deep Mind (google) playing ATARI 2600 games
 - Video: Breakout
 - Learned 7 games
 - Surpasses human expert in 3





BRETT: Berkeley Robot for Learning Tedious Tasks: Deep Reinforcement Learning

- "There are no labeled directions, no examples of how to solve the problem in advance. There
 are no examples of the correct solution like one would have in speech and vision
 recognition programs"
- Learn simple tasks in 10 minutes; learn vision and control together in 3 hours
- Pieter Abbeel of UC Berkeley;
- 2015

http://news.berkeley.edu/2015/05/21/ deep-learning-robot-masters-skillsvia-trial-and-error/

BRETT (Berkeley Robot for the Elimination of Tedious Tasks)

BRETT has acquired the ability to learn to perform tasks on its own through trial and error.

Google Door Opening Project

- Learn to open doors using Reinforcement learning
 - · Learning reward: opening the door
 - Much harder than purely digital learning: very slow iterations!
 - Simulation only helps a bit: real world much more complex
- Google and UC Berkeley Sergey Levine
- Google very secretive ...

https://www.wired.com/2017/01/googles-goplaying-machine-opens-door-robots-learn/



Nvidia end-to-end deep learning self driving car

- Raw pixel of single camera => steering command of car
 - 30 FPS; single-image control (no history)
 - Nvidia Drive PX car computer (ARM cores and Nvidia GPU)
 - Human steering angle for training
- End-to-end: NO explicit:
 - Lane detection
 - Road detection
- Obstacle detection
 <u>https://devblogs.nvidia.com/parallelforall/</u>
 <u>deep-learning-self-driving-cars/</u>



DAVE 2 Driving a Lincoln

- A convolutional neural network
- Trained by human drivers
- Learns perception, path planning, and control
 "pixel in, action out"
- Front-facing camera is the only sensor

• Training:

- Additionally use left and right camera: negative examples!
- Highway, residential roads, unpaved roads, car parks
- Different weather conditions
- Result: Autonomous 98% of the time => 2% driver intervention





Output: vehicle contro

Fully-connected layer Fully-connected layer Fully-connected layer

Convolutional feature map 64@1x18

Convolutional feature map 64@3x20

Convolutional feature map 48@5x22

Convolutional feature map 36@14x47

Convolutional feature map 24@31x98

Normalized input planes 3@66x200

Problems with Deep Learning

- 99% success rate sounds good, but 1% failure is often unacceptable (e.g. autonomous car)
 - Failures are unavoidable =>
 - need quality estimate/ uncertainty of the result!
 - Often not available for DL ☺
- Lack of theory regarding deep learning
 - Acts like a black box...
- No introspection of how or why a DL system is behaving like it is =>
 - No safety guarantees possible
- Deep learning only part of an overall AI system
 - Hand-crafted methods can still be very powerful
 - Modelling useful (with input from DL)
 - Statistical methods
 - Reasoning
 - Planning

ADMIN

- Final Exam: Dec 5 during lecture hours
- HW 4: will be published soon...

Robotics

Paper Presentation

- Presentation Schedule:
 - During lecture hours
 - 4 Presentation slots:
 - Presentation 1: Nov 12
 - Presentation 2: Nov 19
 - Presentation 3: Nov 21
 - Presentation 4: Nov 28
- After Oct 21st: loose 33%; After Nov 2nd: loose 50%
- 10 minute presentation plus 1 minute project relevance plus 3 minutes questions =>
 - 15 minute per student x 8 students => 2 hours
- Every student has to attend the 2 presentations slots defined in the schedule!
 - Attendance will be checked!
- You will be using my Laptop
- A laser pointer will be provided

Robotics Project Teams

Project	姓名	Name	Presentation	Attendence	Student Advisor
Life science Eetch robot	张亦正	Yizheng Zhang	1	1 & 2	Xiaoling
Life science retch robot	朱佳会	Jiahui Zhu	1	1 & 2	
	余泽浩	Zehao Yu	1	1 & 2	Xiaoling
Elevator	钱深瀚	Shenhan Qian	1	1 & 2	
	陈夏宁	Xianing Chen	1	1 & 2	
	李阳	Yang Li	1	1 & 2	Xiaoling
Rover Manipulation	陈睿卿	Ruiqing Chen	1	1 & 2	
	陈亮	Liang Chen	1	1 & 2	
Boyor SLAM	王志伟	Zhiwei Wang	2	2 & 3	Hongyu
Rover SLAM	严亦晖	Yihui Yan	2	2 & 3	
Conpresent	唐伟鸿	Weihong Tang	2	2 & 3	Hongyu
car project	唐韧之	Renzhi Tang	2	2 & 3	
Carproject	侯镜阳	Jingyang Hou	2	2 & 3	Hongyu
	王翌舟	Yizhou Wang	2	2 & 3	
Eurpituro Eroo Mapping	何振鹏	Zhenpeng He	2	2 & 3	Sören
Furniture Free Mapping	孙豪	Hao Sun	2	2 & 3	
	赵希亭	Xiting Zhao	3	3 & 4	Hongyu
Mapping Robot	杨之杰	Zhijie Yang	3	3 & 4	
	万浩川	Haochuan Wan	3	3 & 4	
WifiLocalization	祝宁之	Ningzhi Zhu	3	3 & 4	Xiaoling
Wifi Localization	周宇	Yu Zhou	3	3 & 4	
	李润东	Rundong Li	3	3 & 4	Haofei
Event Camera	黄坤	Kun Huang	3	3 & 4	
	高翎	Ling Gao	3	3 & 4	
	张苁卉	Conghui Zhang	4	1 & 4	Haofei
Underwater stereo SLAM	吴德明	Deming Wu	4	1 & 4	
	牛天星	Tianxing Niu	4	1 & 4	
Omni Camora	崔佳迪	Jiadi Cui	4	1 & 4	Qingwen
On in Cantera	金磊	Lei Jin	4	1 & 4	
Eactorization	林洲洋	Zhouyang Lin	4	1 & 4	Qingwen
Factorization	高国亮	Guoliang Gao	4	1 & 4	

Projects: Safety is important!



AI ETHICS



https://cybersecuritydegrees.com/ethical-ai/

FROM 2035 TO 2045





Consumers will regain up to 250 MILLION HOURS OF FREE TIME from behind the wheel

\$234 BILLION IN PUBLIC COSTS will be saved by reducing accidents from human error

Driverless cars can ELIMINATE 90% OF TRAFFIC FATALITIES — Saving I million lives every year

HOW WILL DRIVERLESS CARS DETERMINE WHOSE LIFE SHOULD BE SPARED?

MORALITY IN MACHINES

Driverless cars "must decide quickly, with incomplete information, in situations that programmers often will not have considered, using ethics that must be encoded all too literally"

NOAH J. GOODALL Senior Research at the Virginia Transportation Research Council

Who should A.I. save?

IN A GLOBAL STUDY, MOST PEOPLE PREFERRED

- Swerving over staying the course
- Sparing passengers over pedestrians
- 🗢 Saving as many lives as possible

Participants were most likely to spare the lives of a child, and least likely to spare animals and criminals

MINIMIZED HARM VS. PASSENGER PROTECTION







of people felt driverless cars should SAVE AS MANY LIVES AS POSSIBLE BUT, very few were willing to buy a vehicle programmed to minimize harm They prefer cars programmed to PROTECT PASSENGERS AT ALL COSTS

DRIVERLESS CARS WILL SAVE LIVES, BUT PROGRAMMING THEM TO DO SO COULD SLOW THEIR ADOPTION AND COST MANY MORE LIVES

REAL LIFE APPLICATIONS GROW EVEN MORE COMPLEX

In an accident causing injuries but not fatalities, should A.I.

DISTRIBUTE INJURIES EVENLY, harming more people less severely?

CONSIDER THE LIKELIHOOD and severity of potential injuries?

Take into account the **QUALITY OF LIFE EFFECT** of resulting injuries?

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Is it better to
HOSPITALIZE 5
PEOPLE, OR KILL I?
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AS A.I. ADVANCES, IT BECOMES RESPONSIBLE FOR More moral and ethical decision making

When Al goes wrong



AMAZON'S REKOGNITION

REKOGNITION'S FACIAL RECOGNITION ALGORITHMS CAN

- Identify up to IOO faces in a single image
- Track people in real time through surveillance cameras
- Scan footage from police body cameras

IN 2018, THE ACLU COMPARED 25,000 MUG SHOTS To photos of every member of congress USING Rekognition - They found

B False match

False matches

Were people of color, who make up just 20% of Congress

LAW ENFORCEMENT AGENCIES ARE Already Using Rekognition

- Orlando Police Department (Florida)

- Washington County Sheriff's Office (Oregon)
- In 2016, half of Americans adults were included in a law enforcement facial recognition network



HOW A.I. BIAS HAPPENS

WOMEN NEED NOT APPLY

Starting in 2014, Amazon began training an A.I. to review job candidates

- The system was trained using resumes submitted over IO years MOST CAME FROM MEN
- The A.I. concluded that "male" was a preferred quality for new hires, and started FILTERING OUT FEMALE CANDIDATES

DETECTING DARKER SKIN TONES

In a 2019 study, researchers found that the object detection models used in driverless cars were better at identifying pedestrians with lighter skin

- The study used a standardized set of photos to train their A.I. but found their DATASET CONTAINED 3X AS MANY LIGHT SKINNED PEOPLE
- The A.I. quickly learned to identify light skinned pedestrians, but STRUGGLED TO IDENTIFY DARKER SKIN TONES

BOTH RECRUITING AND PEDESTRIAN DETECTION ALGORITHMS FAILED BECAUSE THEY WERE TRAINED ON BAD DATA — A.I. LEARNED BIAS FROM HUMANS

MAKING ETHICAL A.I.



START WITH DATA

A.I. training data must reflect real diversity and control for existing bias

- Amazon's recruiting algorithm was trained to eliminate female candidates.
 INSTEAD, IT COULD HAVE BEEN PROGRAMMED TO IGNORE GENDER
- Pedestrian identification algorithms struggle to identify darker skin tones.
 Rather than monitoring success overall, the TRAINING DATA COULD HAVE
 WEIGHTED DARK SKIN DATA POINTS MORE HEAVILY



CONSIDER THE PROCESS

When training A.I., programmers typically split their dataset into 2 parts

- Half is used to **TRAIN THE A.I**.
- Half is used to VERIFY AND MEASURE SUCCESS

If the initial dataset is flawed, the test will have the same bias



MONITOR FOR UNKNOWNS

Programmers must monitor for unintentional bias appearing in their A.I.

- Subtle patterns can lead A.I. to PERPETUATE HUMAN BIAS
- Amazon's recruiting algorithm preferred VERBS LIKE "EXECUTED" AND "CAPTURED" — WHICH TEND TO BE MORE USED BY MALES

8 Ethical Questions in Al





Liability: Who is responsible for AI?



Security: How do we protect access to AI from bad actors?

 $\nabla \Box$ 88

Human Interaction: Will we stop talking to one another?



Employment: Is AI getting rid of jobs?



Wealth Inequality: Who benefits from AI?

https://www.logikk.com/ articles/8-ethicalquestions-in-artificialintelligence/





www.logikk.com

Robot Rights: Can Al suffer?



Ethical AI: Many open questions and topics:

- Autonomy and liability
- Ethical principles in robotics
- Defining ethical guidelines for the design, use and operation of robots
- Enhancement technologies: ethical issues
- Privacy and the management of personal data
- Ethical frameworks: universal or region specific?
- The role of industry and society in the definition of safety standards
- AI technology to block unethical/ mendacious social-media communication

- Accountability in autonomous systems
- Transparency in autonomous systems
- Embedding values and norms into intelligent systems
- Ethics and standardization
- Raising ethical awareness among stakeholders
- Political and legal frameworks
- Formal and mathematical frameworks for robot ethics
- Implementations and engineering studies

Ethical AI: Scientific Discussion

- IEEE Robotics and Automation Society: Technical Committee on Robot Ethics
 - Framework for raising and addressing the urgent ethical questions prompted by and associated with robotics research and technology.
 - https://www.ieee-ras.org/robot-ethics
- ICRES 2019 is the fourth edition of the International Conference on Robot Ethics and Standards series
 - https://www.icres2019.org/
- Conference on Robotics, AI and Humanity, Science, Ethics and Policy organized jointly by the Pontifical Academy of Sciences (PAS) and the Pontifical Academy of Social Sciences (PASS)
 - <u>http://www.pas.va/content/accademia/en/events/2019/robotics/statementrobotics.html</u>

Don't be evil?

A survey of the tech sector's stance on lethal autonomous weapons

- Table ranks companies according to the level of concern regarding their potential (unintended) contribution to the development of lethal autonomous weapons.
 - <u>https://www.paxforpeace.nl/publications/all-publications/dont-be-evil</u>
- Autonomous weapons: Good? Or Bad?

HIGH CONCERN	Company working on military/security applications of relevant technologies + chose not to answer our survey's questions in a meaningful way.
MEDIUM CONCERN	Company working on military/security applications of relevant technologies + answered that it was not working on lethal autonomous weapons;
	or Company not known as working on military/security applications of relevant technologies + chose not to answer our survey's questions in a meaningful way.
BEST PRACTICE	Company answered to explain its policy on how it ensures its technology is not contributing to lethal autonomous weapons.
	Unknown.

BEST MEDIUM HIGH HQ PRACTICE CONCERN CONCERN

RELEVANT TECHNOLOGY

RELEVANT MILITARY/ сомміт SECURITY PROJECTS

то нот DEVELOP

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AerialX Canada Counter-drone systems Airobotics Israel Autonomous drones Airspace Systems US Counter-drone systems Alibaba China Al chips, Facial recognition Amazon US Cloud, Drones, Facial and speech recognition Anduril Industries US Al platforms Animal Dynamics US Computers, Facial and speech recognition Arbe robotics Israel Autonomous drones ATOS France Al architecture, cyber security	
AerialX Canada Counter-drone systems Airobotics Israel Autonomous drones Airspace Systems US Counter-drone systems Alibaba Image: China Al chips, Facial recognition Amazon Image: China Al chips, Facial recognition Anduril Industries Image: China Al platforms Animal Dynamics Image: China US Counter-drone systems Apple Image: China Image: China Autonomous drones Arbe robotics Image: China Image: China Image: China ATOS Image: China Image: China Image: China Al chips, Facial and speech recognition Speech recognition Speech recognition Arbe robotics Image: China Image: China Image: China ATOS Image: China Image: China Image: China	
Airobotics Israel Autonomous drones Airspace Systems US Counter-drone systems Alibaba China Al chips, Facial recognition Amazon US Cloud, Drones, Facial and speech recognition Anduril Industries US All platforms Apple US Computers, Facial and speech recognition Arbe robotics Israel Autonomous drones ATOS All chips, Facial recognition All chips, Facial recognition	DroneBullet
Airspace Systems US Counter-drone systems Alibaba China Al chips, Facial recognition Amazon US Cloud, Drones, Facial and speech recognition Anduril Industries US Al platforms Animal Dynamics US Computers, Facial and speech recognition Arbe robotics Image: Computers, Facial and speech recognition Speech recognition Arbe robotics Image: Computers, Facial and speech recognition Speech recognition Artos Image: Computers, Facial and speech recognition Speech recognition	Border security patrol bots
Alibaba Al chips, Facial recognition Amazon US Cloud, Drones, Facial and speech recognition Anduril Industries US Al platforms Animal Dynamics US Autonomous drones Apple US Computers, Facial and speech recognition Arbe robotics Image: Computers, Facial and speech recognition Speech recognition ATOS Image: Computers, Facial and speech recognition Speech recognition	Airspace interceptor
Amazon US Cloud, Drones, Facial and speech recognition Anduril Industries US AI platforms Animal Dynamics UK Autonomous drones Apple US Computers, Facial and speech recognition Arbe robotics Image: Computers, Facial and speech recognition ATOS Image: Computers, Facial and speech recognition	n -
Anduril Industries Image: Speech recognition Animal Dynamics Image: Speech recognition Apple Image: Speech recognition Arbe robotics Image: Speech recognition ATOS Image: Speech recognition	JEDI, Rekognition
Anduril Industries US AI platforms Animal Dynamics UK Autonomous drones Apple US Computers, Facial and speech recognition Arbe robotics Israel Autonomous vehicles ATOS France Al architecture, cyber security	
Animal Dynamics UK Autonomous drones Apple US Computers, Facial and speech recognition Arbe robotics Israel Israel ATOS France Al architecture, cyber security	Project Maven, Lattice
Apple US Computers, Facial and speech recognition Arbe robotics Israel Autonomous vehicles ATOS France Al architecture, cyber security	Skeeter
Arbe robotics Israel Autonomous vehicles ATOS France Al architecture, cyber security	-
Arbe robotics Israel Autonomous vehicles ATOS France Al architecture, cyber security	
ATOS France Al architecture, cyber secu	-
	rity, -
data management	
Baidu China Deep learning, Pattern reco	ognition -
Blue Bear Systems UK Unmanned maritime and a	aerial Project Mosquito/LANCA
systems	
Cambricon China Al chips	-
Citadel Defense US Counter-drone systems	Titan
Clarifai US Facial recognition	Project Maven
Cloudwalk Technology China Facial recognition	-
Corenova Technologies US Autonomous swarming sys	stems HiveDefense, OFFSET
DeepGlint Facial recognition	-
Dibotics France Autonomous navigation, D	rones 'Generate'
EarthCube France Machine learning	'algorithmic warfare tools
	of the future'
Facebook US Social media, Pattern recog	gnition, -
Virtual Reality	-
General Robotics Israel Ground robots	Dogo
Google US Al architecture, Social med	lia, -
Facial recognition	
Heron Systems US AI software, ML, Drone appl	lications 'solutions to support
	tomorrow's military
	aircraft'



	Pattern recognition, Mapping	HiveMapper app	Х
	AI chips, Cloud, Super computers,	Nuclear testing super	
	Facial recognition	computers, ex-JEDI	
	Autonomous vehicles	-	
	AI chips, UAS	DARPA HIVE	
	Facial recognition	-	
	Cloud, Facial recognition	HoloLens, JEDI	
	Data analysis, Deep learning	'Revolutionise human	
		information relationship	
		for defence'	
	'Ambient Intelligence', Autonomous	-	
	robots, Machine vision systems		
	Deep learning neural network	Target identification soft-	
	software	ware for military drones	
	Cloud, AI infrastructure, Big data	ex-JEDI	
	Geospatial analytics	-	
	Data analytics	DCGS-A	
	Autonomous drones	-	
	Unmanned systems; AI software	Semi-autonomous military	
		UGVs	
	Computers and AI platforms	-	
	Computer vision, Deep learning	SenseFace, SenseTotem	
		for police use	
	Autonomous (swarming) drones	Nova	
y	Al, Automation	KRNS, TRADES	
	Telecom, Robotics	-	Х
	AI systems, Swarm technology	'works across the defense	
		and national security space	
		in the U.S.'	
	AI- and Cloud-based applications,	Kipod	
	Pattern recognition		
	Al chips	-	
	AI applications, Cloud, ML, Pattern	-	
	recognition		
	Robotics	-	
	Visual recognition	-	Х
	Facial recognition	Police use	

33

DISRUPTIVE AI & ROBOTICS

Disruptive Innovation

 Disruptive Innovation is an innovation that creates a new market and eventually disrupts an existing market, displacing established marketleading firms, products, and alliances.

• Examples:

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- Automobiles (Disrupts Railway, Horse carriage)
- Smartphones -> Compact Digital Cameras -> Analog (Chemical) Cameras
- Smartphones -> Laptops, Computers, PDAs
- Streaming Videos -> Video Rentals
- Internet -> Mail, Telephone, TV, Books, basically everything



Time



D/SRUPTION

disruptionhub.com

AI & Robotics may change Everything

- AI & Robots will change our daily life:
 - At work (if we have work) we will interact with them daily
 - Autonomous transportation services (cars/ Didi, Uber) may replace privately owned cars (and public transport?)
 - In our home they (hopefully) will do work
- Most work may be done by AI & Robots =>
 - Great productivity: Products and services may become VERY cheap!
 - Unemployment: Many jobs will be lost.
 - Option 1: Lost jobs will be replaced by new jobs (e.g. robot engineer, AI programmer)
 - Option 2: Most jobs will no be replaced => big unemployment
- Potentially: new (updated) social systems might emerge
 - Unconditional basic income?
 - Communism 2.0?

• • • •

DISCUSSION



iendly

Robots for Elderly care...

- Over 80% of Japanese positive about robotic nursing care
 - Respondents who said they are ready to or want to receive nursing care from robots: 84.3%. Of the respondents who prefer not to use robotic nursing care, 46.9 percent — the largest group said the reason for their choice was that they would prefer to be taken care of by humans.
 - <u>https://www.japantimes.co.jp/news/2018/11/15/national/80-japanese-positive-robotic-nursing-care/#.XV-</u> r_ZMza9Y
- Paper: Granny and the robots: Ethical issues in robot care for the elderly. Issues:
 - 1. the potential reduction in the amount of human contact;
 - 2. an increase in the feelings of objectification and loss of control;
 - 3. a loss of privacy
 - 4. a loss of personal liberty;
 - 5. deception and infantilisation;
 - 6. the circumstances in which elderly people should be allowed to control robots
 - http://staffwww.dcs.shef.ac.uk/people/a.sharkey/sharkey-granny.pdf

This August: Ma vs Musk: Tech tycoons spar on future of artificial intelligence



Jack Ma believes artificial intelligence poses no threat to humanity, but Elon Musk called that "famous last words" as the billionaire tech tycoons faced off on Aug 29 in an occasionally animated debate on futurism in Shanghai.

> https://www.thehindubusinessline.com/info-tech/ma-vs-musk-techtycoons-spar-on-future-of-artificial-intelligence/article29291335.ece