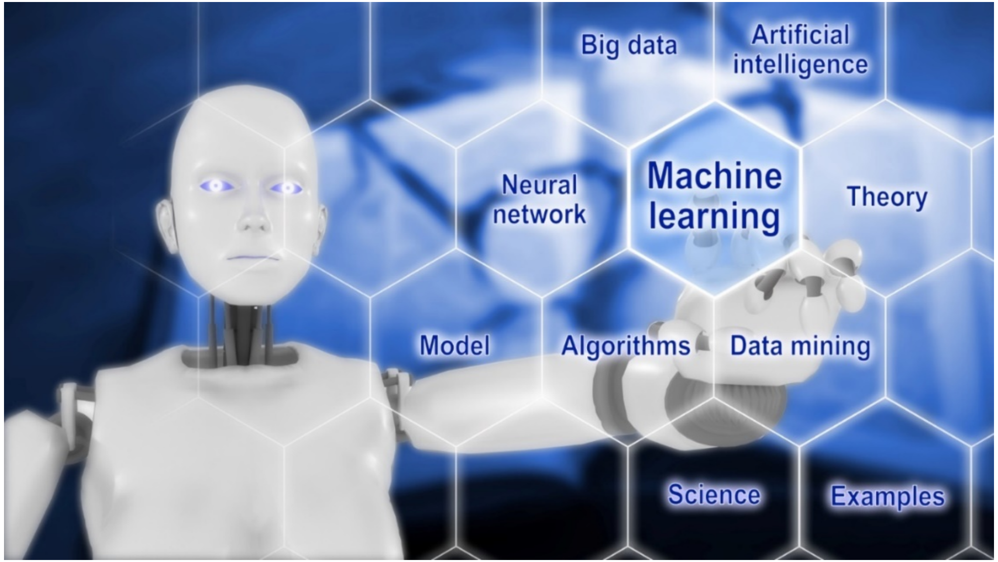
Worker—Machine Relationship in the 21st Century



John Howard
National Institute for Occupational Safety and Health
Centers for Disease Control and Prevention
U.S. Department of Health and Human Services

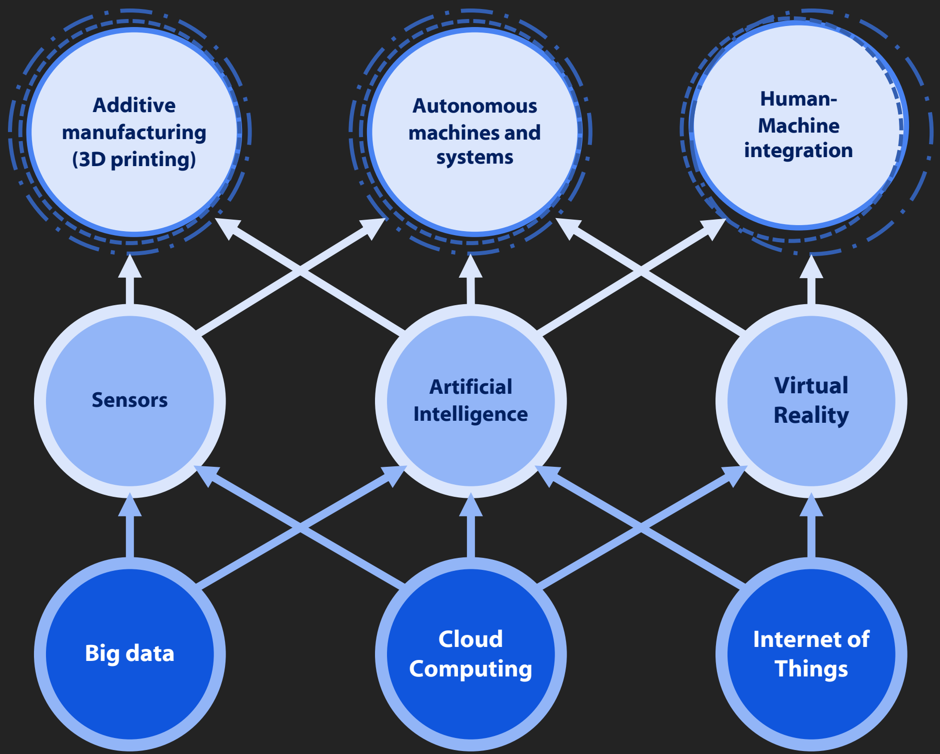
MAP ERC Annual Research Day
Westminster, Colorado

26 March 2020

Industrial Revolutions

- **First Industrial Revolution**
  – Used water and **steam power** to mechanize production
- **Second Industrial Revolution**
  – Used **electric power** to create mass production
- **Third Industrial Revolution**
  – Uses **electronics** to automate production
- **Fourth Industrial Revolution**
  – Uses physical entities controlled by **artificial intelligence**

Key Technologies Enabling the Future



Source: OECD (2017)

Overview

- Decision agent capabilities
- Theory of robotics
  - Embodied robots
  - White collar robots
- Safety
- Automation

Decision Making Agents

- **Decision Making Agent**
  - Thinks and acts on observations of its environment
    - ***Physical*** or **embodied** devices
      - Human workers
      - “Steel-collar” workers
    - ***Non-physical*** devices
      - Decision support systems=software ***code***
        - » “White collar” robots
        - » “Synthetic” workers

Agent Capabilities

- Humans have 3 major capabilities:
  - Physical, cognitive, and emotional
- Machines that can perform these 3 capabilities in *physical space* are known as “robots.”
  - Robot derives from Czech word “robota,” meaning forced labor
  - *R.U.R*. (Rossum’s Universal Robots) is a 1920 play by Karel Čapek
- Machines that can perform cognitive decision making through AI are known as “intelligent assets”
  - *Watson* (IBM)
  - *AlphaGo* (Google)
  - *Alexa* (Amazon)
  - *Siri* (Apple)

Theory of Robotics

- How a robotic device works is as follows:
  - The robot **senses**, the robot **thinks,** and the robot ***acts***…

- How?
  - **Sensing** is done through *interpretation* of data perceived by:
    - Environmental sensors for an embodied robotic device
    - Data inputs from a digital assistant
  - **Thinking** is done through the use of AI methods
  - **Acting** is done through:
    - *Effectors* or *actuators* for embodied robots
    - *Decision* outputs for white collar robots

Sensing

Sensor Technology Is Expanding

- **Enabling capabilities increasing exponentially because of:**
  - Improvements in measurement science
  - Readily available geographic and spatial information locators
  - Miniaturization of sensing instruments
  - Promising technical solutions increasing the quality, reliability, and economic efficiency of sensors.

- **Types of “Smart” Sensors**
  - Placeables
    - Ground, air, water
    - In-vehicle monitors
  - Wearables
    - Clothing
    - PPE
  - Implantables
    - Transcutaneous
    - Ingested

NIOSH Center for Direct Reading and Sensor Technologies

The NIOSH Center for Direct Reading and Sensor Technologies (NCDRST) was established in May 2014 to coordinate research and to develop recommendations on the use of 21st century technologies in occupational safety and health. The NCDRST is a virtual center hosted by the NIOSH Division of Applied Research and Technology and the NIOSH Exposure Assessment Cross Sector Program.

NCDRST Objectives

1. Coordinate a national research agenda for direct-reading methods and sensor technologies. Research on these technologies has been incorporated into the goals of the NIOSH Strategic Plan for fiscal years 2019-2023.
2. Develop guidance documents pertinent to direct-reading methods and sensors, including validation and performance characteristics;
3. Develop training protocols; and
4. Establish partnerships to collaborate in the Center’s activities.

Examples of Types of Sensor Inputs

- **Self-Awareness**
  - Perceptual awareness for embodied robots
    - Range finders
    - Location sensors
    - Proprioceptive sensors
    - Force sensors and torque sensors

- **Information**
  - Visual, tactile, numerical data

Internet of Things (IoT)

- **OMO (online-merge-of-offline)**
  - Combining of our digital and physical worlds such that every object in our surrounding environment will become an data input for the Internet

- **Sensors are at the heart of the *Industrial Internet***
  - Deploying sensors, entire workplace and everyone in it become *data input* sources.
  - Workplace sensors become intelligent assets operating in physical and virtual space.

- **Sensor improvements can be easily uploaded to the cloud**
  - Immediate and universal sensor connectivity
  - Universal sensor upgradability (not like humans with their meetings)

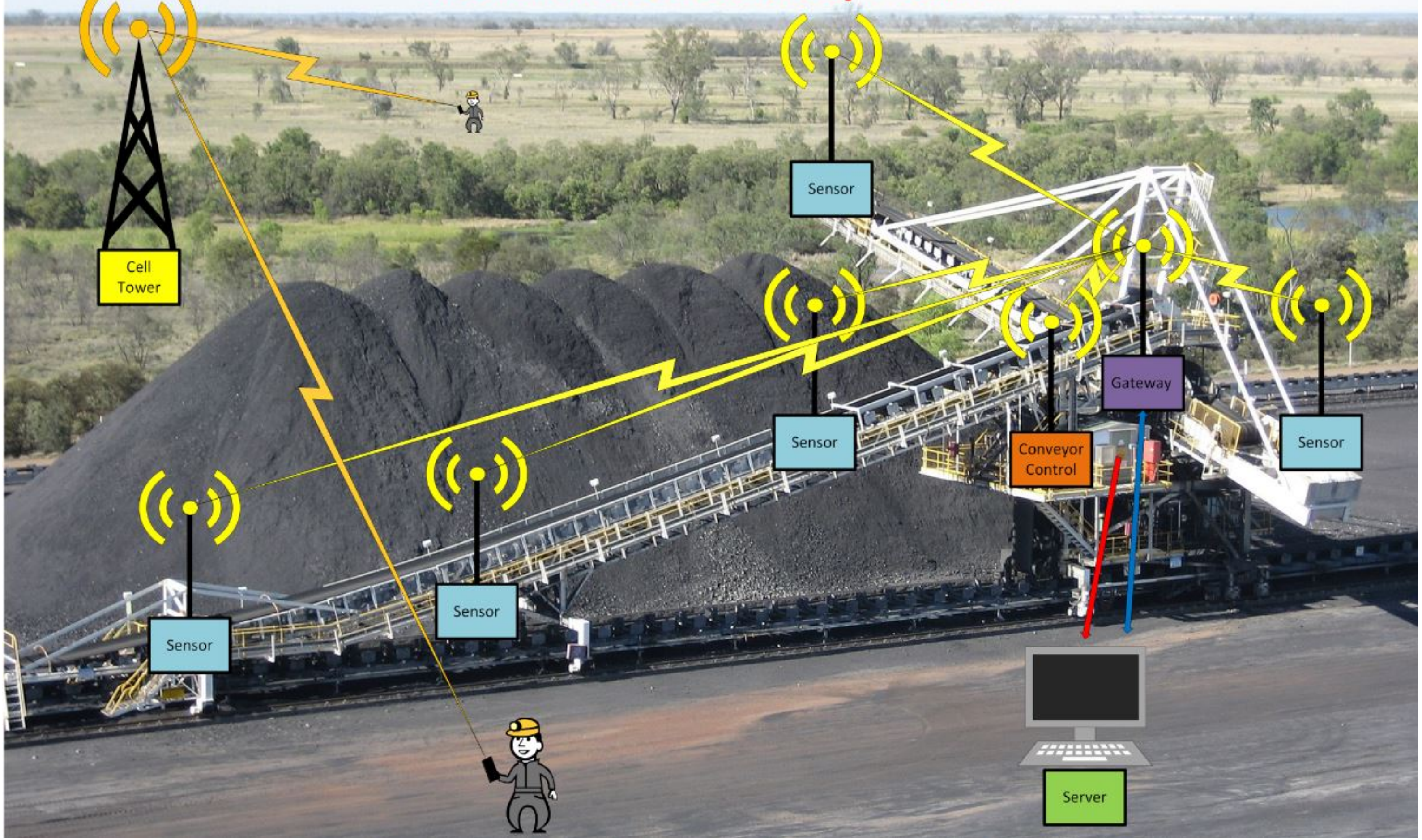
- **Cloud-based sensor data inputs**
  - Birth of occupational data analytics—new era of surveillance technology?
  - Use of AI to support risk assessment and management decision making
  - Occupational safety and health professionals now are “data decision” scientists

Functional Fabrics—Wearable Sensors

Future of Exposure Assessment?

Marty Ellis, of Inman Mills in South Carolina, checks a machine manufacturing fabric developed through AFFOA.

Application of Internet of Things Technology to detect and mitigate machine related safety hazards

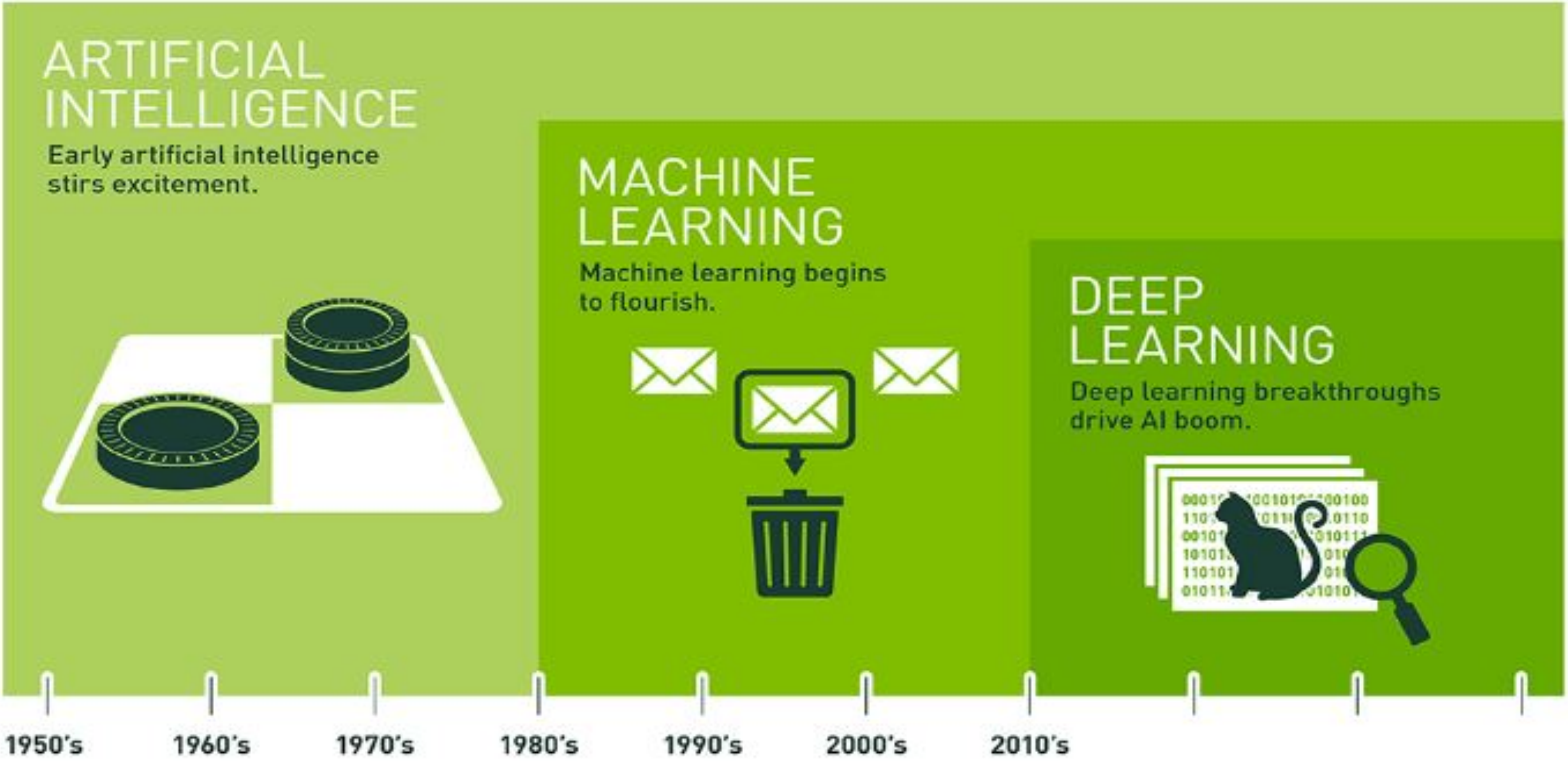


Sensor Challenges

- **Challenges**
  - Precision calibration and validation of sensor instruments—technical challenge
  - Accuracy of sensor measurement outputs—basis for interpretation
  - Correct hazard characterization?

- **Questions**
  - Given the vast amounts of sensor data that is expected to be generated, how can such data be collected, analyzed, and interpreted by an ***occupational safety and health data decision scientist*** using AI computational methods?
  - How can the occupational safety and health data decision scientist add value to sensor-generated exposure data?

Thinking


ARTIFICIAL INTELLIGENCE
Early artificial intelligence stirs excitement.
MACHINE LEARNING
Machine learning begins to flourish.
DEEP LEARNING
Deep learning breakthroughs drive AI boom.
1950's
1960's
1970's
1980's
1990's
2000's
2010's

Artificial Intelligence

- **Central Idea** —Using *probability* functions to represent reality.

- **Origin**— 1956 Dartmouth College workshop computer scientists predicted that machines that could reason as well as humans would require, at most, a generation to come about—so-called ***Artificial General Intelligence*** (AGI). What we experience now is ***Narrow AI***.

- **Current AI has grown exponentially due to 3 things:**
  - **Explosion in computing power**
    - Graphical processing units operating in parallel
  - **Increase in storage capacity capabilities**
    - Cloud computing
  - **Data accumulation ('big data')**
    - Made possible by the Internet

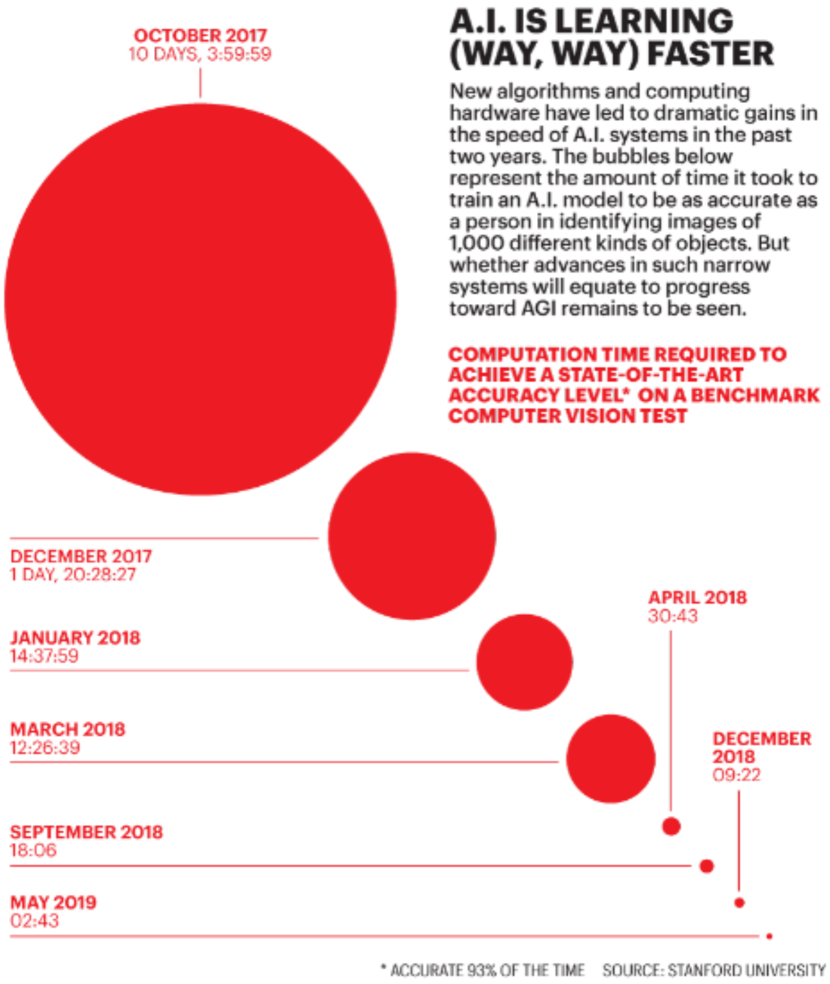
Artificial Intelligence

- **Common Definition**
  - Machines that can do tasks that were traditionally in the realm of human beings like recognizing objects in images and understanding and responding to natural language
  - Once we see tasks that are in the human domain, we assume that is intelligence, but humans are terrible at solving problems that involve more than seven things.

- **Advanced Definition**
  - Intelligence is goal-directed, *adaptive* behavior
    - "If your computer system is not making a decision and then learning whether that decision was good or bad, and adapting its own internal model of the world, then it is not true AI."
      - » Daniel Hulme, https://www.strategy-business.com/article/Understanding-the-Potential-of-Artificial-Intelligence
  - True AI involves computer systems that can learn and adapt without the aid of an human.
  - Adaptability = intelligence

AGI & Decision-Making

- Imagine
- Rather than assign a 15-person task force to decide where a firm should build a new factory, you ask your firm's AGI.
- System would research decision factors:
  - Proximity to suppliers
  - Transportation and labor costs
  - Tax incentives and regulatory issues
- Make a recommendation & produce a report explaining decision
- Would do this in minutes, not weeks or months
- If management agreed, AGI would generate all relevant work orders to start the process.
  - *Fortune*, Quest for Human-Level AI, February 2020



Machine Learning

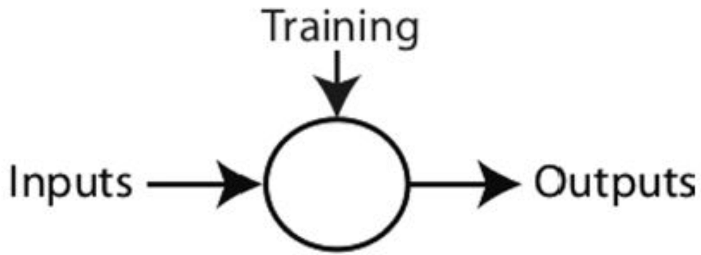
- Machine learning at its most basic is the practice of using algorithms to parse data, learn from it, and then make a determination or prediction about something in the world.

- Machine is “trained” using large amounts of data (***big data***) and algorithms that give it ability to learn how to perform the task more and more accurately

- Machine-learning technology powers many aspects of modern society:
  - From web searches to content filtering on social networks to recommendations on e-commerce websites; spoken language and computer vision
  - Increasingly present in consumer products such as cameras and smartphones.

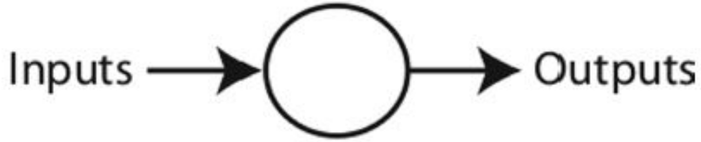
Supervised learning

Learns known patterns
Takes labeled input data
Predicts outcome/future



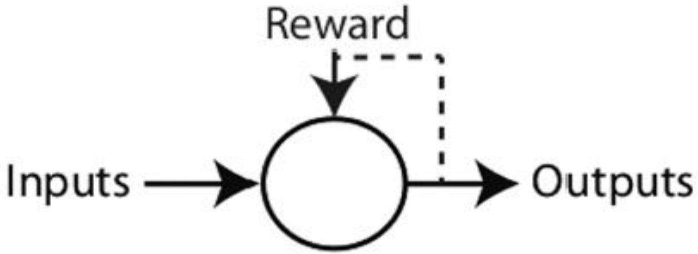
Unsupervised learning

Learns unknown patterns
Takes unlabeled input data
Finds hidden patterns



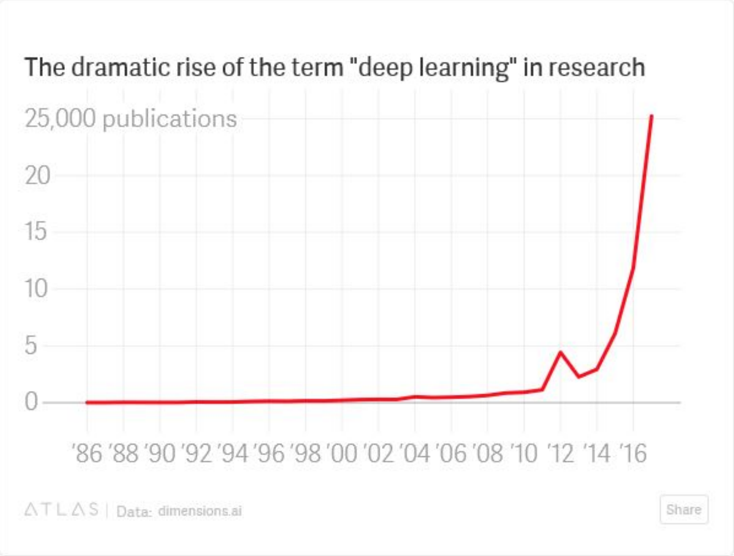
Reinforcement learning

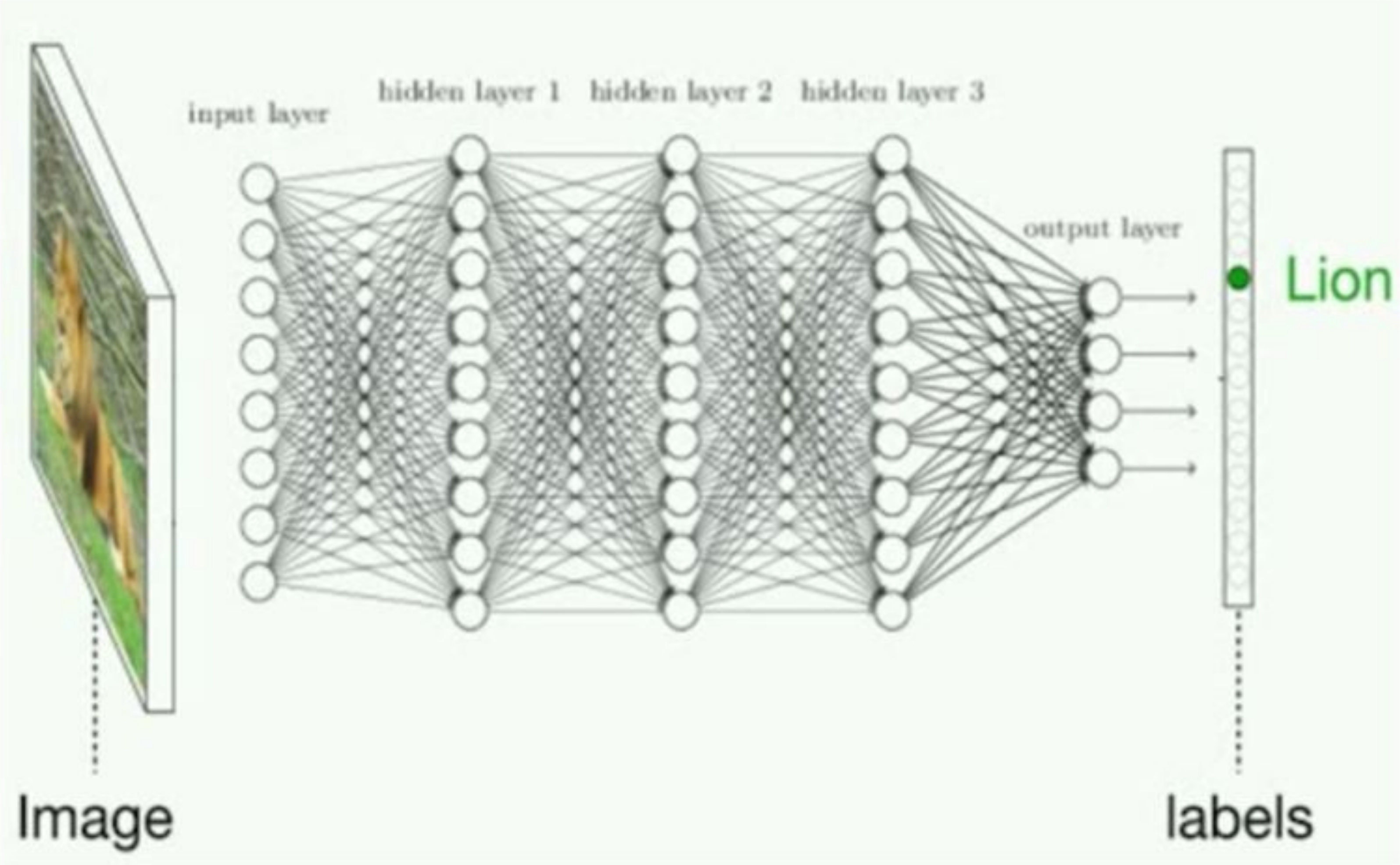
Generates data
Takes labeled input data
Interacts with environment
Learns series of actions

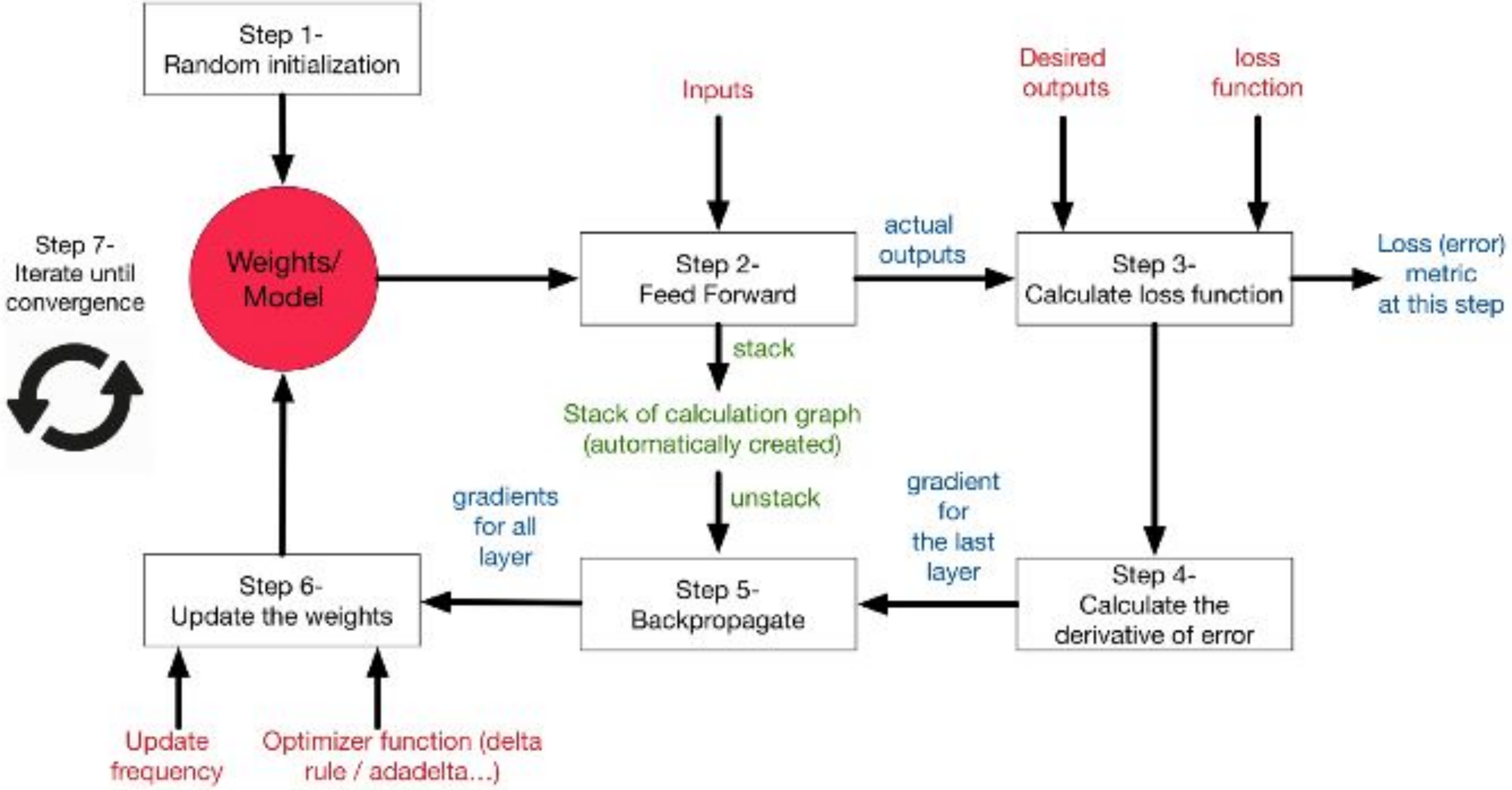


Deep Learning & Neural Networks

- Human learning occurs by modifications of synapses between neurons based on stimuli received by trial and error experience.
- Neural networks provide a way to replicate this process:
  - Neural networks have different layers, each one having its own **weights.**
  - Uses a mathematical method called *backpropagation*—correction—weights can be changed to limit the "loss function."
  - N*eural network* is asked to solve a problem, which it attempts to do over and over, each time strengthening the connections that lead to success and diminishing those that lead to failure, i.e., the loss function.
  - Open source framework for neural networks at http://playground.tensorflow.org/




input layer
hidden layer 1
hidden layer 2
hidden layer 3
output layer
Lion
Image
labels



Neural networks step-by-step

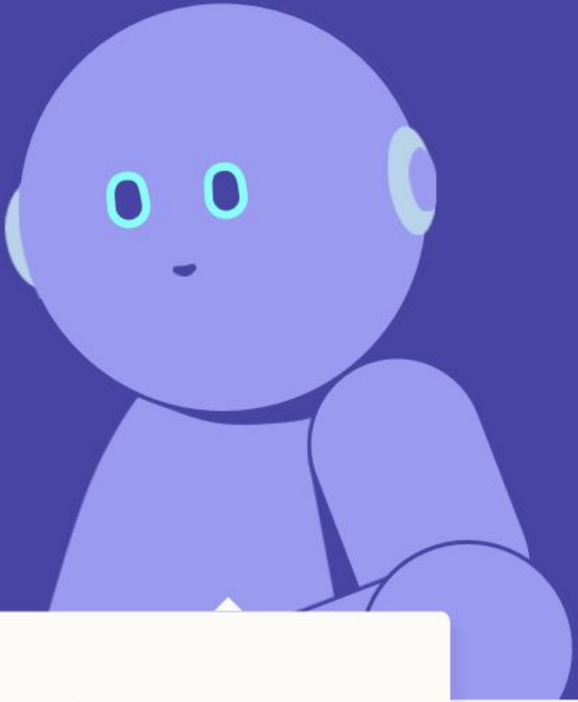
Elements of AI

Select language

Welcome to the Elements of Artificial Intelligence free online course

English

Start the course



- Do you wonder what AI really means?
- Are you thinking about the kind of impact AI might have on your job or life?

Other language versions are on the way!

Get notified when the language versions are available

Acting

Occupational Robotics

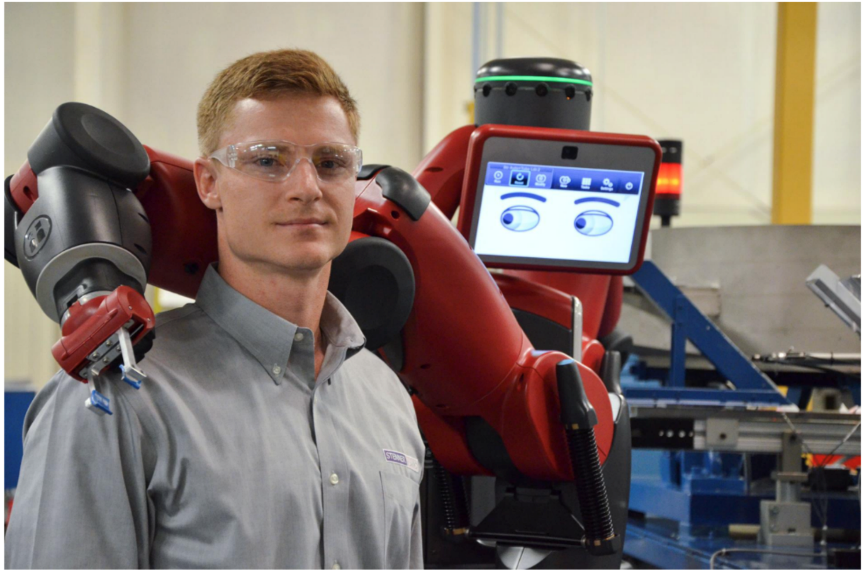
- Types:
  - In ***physical*** space
    - Manipulators (or robotic arms)
    - Mobile robots
      - Unmanned vehicles
        - » Ground
        - » Aerial
        - » Water
      - Mobile manipulators
      - Humanoid (mimic human torso)
  - In ***digital*** space
    - Intelligent decision making agents

Robots: Organizational Advantages

- **Better at Routine Tasks**
  - Better than people at precise and repetitive tasks
- **Better at Finding Patterns**
  - Humans are good at finding patterns in four to seven dimensions, machines can find patterns in thousands of dimensions
- **Dangerous Tasks**
  - Venturing into dangerous environments
  - Completing hazardous activities
- **Better at Managerial Tasks**
  - Remind a team of deadlines, procedures, and progress
    - Keep perfect record of project progress
    - Provide real-time scheduling and decision support
    - Demonstrate perfect recall
- **Lower Operational Costs**
  - Costs average $8 an hour to use a robot for spot welding in the auto industry, compared to $25 for a worker—and the cost savings quotient is only going to widen.

Commercial Types of Robotics

- **Traditional Industrial robots**
  - Fixed in location
  - Humans and robots are separated from each other
- **Collaborative robots**
  - Designed to work together with humans
- **Service robots**
  - Autonomous ground vehicles
  - Unmanned aerial vehicles
  - Household service robots
- **Social Robots**
  - Detect and express human emotion
  - Act as companions
- **Wearable Robotics**
  - Exoskeletons



Traditional Industrial Robots

- Decades of safety experience
- Used since the 1970s in auto manufacturing industry
- Safety measures that keep human workers ***separated*** from robot workers is standard

Collaborative Robots or Cobots

ROBOTICS

Collaborative Robots: Challenge

- Designed to work alongside human workers.
- Controlled by human workers, by an algorithm, or by both.
- Equipped with sensors designed to stop robot when contact with human worker occurs.
- ***Grasping*** a previously unknown object, one for which a 3-D model is not available, is the biggest challenge.
  - https://berkeleyautomation.github.io/dex-net/

Filling a bin with objects for the Dex-Net 4.0 robot grasping research. Credit: Adriel Olmos, UC Berkeley

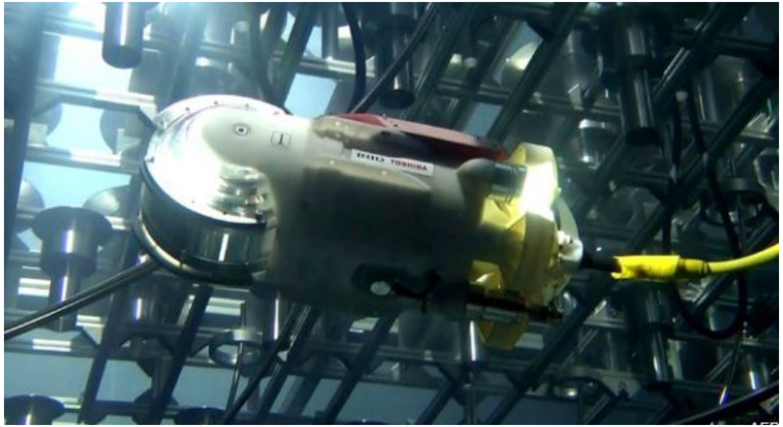
Service Robots

- Move alongside, and in shared space, with human workers

Service Robot: 'Little Sunfish'

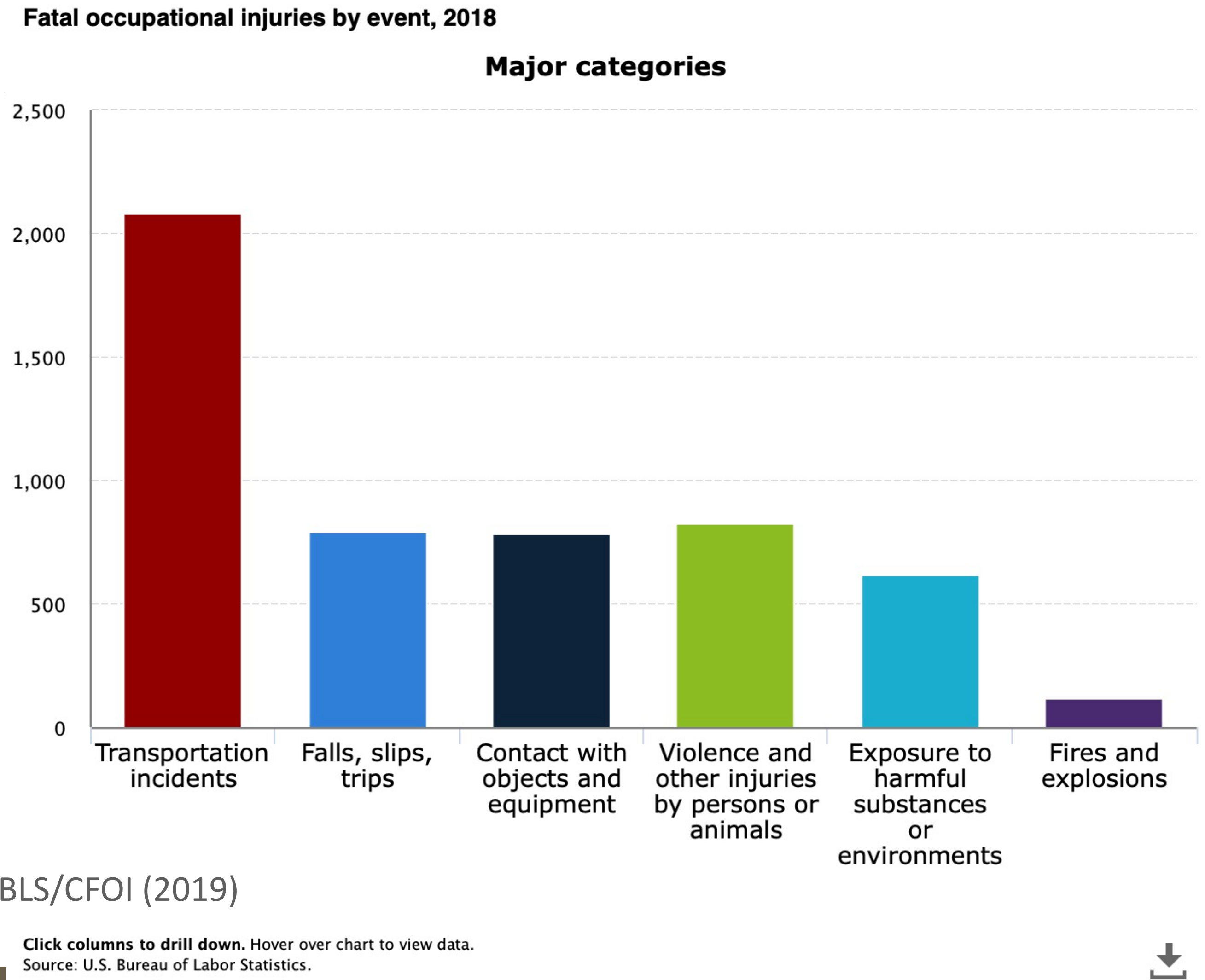
- When a tsunami devastated parts of Japan's coastline in 2011, killing more than 18,000 people, it also hit the Fukushima Nuclear Power Plant, triggering the most serious nuclear accident since Chernobyl.

- Parts of the damaged reactors are still highly contaminated with radiation and robots are playing a crucial part in the clean-up.



Service Robots: Autonomous Ground Vehicles

- Service robots used by Rio Tinto in Pilbara, Western Australia
  - No coffee breaks, fatigue and driver changeovers.
  - Stops only once a day for refueling.
- Autonomy enables drilling to run for almost a third longer on average than with manned rigs, and to churn through 10% more ground meters/hour.
- Engineers at Rio's operations center in Perth (2 hours flight away) remotely control the trucks.
- Workforce at the mine is already about one-third lower as a result of autonomy of the trucks.



- Source, BLS/CFOI (2019)

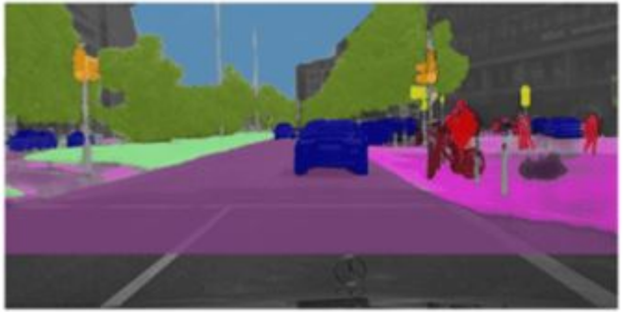
Service Robots: Truck Platoons

- **Safety**
  - With the following trucks braking immediately, with zero reaction time, platooning can improve traffic **safety**.
- **Cost**
  - Platooning is also a **cost-saver** as the trucks drive close together at a constant speed. This means lower fuel consumption and less CO2 emissions.
- **Efficiency**
  - Platooning **efficiently** boosts traffic flows thereby reducing tail-backs. Meanwhile the short distance between vehicles means less space taken up on the road.

Self-Driving Challenge:

Computer Vision

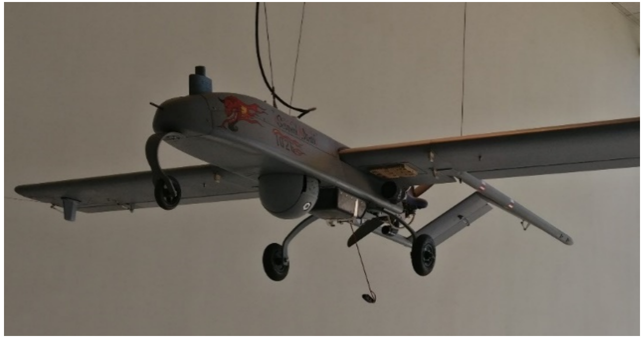
- You cannot write rule-based algorithms that anticipates every possible scenario a self-driving car might encounter.
- That's the value of AI deep learning; it can learn, *adapt*, and improve—distinguishing a pedestrian from a shadow.



Daimler was able to bring "the vehicle's environment perception a significant step closer to human performance and exceed the performance of classic computer vision" with NVIDIA DriveNet.

Using a dataset from our partner Audi, NVIDIA engineers rapidly trained NVIDIA DriveNet to detect vehicles in an extremely difficult environment – snow.

Unmanned Aerial Vehicles



Military

Recreational

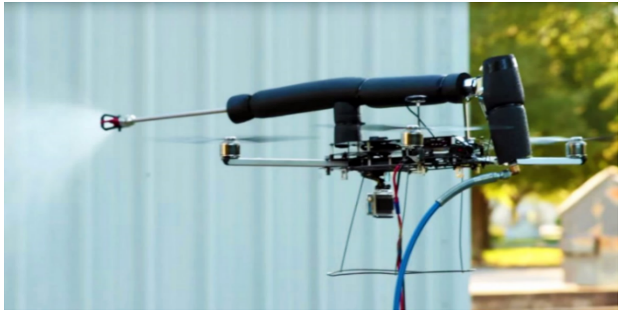
Public Safety

Commercial

UAVs Uses in Construction

Monitoring

Inspection



Maintenance

Hazardous Applications

Confined Space Entry

UAVs

- **Engineering**
  - Errors in the drone’s mechanics (e.g., loose connections across parts, faulty electronics and sensors).
- **Human**
  - Errors in programming, interfacing peripheral equipment, and connecting input/output sensors resulting in unpredicted movement or action by the drone;
  - Errors in judgment resulting from “over-attributing” to autonomous robots more human-like qualities and capabilities;
  - Errors in remote operating.
- **Environmental**
  - Unstable flying conditions, extreme temperature, poor sensing in difficult weather or lightning conditions leading to incorrect response.

ANSI: Unmanned Aircraft Systems Standardization Collaborative (UASSC)

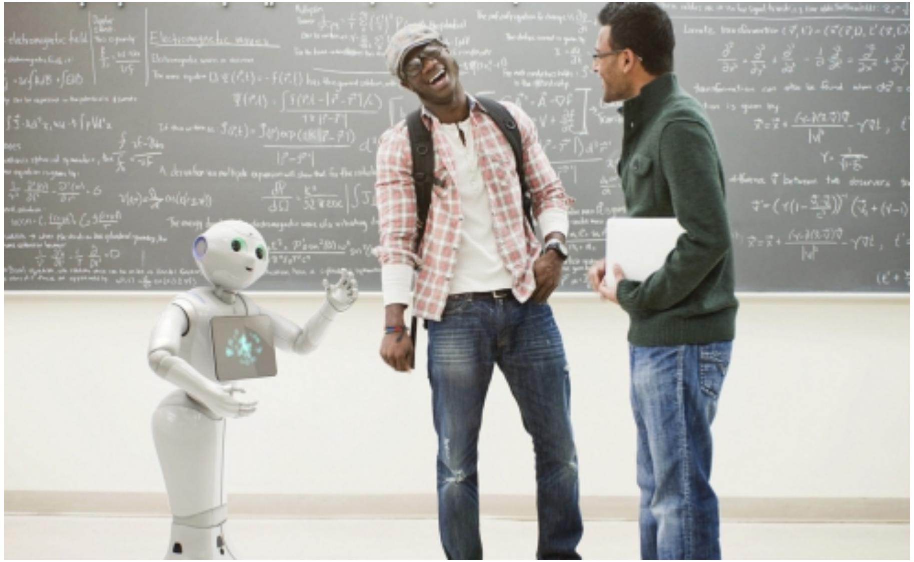
- In 2017, ANSI launched UASSC to coordinate and accelerate the development of the standards and conformity assessment programs needed to facilitate the safe integration of UAVs into the U.S. airspace system.

- Roadmap identified 60 gaps and recommendations across the topical areas of airworthiness; flight operations; and personnel training, qualifications, and certification.

- https://share.ansi.org/Shared%20Documents/Standards%20Activities/UASSC/ANSI_UASSC_Roadmap_December_2018.pdf

Social Robots

- ***Pepper*** is a humanoid robot by *SoftBank* Robotics
- Designed with the ability to read emotions. An emotional robot.
  - Introduced on 5th June 2014 to enhance human well-being.
  - Available at a base price of JPY 198,000 ($1,931).
  - $134 per month maintenance and $89 per month insurance.
- Pepper's emotion comes from the ability to analyze expressions and voice tones.



Industrial Exoskeletons

Exoskeleton devices are being introduced across several industry sectors to augment, amplify, or reinforce the performance of a worker's existing body components-primarily the lower back and the upper extremity.

- May play a role in reducing work-related MSDs arising from lifting and handling heavy materials or from supporting heavy tools in overhead work. However, wearing an exoskeleton may pose a number of risks that are currently not well-studied.

- There are only a few peer-reviewed, published studies about the safety and health implications of wearable exoskeletons and most of those studies involve only a small number of participants.

- There is need for prospective interventional studies to evaluate the safety effectiveness across industry sectors.
  - Howard et al. Need for interventional effectiveness research. *AJIM* (2019)

Industrial Exoskeletons

Exoskeleton devices are being introduced across several industry sectors to augment, amplify, or reinforce the performance of a worker's existing body components-primarily the lower back and the upper extremity.

- May play a role in reducing work-related MSDs arising from lifting and handling heavy materials or from supporting heavy tools in overhead work. However, wearing an exoskeleton may pose a number of risks that are currently not well-studied.

- There are only a few peer-reviewed, published studies about the safety and health implications of wearable exoskeletons and most of those studies involve only a small number of participants.

- There is need for prospective interventional studies to evaluate the safety effectiveness across industry sectors.
  - Howard et al. Need for interventional effectiveness research. *AJIM* (2019)

Intelligent Digital Assets

White Collar Robots

“Synthetic” Workers

Theory of Intelligent Digital Assistants

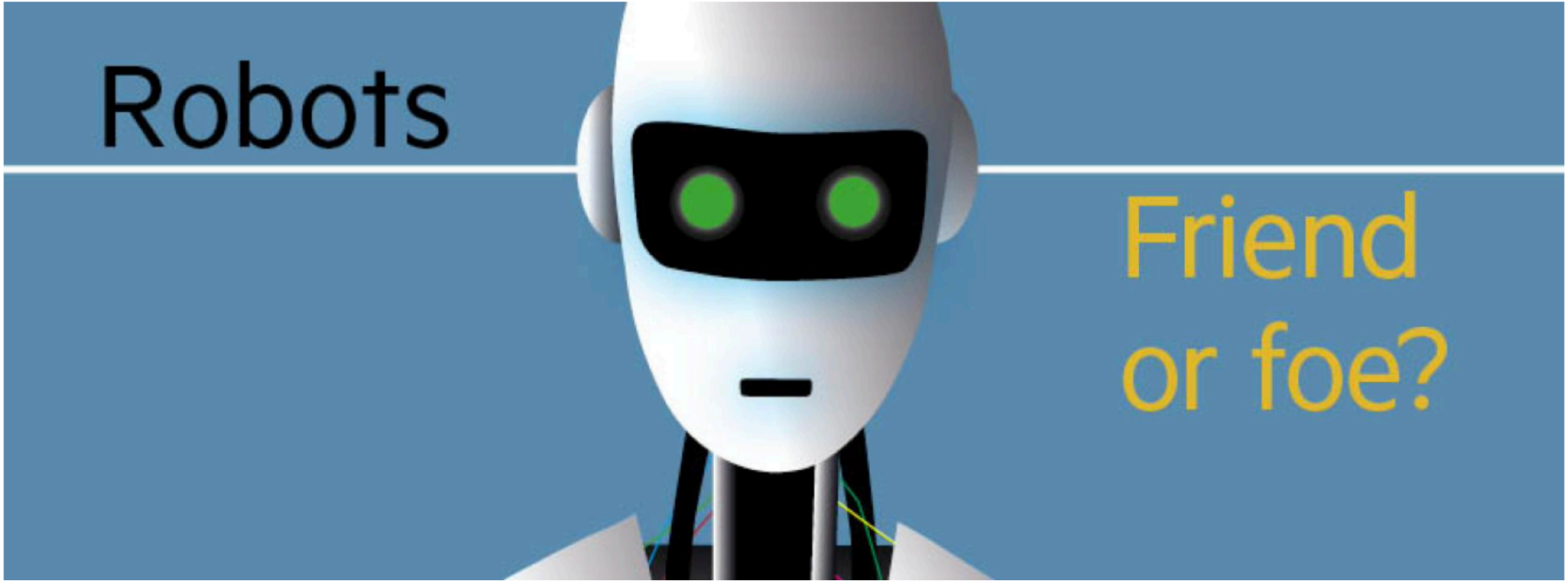
Sensors → Data Inputs

Thinking → Artificial Intelligence

Acting → Decision Support Systems

Workplace White Collar Robots

- Amelia
  - Works at Swedish Bank SEB and in Zurich for UBS
  - Speaks 20 languages (at same time)
  - Handles thousands of call simultaneous and can memorize a 300 page manual in 30 seconds
- Advantages
  - Cheaper than a human worker times many, many
  - Leaves digital trail that makes reporting for regulatory compliance faster and higher quality
- Other WCRs
  - Erica—Bank of America
  - Watsons—IBM
  - Einstein—Salesforce
  - Nia—Infosys
  - Cortana—Microsoft
  - Alexa—Amazon

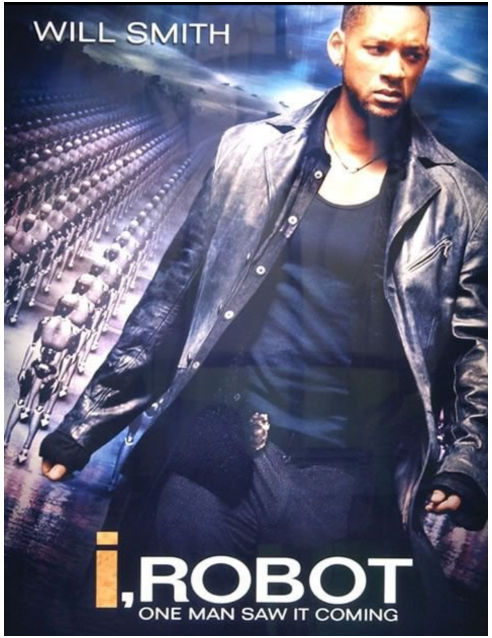

Robots
Friend
or foe?

AI Ethics: Playing the Probabilities

- **Two cars sinking in the water**
  - Detective Del Spooner (Will Smith)
  - Young girl, Sarah

- **Robot could save only one of them, Spooner yells *"Save the girl!"***
  - Probability of survival for Spooner was 45%
  - Probability of survival for Sarah was 11%

- **Robot saved Spooner; girl drowned.**
  - Fleetwood, J. Public Health, Ethics, and Autonomous Vehicles. *Am J Pub Health*. 2017; 107(4): 532-537



Robotics & Safety

Potential

- Expand dangerous work done by robots
- Robotic systems augment workers' abilities—teams of human workers and robot workers are more productive

Concerns

- Likely increase in robot-related human injuries
- New types of robots will require refined and new protection strategies
  - Robot with **dynamic machine learning** capabilities can challenge **static safety procedures**
- Rapid advances in robot and sensor technology will outpace national standards setting
  - Impetus for international consensus standard-setting
- Worker stress associated with changing workplace
- Potential for technological displacement

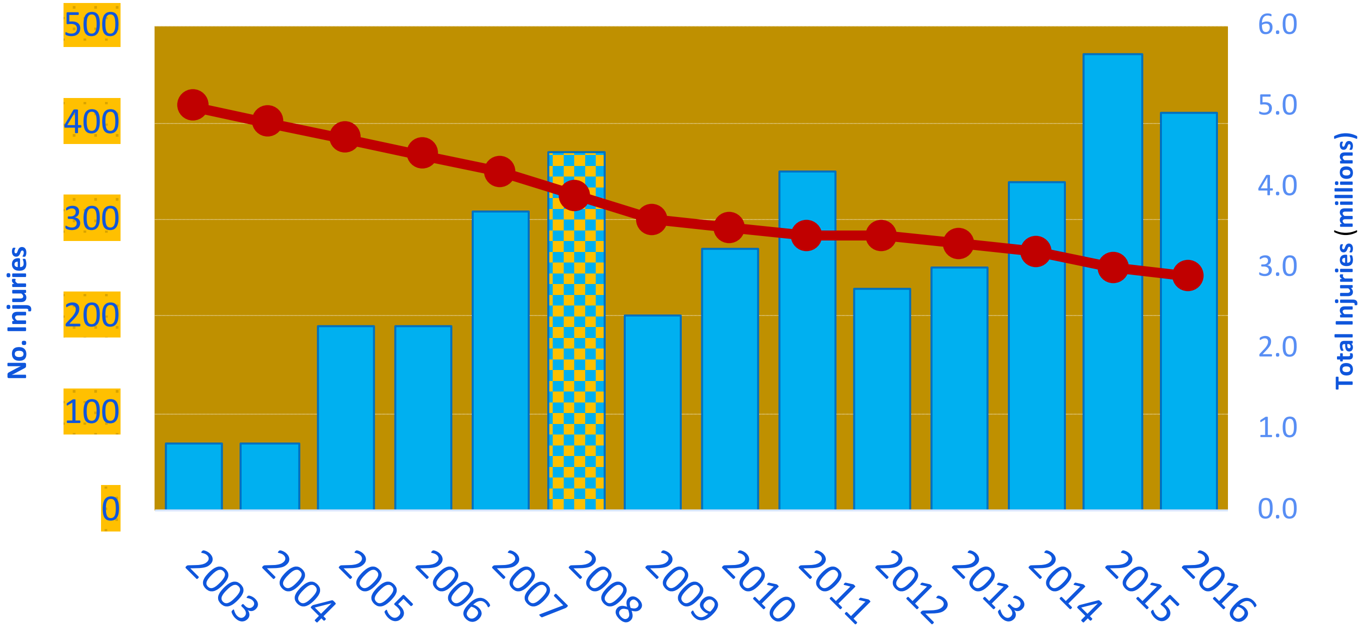
Industrial Robots: Safety Record

- Estimated 61 robot-related deaths, 1992-2015, CFOI*
  - Identified using keywords

- < 1% of more than 190,000 workplace injury deaths during that timeframe**

*Unpublished analyses by NIOSH. Through a MOU with BLS, NIOSH receives Census of Fatal Occupational Injury (CFOI) research files with restricted access requirements. Views expressed herein to not necessarily reflect the views of BLS.
** Data from publicly available CFOI data.

Estimated 3,730 Robot Injuries in U.S., SOII 2003-2016



Ability to Identify and Track Injuries

- Need to refine keyword searches and need to explore the ability to identify cases in different databases.

- NIOSH made recommendations to BLS for potential changes to Survey of Occupational Injuries and Illnesses (SOII).

- BLS currently lacks a direct way to identify truly robotic systems.

- Some solutions:
  - Add a 5th digit to the source codes to denote robotic systems; or
  - Create a standalone variable for robotic systems.

ANSI/RIA Robotic Safety Standards

- **ANSI/RIA R15.06-2012**
  - American National Standard for Industrial Robots and Robot Systems—Safety Requirements (revision of ANSI R15.06-1999)
    - Approved March 28, 2013
    - Revision underway
  - Provides guidelines for the manufacture and integration of industrial robots and robot systems
    - Emphasis on their safe use, the importance of risk assessment and establishing personnel safety.
    - Key feature in the standard is “collaborative operation”
      - Introduction of a worker to the loop of active interaction during automatic robot operation.

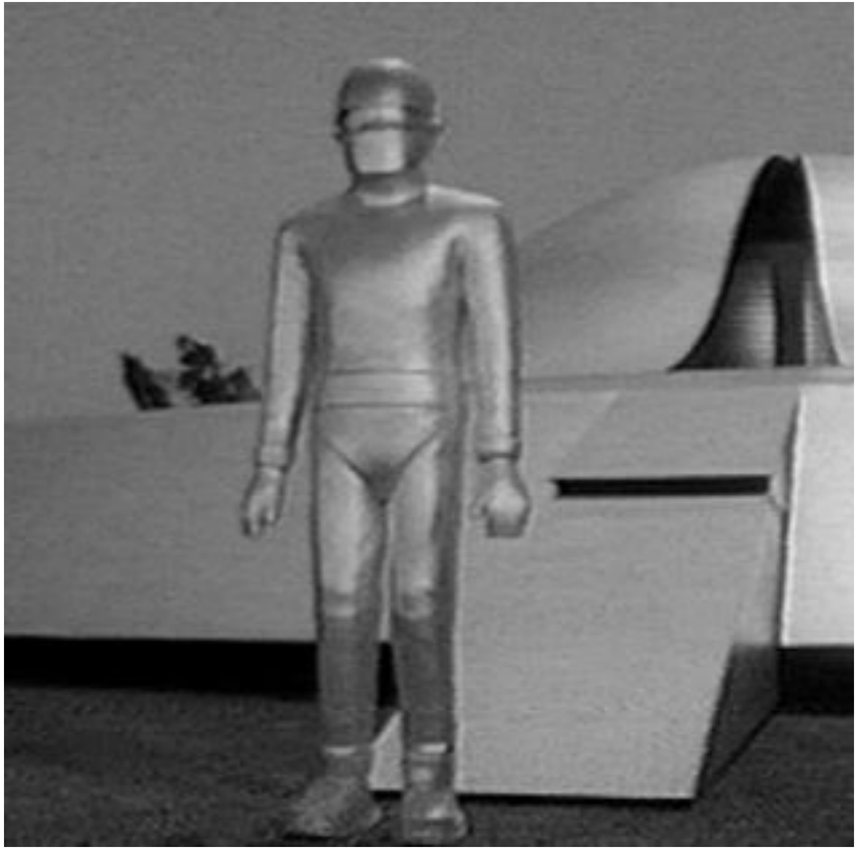
Consensus Standards Setting

- ANSI/RIA R15.06 – Industrial **Robots and Robot Systems Safety** (*Update)*
- ANSI/RIA R15.08 – Industrial **Mobile Robot Safety** *(New)*
- ASTM F48 – **Exoskeletons and Exosuits** *(New)*
  - Committee addressing safety considerations in designing and selecting exoskeletons; system training; load handling when using an exoskeleton; recording environmental conditions for utilization with exoskeleton test methods; labeling and information for exoskeletons and exosuits; and wear, care, and maintenance instructions.
- ANSI/ASSP/NSC Z15.3- Safety Management of **Partially and Fully Automated Vehicles** *(Technical report)*
- ANSI **Unmanned Aircraft Systems** Standardization Collaborative Roadmap *(Groundwork for consideration of a new standard*)

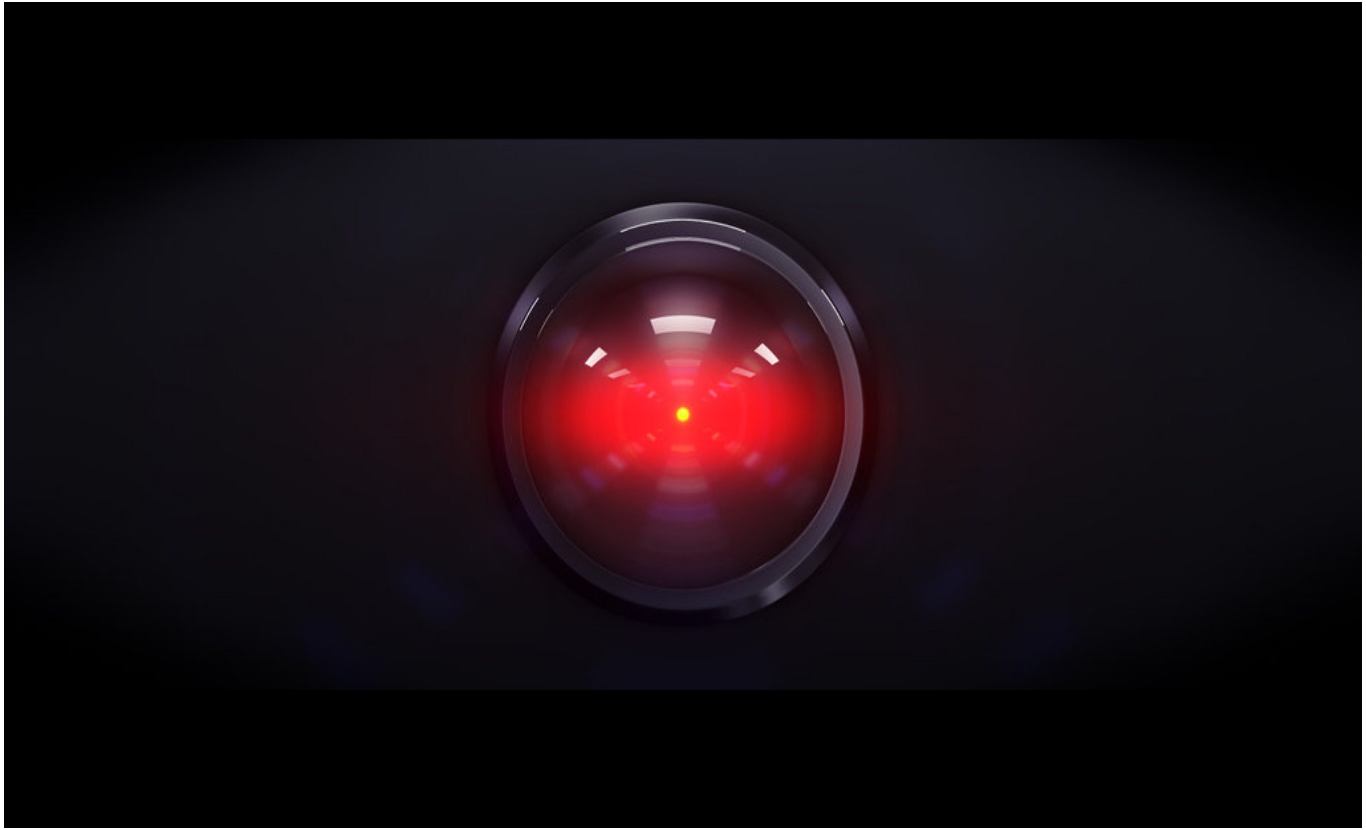
- NIOSH has been aware of an increase in the use of robotics in the workplace for a number of years.
  - NIOSH decided to focus research attention on understanding the aspects of robotics that may affect human workers and the 21st century workplace.
  - In 2016, signed a Memorandum of Understanding between *OSHA* and *Robotics Industry Association*.
  - In 2017, NIOSH stablished a *Center for Occupational Robotics Research*.

AI Safety Management

- Can AI be used to assist humans in recognizing a near-miss?
- Can AI be used to assist humans to offer more accurate risk mitigation recommendations than humans can alone?
- Can AI take control to prevent human actions that may create safety and health hazards?



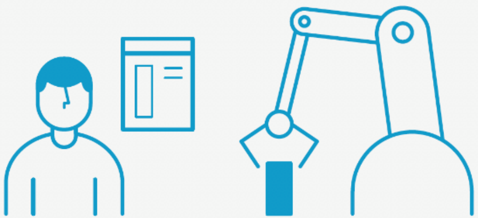
"I'm sorry Dave, I'm afraid I can't do that"



AI and Work

THREE SHIFTS ARE UNDERWAY

1. UNBUNDLING OF WORK FROM JOBS



Jobs are no longer the organizing unit for work; rather, there is a redistribution of tasks between humans and machines, depending on who is best suited to do the job

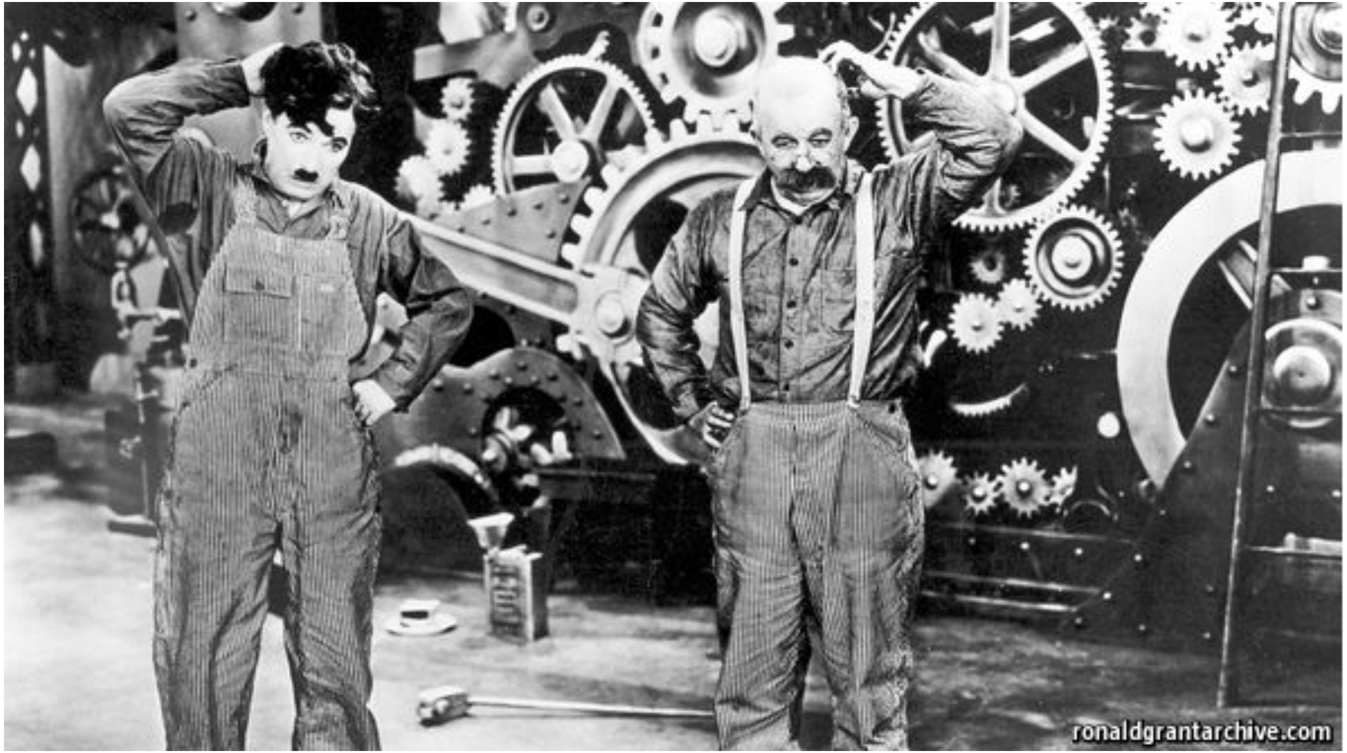
2. NEW WORK, NEW SKILLS

With the rise of new technologies, we will see the emergence of new roles associated with the design, development and maintenance of new technologies

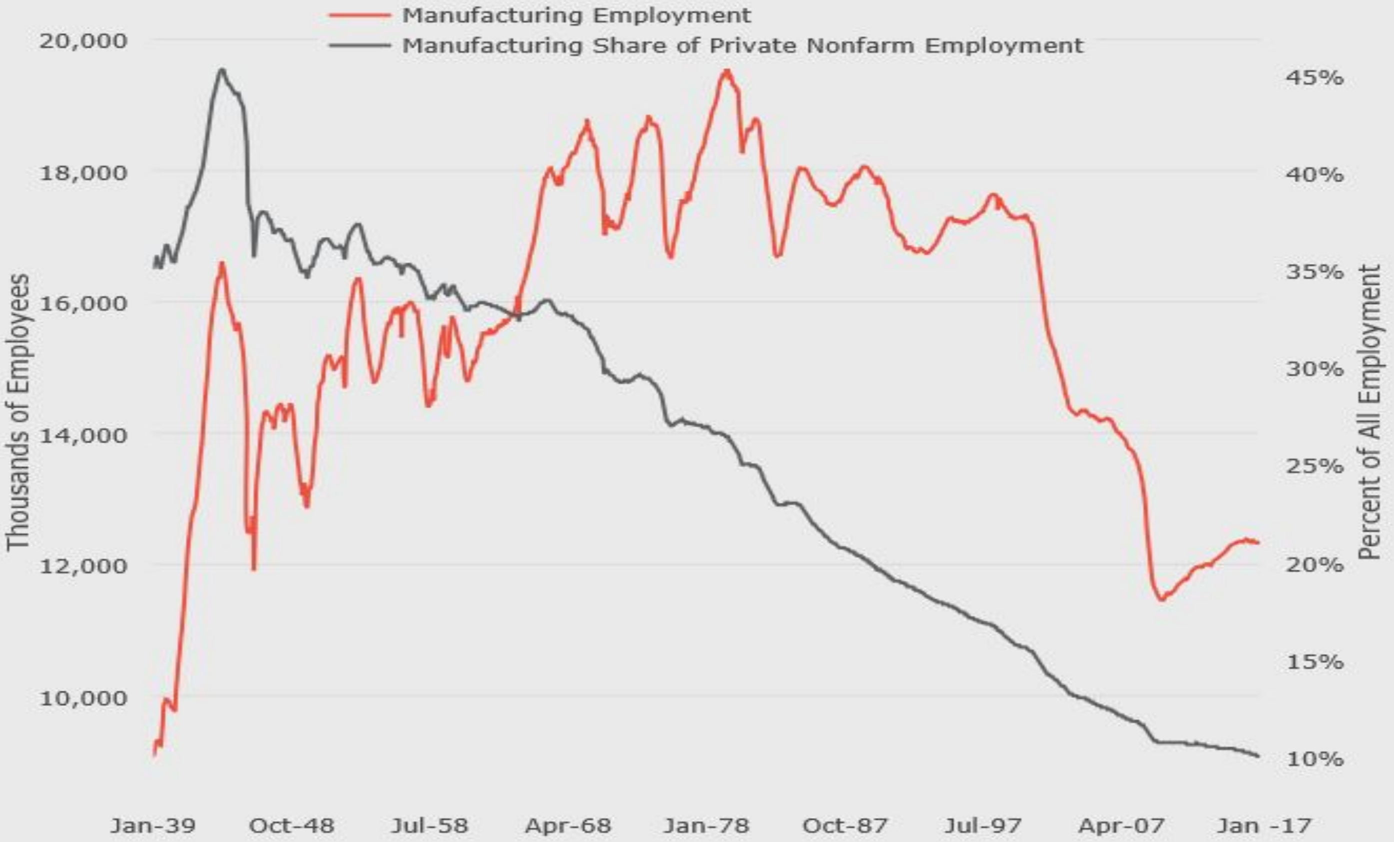
3. HIGHER COGNITIVE COMPLEXITY OF HUMAN WORK

The human workforce of the future will execute tasks requiring higher cognitive and emotive complexity, and activities requiring the application of general intelligence

Technological Displacement



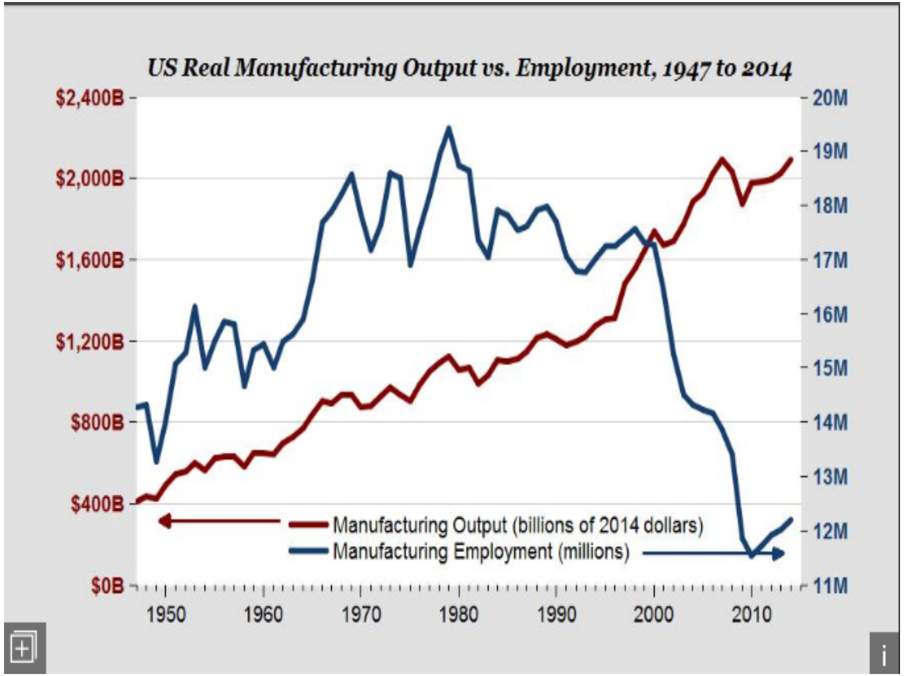
Manufacturing Employment Trends, 1939-2016



Source: Current Employment Statistics.

Job Density

- In manufacturing, job density—the number of jobs per process—is declining.
- In 1980 it took 25 jobs to generate $1 million in manufacturing output in the U.S.
- Today it takes five jobs.
- Why?

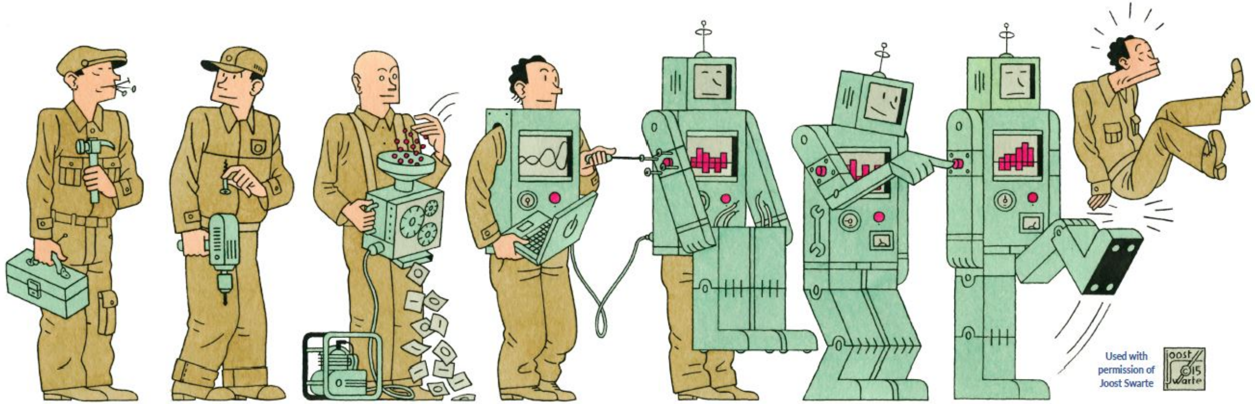


It’s Trade

- **Trade (China)**
  - Between 1990 and 2011 the share of global manufacturing exports originating in China surged from 2% to 16% (Hanson, 2012).
  - Intensifying import competition from China means a reduction in demand for goods U.S. manufacturers produce and a corresponding contraction in the number of workers they employ.
    - Autor, Dorn & Hanson (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review,* 103(6): 2121–2168.

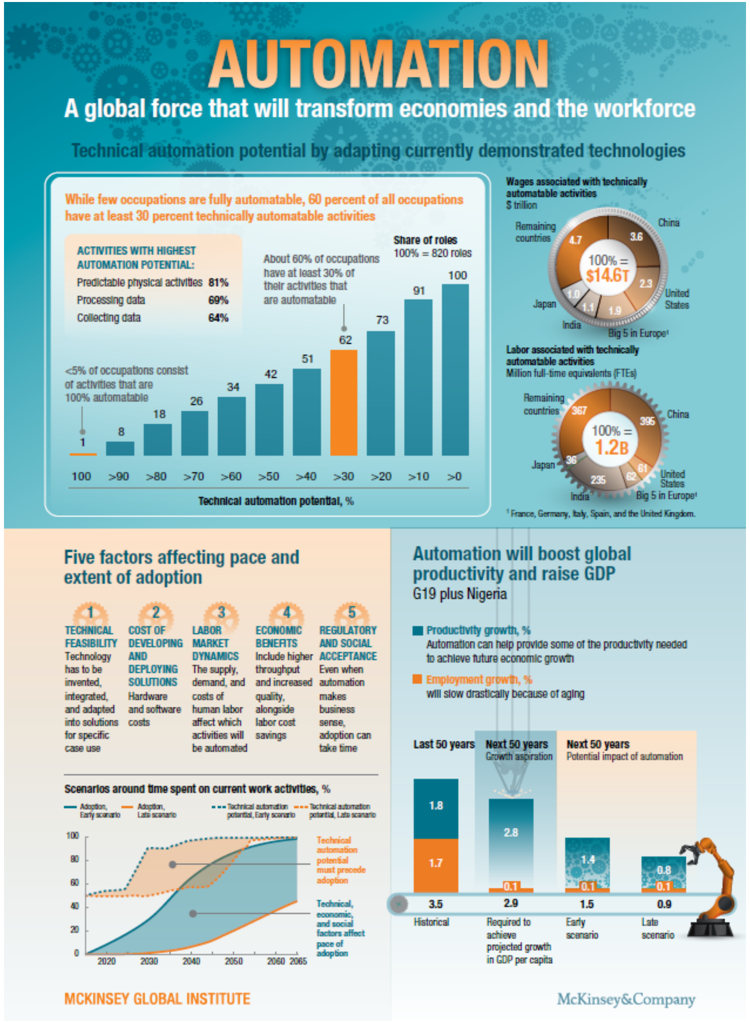
It's Technology

- **Technology (Robotic Automation)**
  - Brynjolfsson, *Race Against the Machine and Second Machine Age*
  - If the trend toward the automation of routine jobs in advanced manufacturing continues, the application of new technologies is likely to do much **more** to boost growth in value added than to **expand** employment on the factory floor.
    - Autor & Dorn (2013). The Growth of Low Skill Service Jobs and the Polarization of the US Labor Market. *American Economic Review*, 103(5):1553-1597.



Machines Replacing Jobs

- Talk of automatic machines replacing humans goes back to the ancient world. Aristotle in 350 BCE:
  - "For if every instrument could accomplish its own work…chief workmen would not want servants, nor masters slaves."
- Machines, Robots and Technological Unemployment
  - Luddites—1811
  - Depression—1873-1879
  - Depression—1890
  - Great Depression—1930
  - Great Recession—2008
- Technological unemployment "narratives themselves have the potential to drive amplified economic booms and recessions as well as public policy."
  - Robert Shiller (2019)



Technological Unemployment

Estimates are Between “Big and Enormous”

Organization	Estimates
University of Oxford	47% of workers in America at high risk of jobs replaced by automation
PricewaterhouseCoopers	38% of jobs in America, 30% of jobs in UK, 21% in Japan and 35% in Germany at risk to automation
ILO	ASEAN-5: 56% of jobs at risk to automation in next 20 years
McKinsey	60% of all occupations have at least 30% technically automatable activities
OECD	OECD average: 9% of jobs at high risk. Low risk of complete automation but an important share (between 50% - 70%) of automatable tasks at risk
Roland Berger	Western Europe: 8.3m jobs lost in industry against 10m new jobs created in services by 2035.
World Bank	2/3 of all jobs in developing countries are susceptible to automation.
Bruegel	EU countries: between 47% and 54% of jobs are risk of automation

Source: Frey and Osborne (2015); Roland Berger (2016); McKinsey Global Institute (2016); PwC (2017); World Bank (2016); Chang and Huynh (2016); Bowles (2014) and Bruegel Blog (2014)

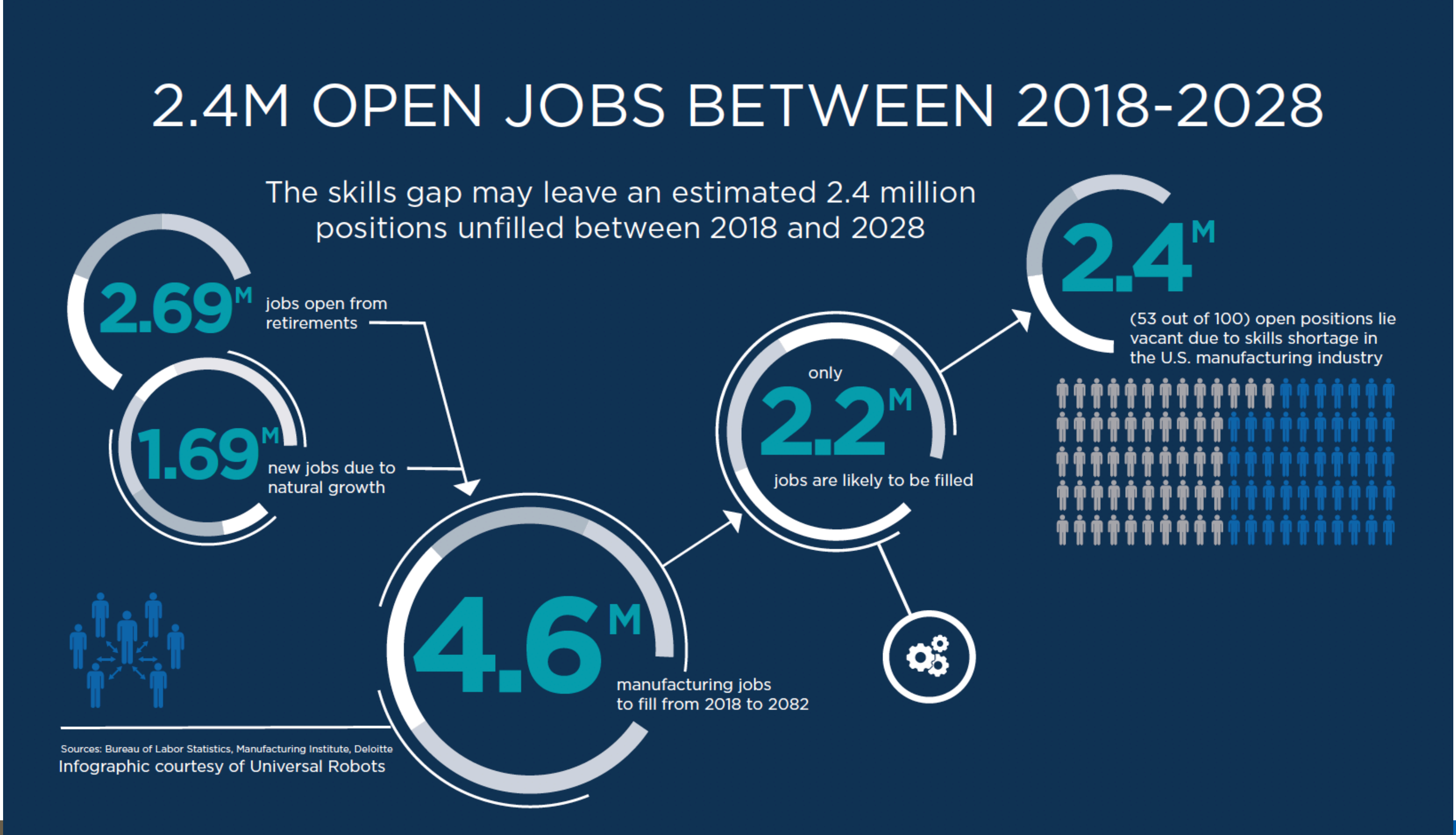
Automation Prediction May Be Wrong

Cass, *The Once and Future Worker*, 2018

- Magnifies current innovations while taking for granted equally fundamental past innovations like steam, electricity, Internet.
- Predictions ignore the gradual timeline on which transformations usually occur. Deployment of new technology is always slow.
- Technology often makes incremental improvements to a worker’s productivity leading to higher quality output rather than to lower demand for her work. Substitute versus complement. An abstract description rarely captures the full complexity of any job.
- Dire predictions ignore the positive. E-commerce is creating new jobs faster than retail is destroying them.

Substitute or Complement?

- In the workplace, robotic device can perform:
  - A job that a human worker once did
    - The robot acts as a ***substitute*** for a human worker.
  - The robotic device can assist a human worker to perform a job
    - The robot acts as a ***complement*** to a human worker.


2.4M OPEN JOBS BETWEEN 2018-2028
The skills gap may leave an estimated 2.4 million positions unfilled between 2018 and 2028
2.69M
jobs open from retirements
1.69M
new jobs due to natural growth
4.6M
manufacturing jobs to fill from 2018 to 2082
only
2.2M
jobs are likely to be filled
2.4M
(53 out of 100) open positions lie vacant due to skills shortage in the U.S. manufacturing industry
Sources: Bureau of Labor Statistics, Manufacturing Institute, Deloitte
Infographic courtesy of Universal Robots

Pace of Automation

- **Adoption Determinants:**
  - Technical feasibility
  - Cost of deployment
  - Labor market dynamics
  - Economic benefits
  - Regulatory/social acceptance

- **Some Things Could Be Automated but…**
  - # School Bus Drivers 2020
  - # School Bus Drivers 2030?

AI Preparedness

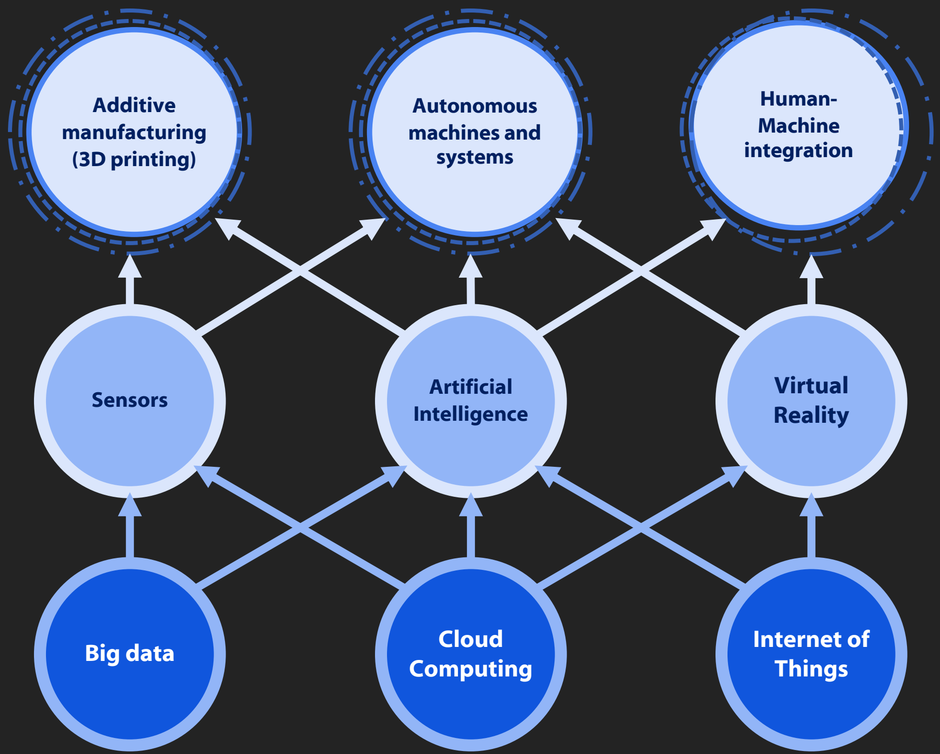
- Is the data collected by sensors in a state that you can use it rapidly?
  - Do you have the AI applications that you can use to derive value from the data?
  - Are we training data decision scientists with the right skills?

- Are occupational safety and health practitioners trained to make sound risk control decisions using AI?

- Have we "built" a digital twin of a work process, a workplace condition, together with the scope of worker actions within that process, in order to test hazard identification & risk control decision making?

  - Russell & Novig, Artificial Intelligence: A Modern Approach, 4th ed. (2020)
  - Daniel Hulme, https://www.strategy-business.com/article/Understanding-the-Potential-of-Artificial-Intelligence

Key Technologies Enabling the Future



Source: OECD (2017)

AIS 2019

References

- Acemoglu D et al. *The race between machine and man: implications of technology for growth, factor shares and employment.* National Bureau of Economic Research, Working Paper 22252, June 2017.
- Alpaydin E. *Machine learning*. Cambridge, MA: MIT Press, 2016.
- Arntz, M, Gregory T, Zierahn U. The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis", *OECD Social, Employment and Migration Working Papers*, No. 189, OECD Publishing, Paris. 2016.
- Autor D. 2019. Work of the past, work of the future. NBER Paper #25588.
- Awad E et al. The moral machine experiment. *Nature* 2018;563:59-64.
- Baldwin R. The globotics upheaval: globalization, robotics and the future of work. Oxford University Press, 2019.
- Barber D. *Bayesian reasoning and machine learning*. 2012. Cambridge University Press.
- Bekey G. *Autonomous robots: from biological inspirations to implementation and control*. Cambridge, MA: MIT Press, 2005.
- Benzell SG et al. *Robots are Us: Some economics of human replacement*. National Bureau of Economic Research, Working Paper 20941, October 2018.

References

- Brynjolfsson E et al. What can machine learning do? Workforce implications. *Science* 2017;358(6370):1530-1534.
- Cass O. The once and future worker: a vision for the renewal of work in America. New York, NY: Encounter Books. 2018.
- Estlund C. Regulating work in the age of fissuring and automation. Reg Review, April 8, 2019.
- Drexler KE. 2019. “Reframing Superintelligence: Comprehensive AI Services as General Intelligence”, Technical Report #2019-1, Future of Humanity Institute, University of Oxford
- Gardner H. “Multiple Intelligences: Prelude, Theory, and Aftermath.” In Sternberg, R.J., S.T. Fiske, and D.J. Foss, *Scientists Making a Difference: One Hundred Eminent Behavioral and Brain Scientists Talk about Their Most Important Contributions*. New York: Cambridge University Press, 2016.
- Gershman SJ et al. Computational rationality: a converging paradigm for intelligence in brains, minds, and machine. *Science*. 2015;349(6245):273-278.
- Harari YN. *21 lessons for the 21st century*. London, UK: Penguin Books, 2018.
- Hirsch JM. Future of work. University of Illinois Law Review (2020 forthcoming).
- Hirschberg J, Manning CD. Advances in natural language processing. *Science*. 2018;349(6245):261-266.

References

- Howard J et al. Unmanned aerial vehicles in construction and worker safety. *Am J Ind Med*. 2018;61:3-10.
- Jordan J. *Robots*. Cambridge, MA: Cambridge, MA: MIT Press, 2016.
- Jordan MI et al. Machine learning: trends, perspectives, and prospects. *Science*. 2015;349(6245):255-260.
- Kahan J. The quest for human-level A.I. *Fortune*, February, 2020
- Krizhevsky A et al. ImageNet classification with deep convolutional neural networks. *Advances in neural information processing systems*. 2012;25(2):1-9. DOI:10.1145/3065386.
- Kochender M. Decision making under uncertainty: theory and application, MIT Press, 2015.
- LeCun Y et al. Deep learning. *Nature* 2015;521:436-444.
- Lee K-F, *AI Superpowers: China, Silicon Valley, and the new world order*. 2018, Houghlin-Mifflin.
- McAfee A & Brynjolfsson E. *Machine platform crowd: harnessing out digital future*. New York: Norton, 2017.
- Mori M. The uncanny valley (translated). *IEEE Robotics and Automation*. June, 2012. https://spectrum.ieee.org/automaton/robotics/humanoids/the-uncanny-valley

References

- Murashov V et al. Working safely with robots: recommendations for the new workplace. *JOEH.* 2016;13(3):D61-D71.
- National Academy of Sciences. *Information technology and the U.S. Workforce: where we are and where do we go from here*. 2017. https://www.nap.edu/catalog/24649/information-technology-and-the-us-workforce-where-are-we-and
- Parkes DC & Wellman MP. Economic reasoning and artificial intelligence. *Science*. 2018;349(6245):267-272.
- Pratt G. Is a Cambrian explosion coming for robotics? *J Econ Persp*. 2015;29(3):51-60.
- Russell S & Norvig P. *Artificial intelligence: a modern approach*. 4th Edition, 2020. Upper Saddle River, NJ: Prentice Hall.
- Shiller R. Narrative economics: how stories go viral & drive major economic events. Princeton, NJ: Princeton University Press, 2019.
- Torresen J. A review of future and ethical perspectives of robotics and AI. *Front Robot & AI*. 2019;4.d
- United Nations, International Labour Office. 2019. Safety and health at the heart of the future of work. https://www.ilo.org/safework/events/safeday/WCMS_686645/lang--en/index.htm
- West DM. *Future of work: robots, AI and automation*. Washington, DC: Brookings Press, 2018.