Human Computer Interaction (HCI) It's *mostly* good !

J.T. Wunderlich PhD

2018

Quick audio overview added in 2020 (during corona virus)

JT Wunderlich PhD, at **ELIZABETHTOWN COLLEGE** since 1999

Associate Professor of Engineering & Computer Science
Computer Engineering Program Coordinator
Architectural Studies Program Coordinator
Founder & Director of Robotics & Machine Intelligence Lab

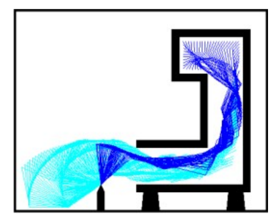
PRIOR TO 1999:

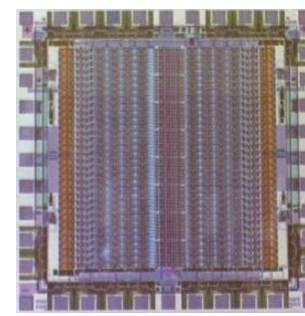
PURDUE UNIVERSITY Assistant Professor of Electrical Engineering Technology

IBM S/390 Supercomputer Research & Development

UNIVERSITY OF DELAWARE PhD in Electrical (& Computer) Engineering

- Robotic-arm design
- Rehabilitation Robotics
- Neural Network chips





PENN STATE M Eng in Engineering Science

- Neural Network chip design

SAN FRANCISCO STATE Physics Grad Student

UNIVERSITY OF CALIFORNIA AT SAN DIEGO Urban Design 2nd Degree program

UNIVERSITY OF TEXAS AT AUSTIN BS in Architectural Engineering *(1984)*

Color Code throughout talk:

GREEN = GOOD

RED = BAD

ALL OTHER COLORS = No Judgment offered

X-Ray

http://www.thehealthsite.com/diseases-conditions/chest-x-ray-everything-you-need-to-know-b1116/

CT Scan (CAT Scan, Computerized Axial Tomography)

MRI (Magnetic Resonance Imaging)

htt

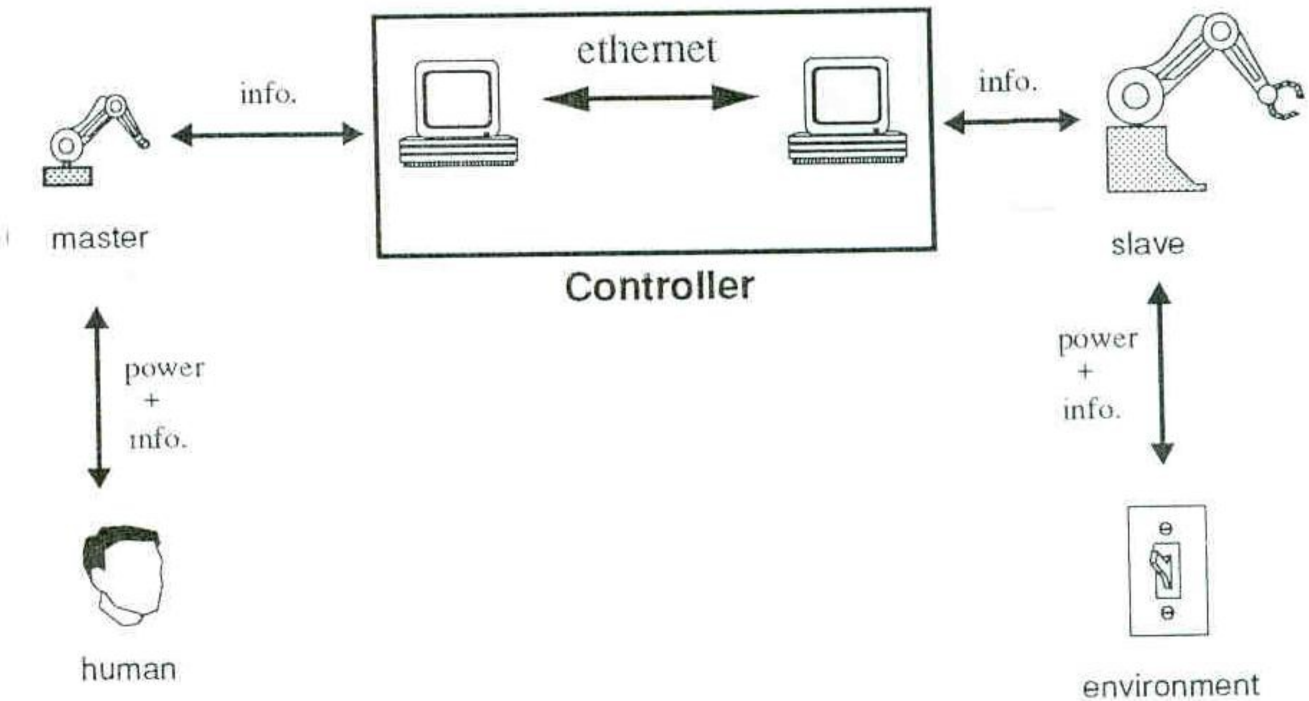
New-School

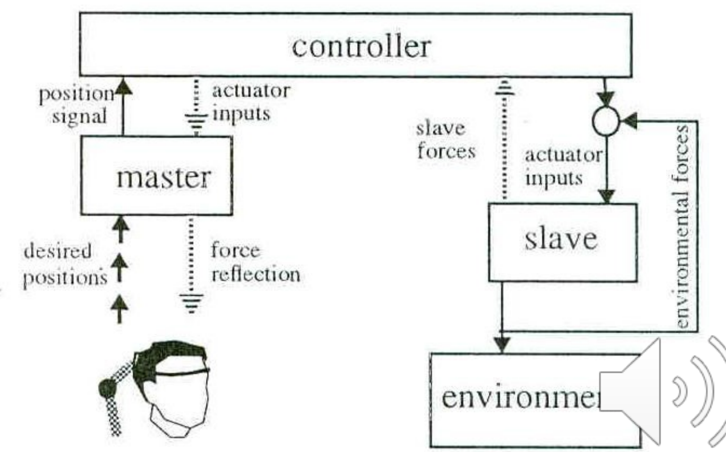
Old-School qualities lost?

None

1993 Wunderlich Research

Designing Robotic Arms for Disabled Children





2014 Mind-controlled Prosthetics

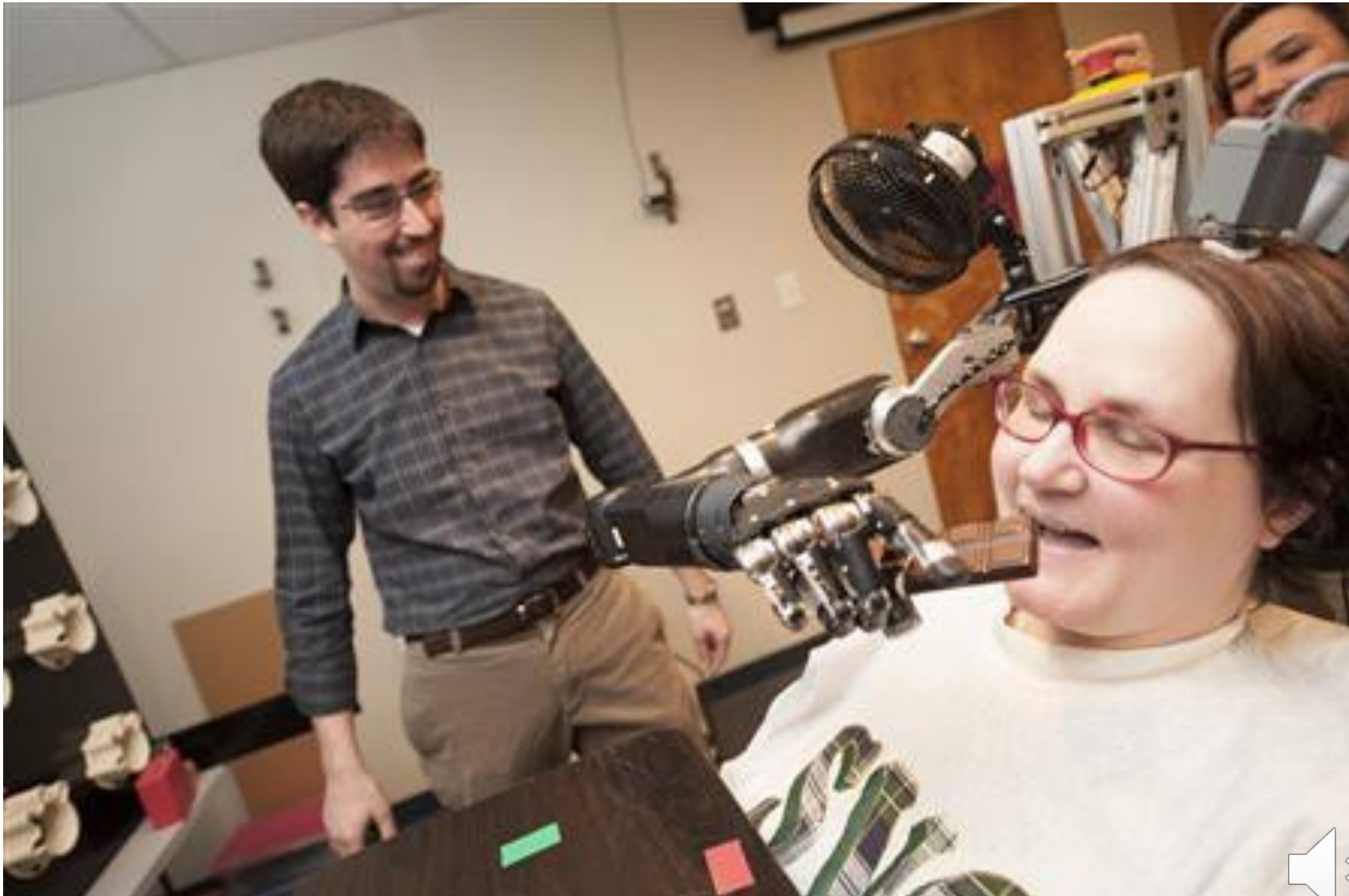


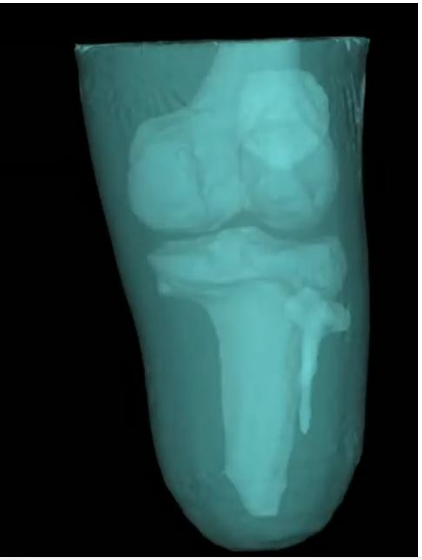
Image from: http://s1.reutersmedia.net/resources/r/?m=02&d=20121217&t=2&i=685403134&w=580&fh=&fw=&ll=&pl=&r=CBRE8BG0IN700

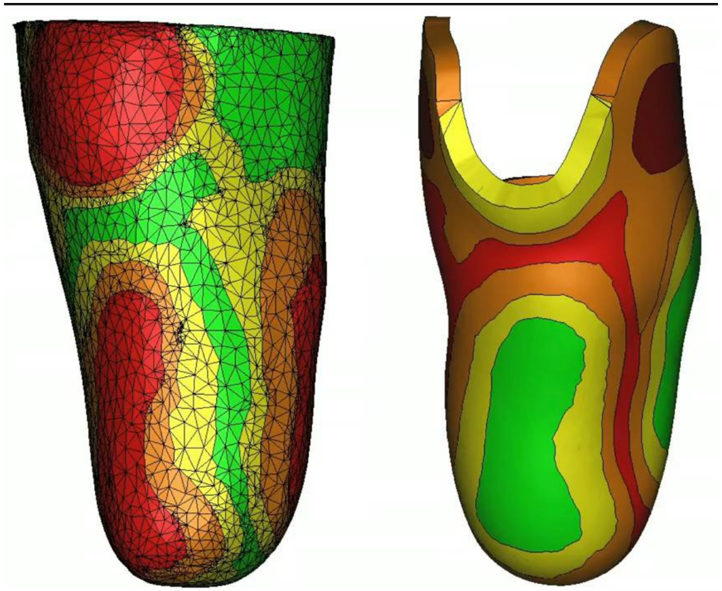
2014 Maneuverability For The Disabled

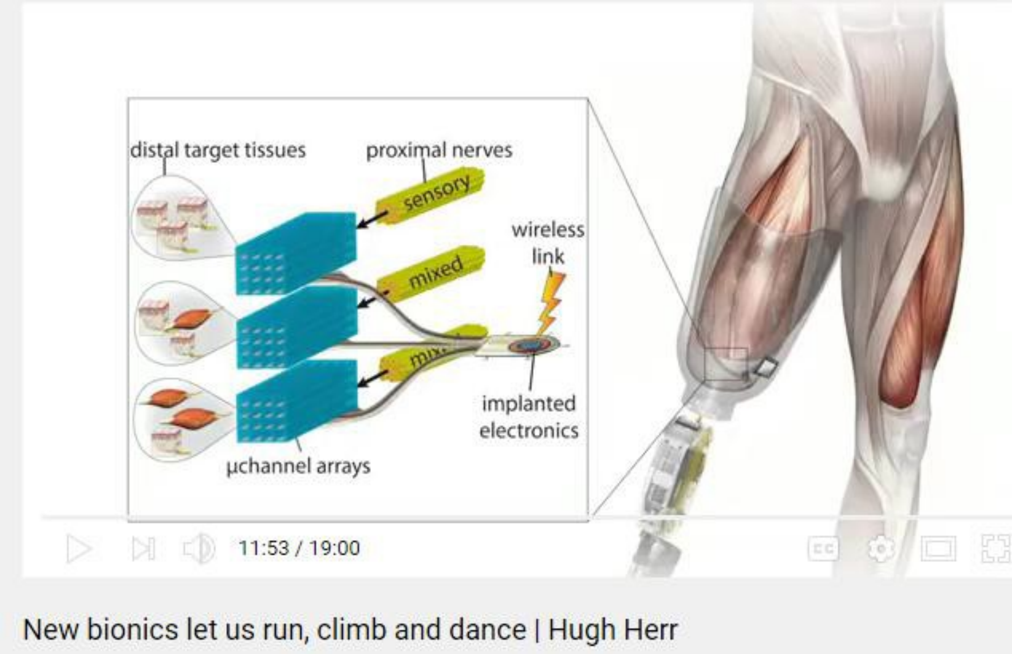
Image from: http://i.dailymail.co.uk/i/pix/2012/10/12/article-2216748-1560FF34000005DC-616_296x331.jpg

2014 Prosthetic Lower Leg

VIDEO: https://www.youtube.com/watch?v=CDsNZJTWw0w

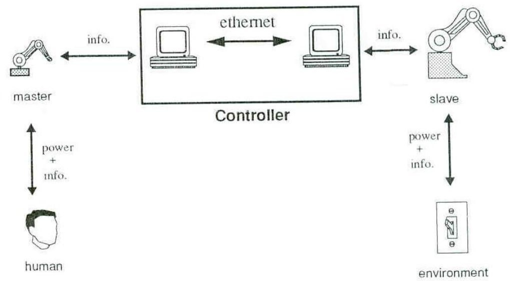


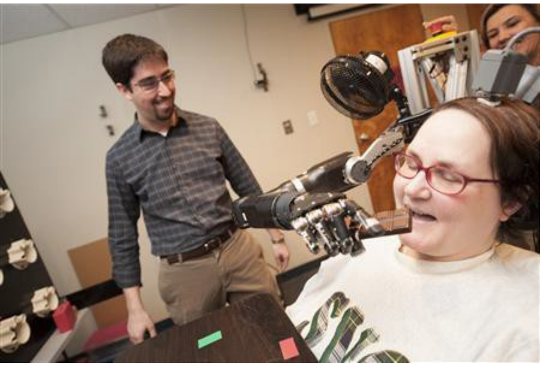




ASSISTING THE DISABLED

New-School





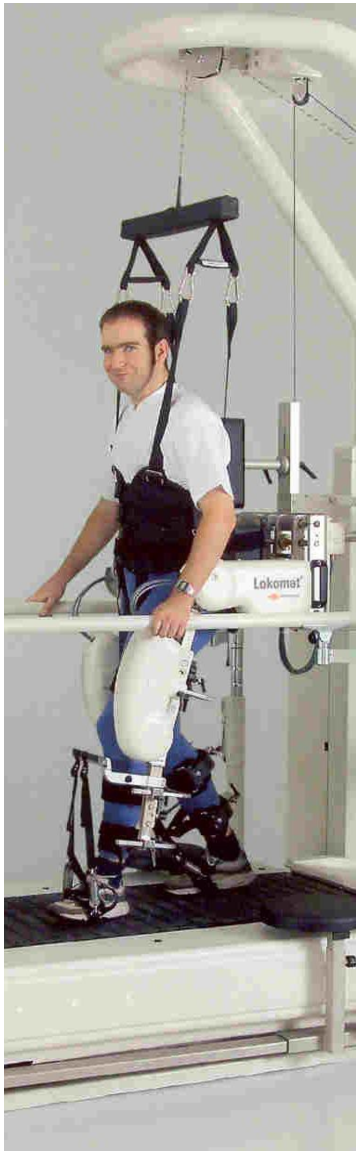
Old-School qualities lost?

None

2014 Robotics-assisted Rehab for Injuries ??

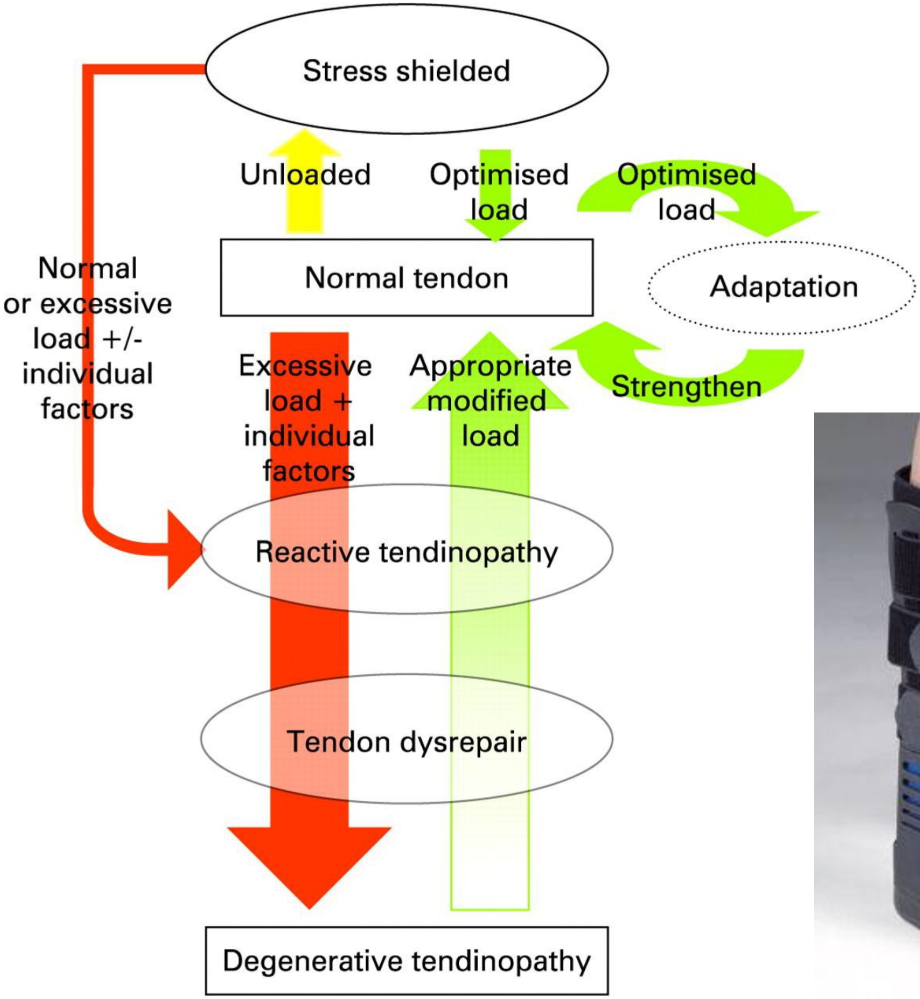
Image from: http://aimlab.wpi.edu/includes/education/Lokomat.jpg

New-School



Old-School qualities lost?

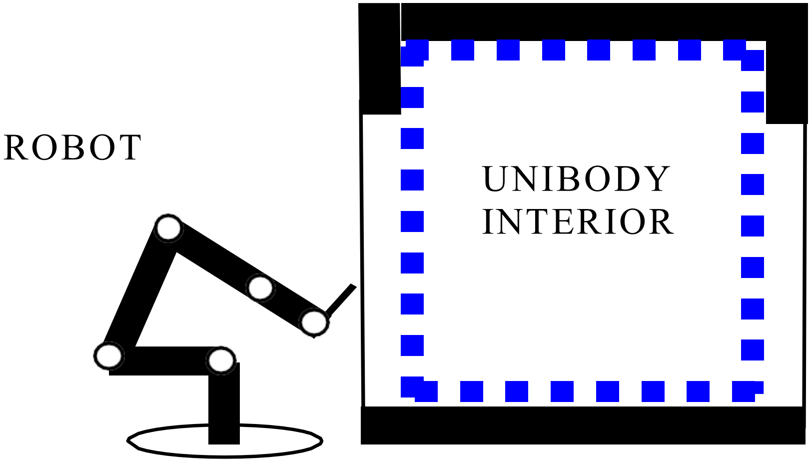
Added strength from healing under load may be lost with too much assistance



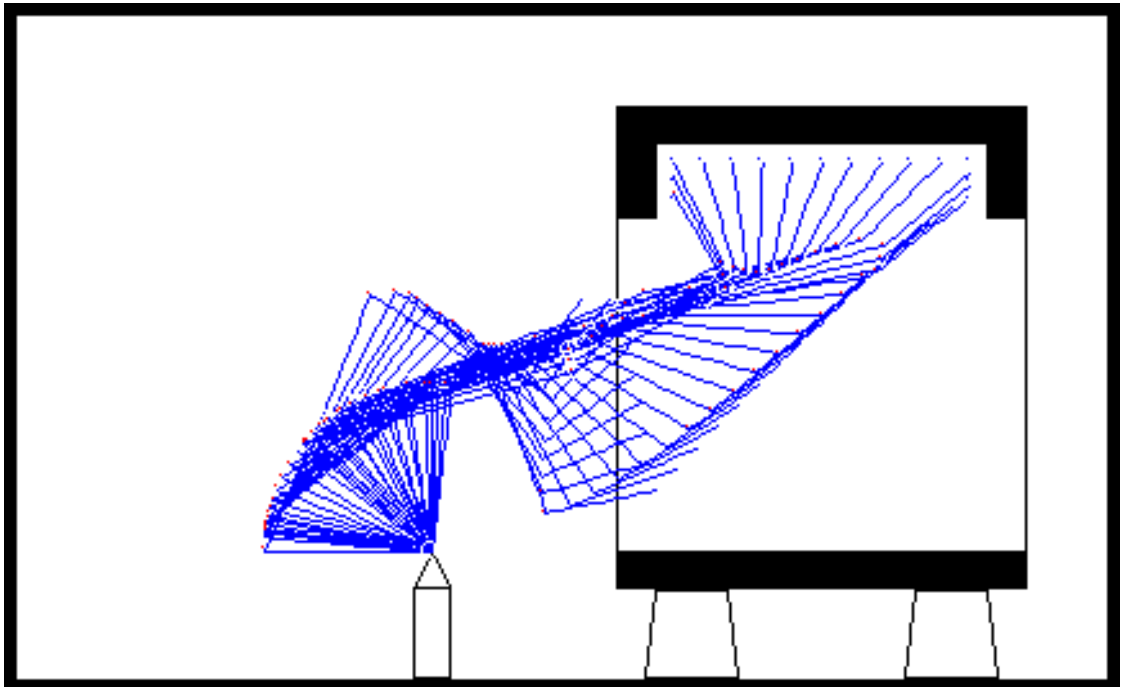
SOURCE: http://www.jeffcubos.com/2011/01/30/diagnosis-and-management-of-tendinopathies/

VIDEO: https://www.youtube.com/watch?v=sjAZGUcjrP8

1994 Wunderlich Research
Designing Robotic Arms for enclosed spaces



EXAMPLE RESULT: **New 4-DOF Design**
(Generated from an original 5-DOF design)

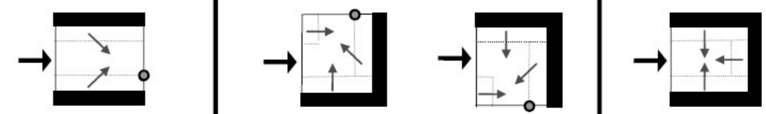


DOF means Degrees Of Freedom,
and for this type arm it means the number of elbows

1994 Wunderlich Research Designing Robotic Arms for enclosed spaces

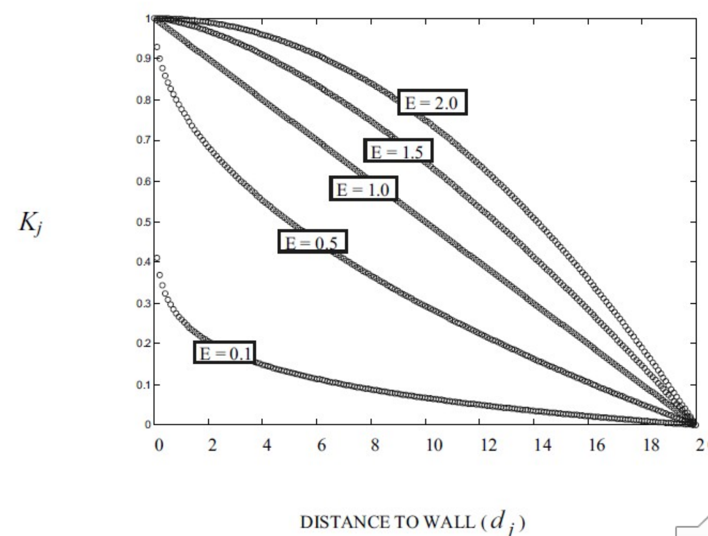
Methodology:

1) Create enclosure from simulation **primitives** designed to allow various specifications of "**Repelling Fie**lds" and "**Local Attractors**"

	TUNNEL	LEFT ELBOW	RIGHT ELBOW	TERMINATOR
ATTRACTIVE POLE (●) REPELLING ANGLES (u_j) ↗				
REPELLING FIELD WIDTH (t_j)	OUTER-BANK: 30% OF ENCLOSURE WIDTH INNER-BANK: 40% OF ENCLOSURE WIDTH	OUTER-BANK: 20% OF ENCLOSURE WIDTH INNER-BANK: 40% OF ENCLOSURE WIDTH		30% OF ENCLOSURE WIDTH
(E)	OUTER-BANK: E = 0.1 INNER-BANK: E = 1.0	OUTER-BANK: E = 0.1 INNER-BANK: E = 0.0		E = 0.1

EXAMPLE K_j's for $t_j = 20$, $d_{ABORT} = 0$, $V_j = V_e = 1$

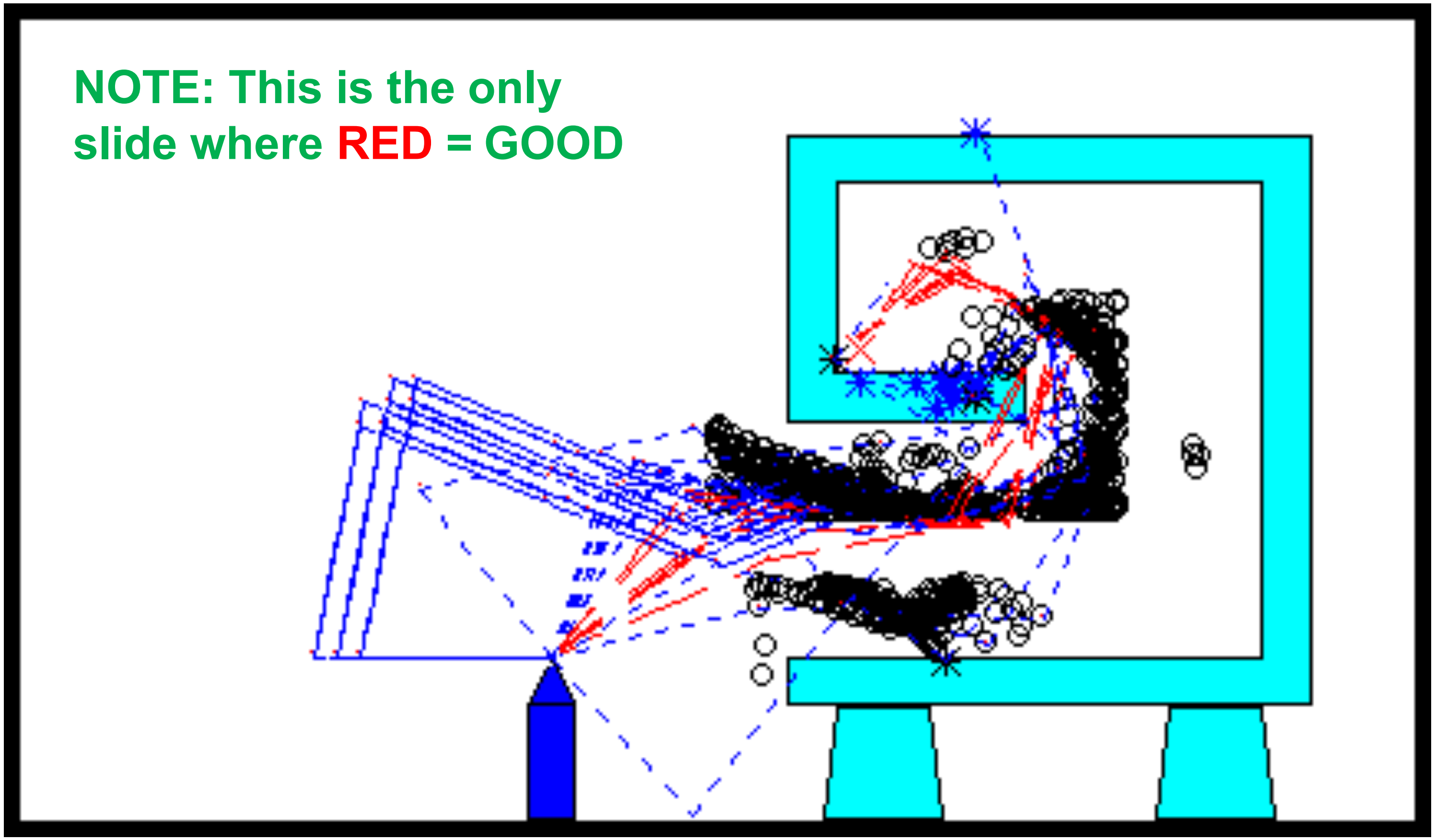
$$K_j = V_j V_e \left[1 - \left(\frac{d_j - d_{ABORT}}{t_j} \right)^E \right]$$



Note: If a goal or *fixed*-trajectory task is specified within primitive, the attractive pole is disabled and repelling-angles are set to 90 degrees.

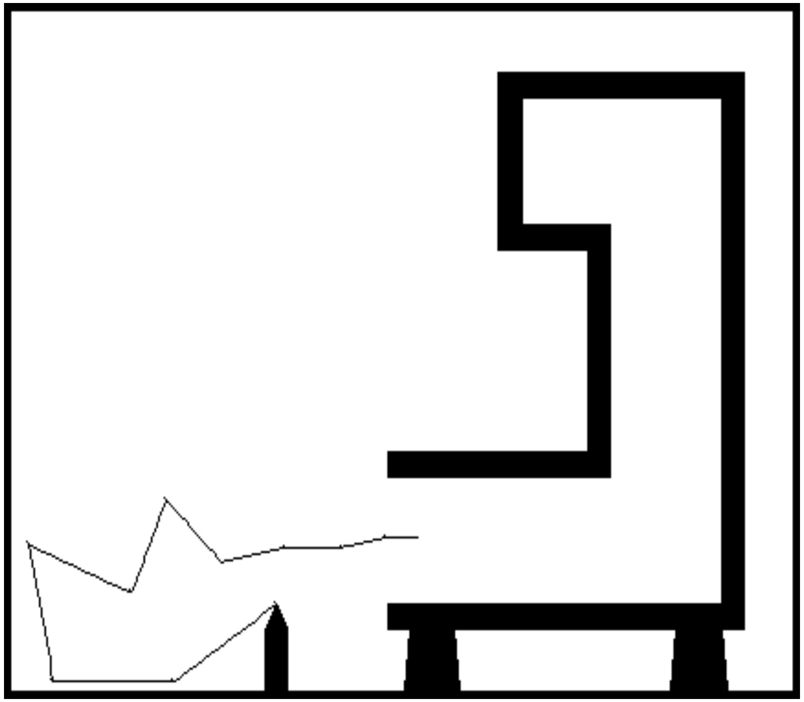
1994 Wunderlich Research
Designing Robotic Arms for enclosed spaces

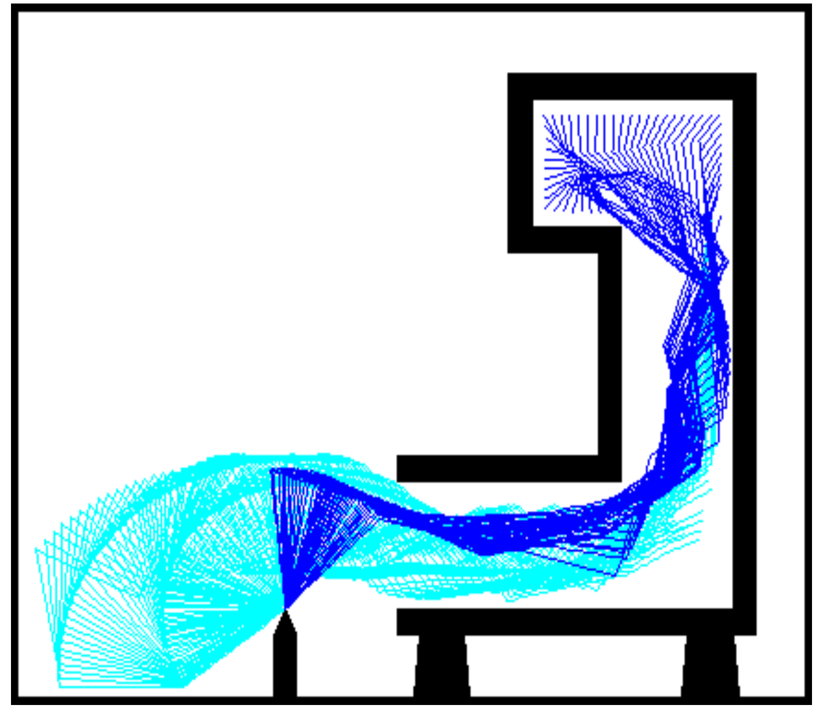
2) Many geometrically-feasibly designs generated by permuting link-lengths and testing candidate designs in enclosure
3) Successful designs used for next generation of permutations



"**O**" = Elbow being repelled from a surface.
Solid Blue Line = Candidate Design tested (in their initial configuration)
Dotted Blue Line = Failed Design at its final configuration (* = crash point)
Dashed Red Line = Successful Design at its final configuration (Reaching Goal at "**X**")

1994 Wunderlich Research
Designing Robotic Arms for enclosed spaces





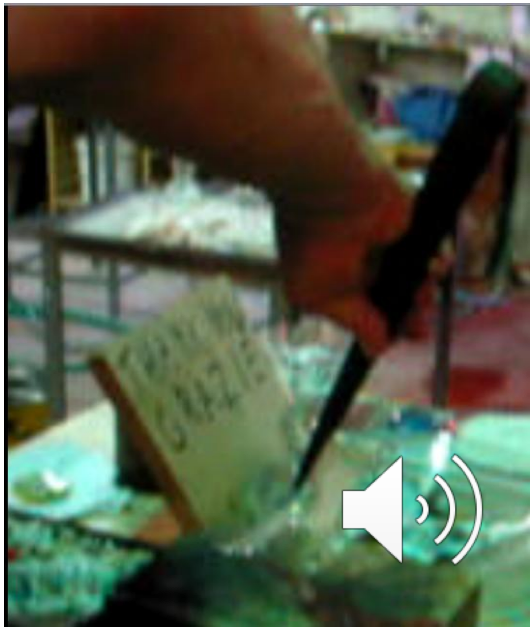
*“**evolved**”* designs capable of most complex task, while optimized for minimal **D**egrees **O**f **F**reedom(**DOF**), Speed, Dexterity, Minimal Energy Consumption, and Minimal **C**onsumption **O**f **A**vailable **R**edundancy (“**COAR**” -- *first derived by JT Wunderlich*)

New-School

Old-School qualities lost?

Artisans disappearing
e.g., Glass-blowing in Italy

VIDEOS by J Wunderlich 2008, Borano Italy:
http://users.etown.edu/w/wunderjt/personal_pictures/MVI_5139.AVI
http://users.etown.edu/w/wunderjt/personal_pictures/MVI_5141.AVI
http://users.etown.edu/w/wunderjt/personal_pictures/MVI_5142.AVI



CLEAN-UP of Human or Nature's Mess

- **Robots don't get sick from contamination**

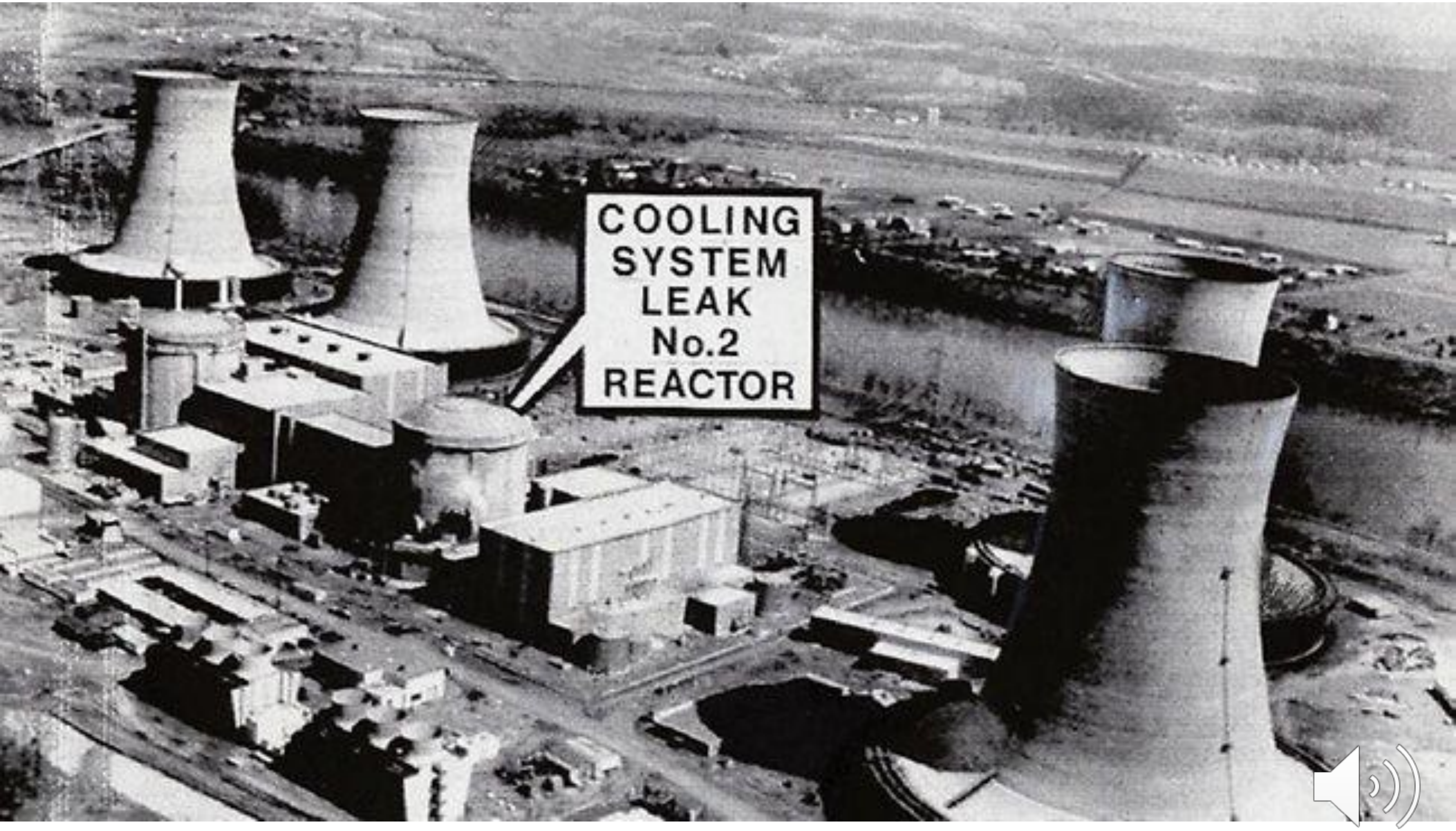


Image from: http://pdxretro.com/wp-content/uploads/2011/03/No.-2-reactor-three-mile-island.jpg

CLEAN-UP of Human or Nature's Mess

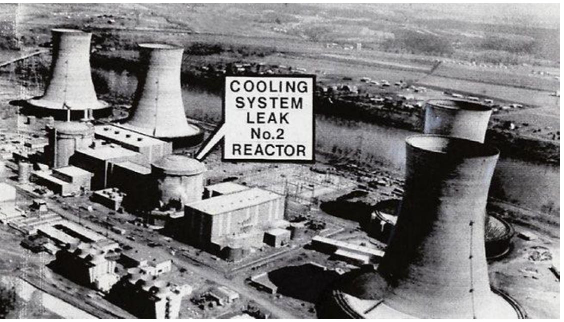
- 2014 US Military robots fight Ebola
- Disinfect in minutes using ultraviolet technology

SOURCE: http://news.discovery.com/tech/robotics/ebola-zapping-robots-unleashed-in-hospitals-141011.htm

Robotic Snow Plow

Image from: http://dvice.com/archives/2007/02/roombalike_snowplow_robot_uses.php

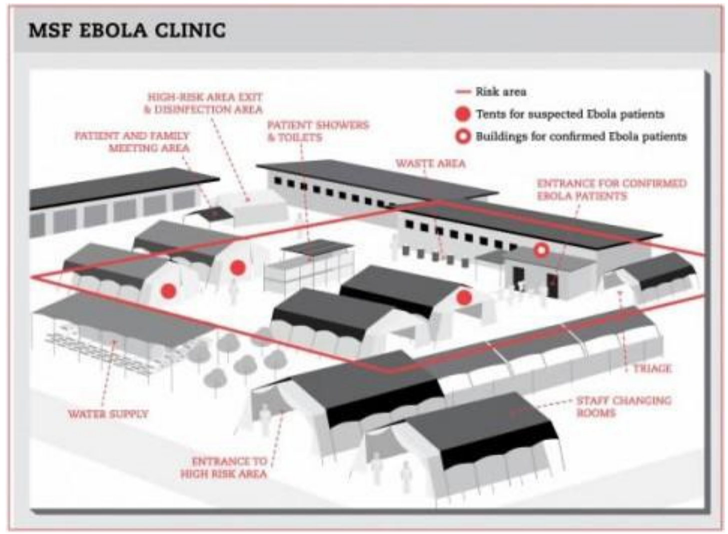
New-School



Old-School qualities lost?

Personal attention less likely ?

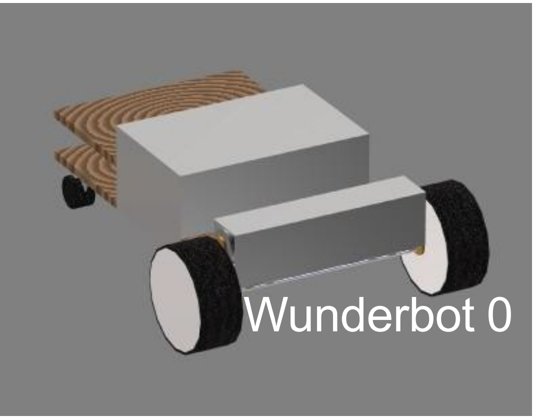
VIDEO: http://www.pbs.org/wgbh/pages/frontline/ebola-outbreak/



2000-2010
Etown Wunderbots

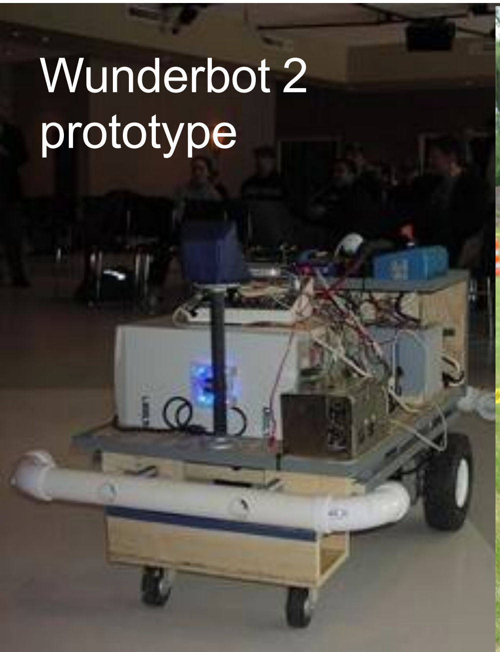
EXPLORATION

http://users.etown.edu/w/wunderjt/Weblab_archive.htm


Wunderbot 0

Wunderbot 1

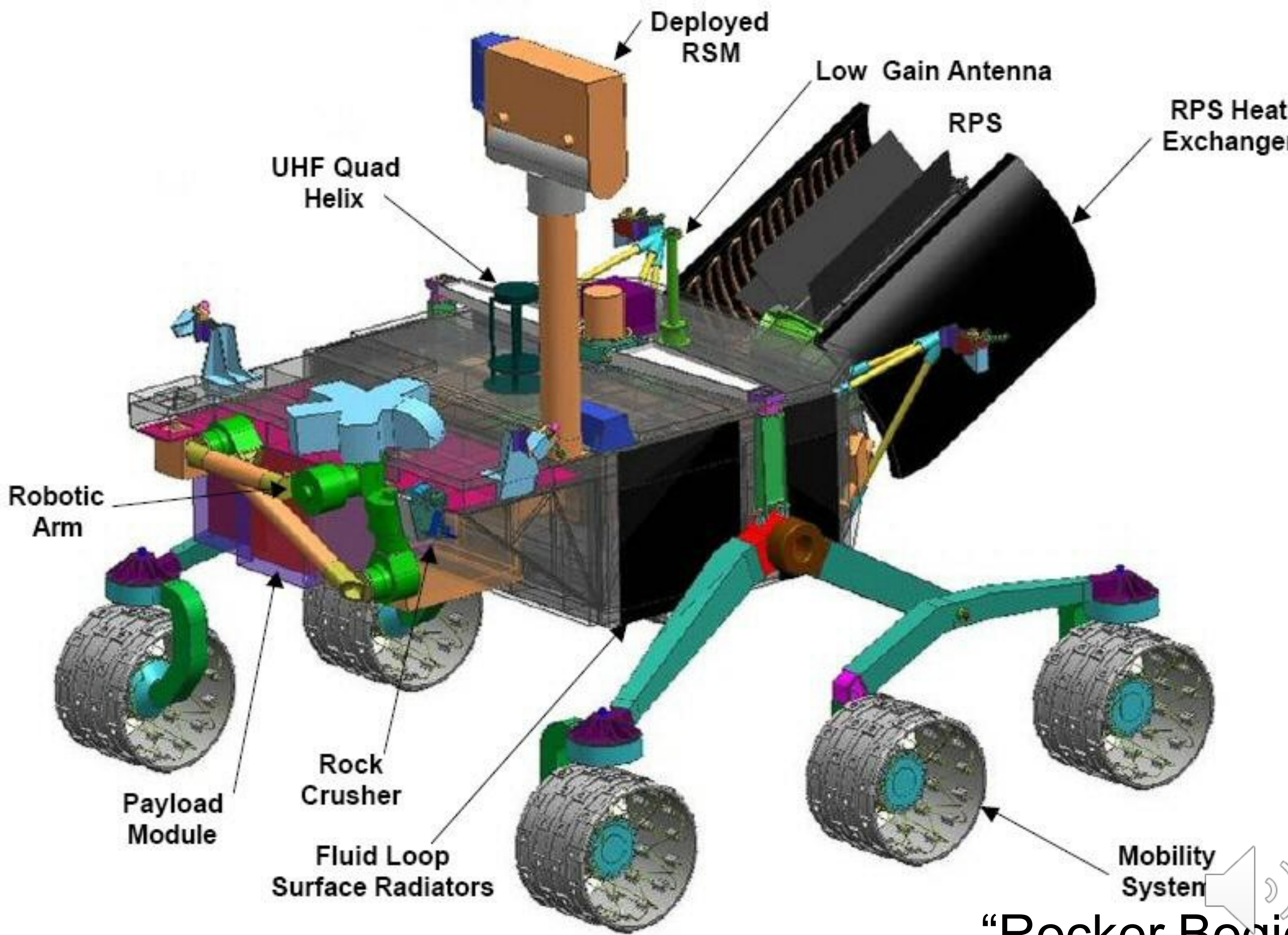
http://www2.etown.edu/wunderbot/


Wunderbot 2 prototype

Wunderbot 3

Wunderbot 4

2014 Mars Science Lab "Curiosity"



"Rocker Bogie"

Image from: http://centauri.larc.nasa.gov/msl/MSL_cfg-dwg_040608.pdf

2014 Mars Science Lab "Curiosity"

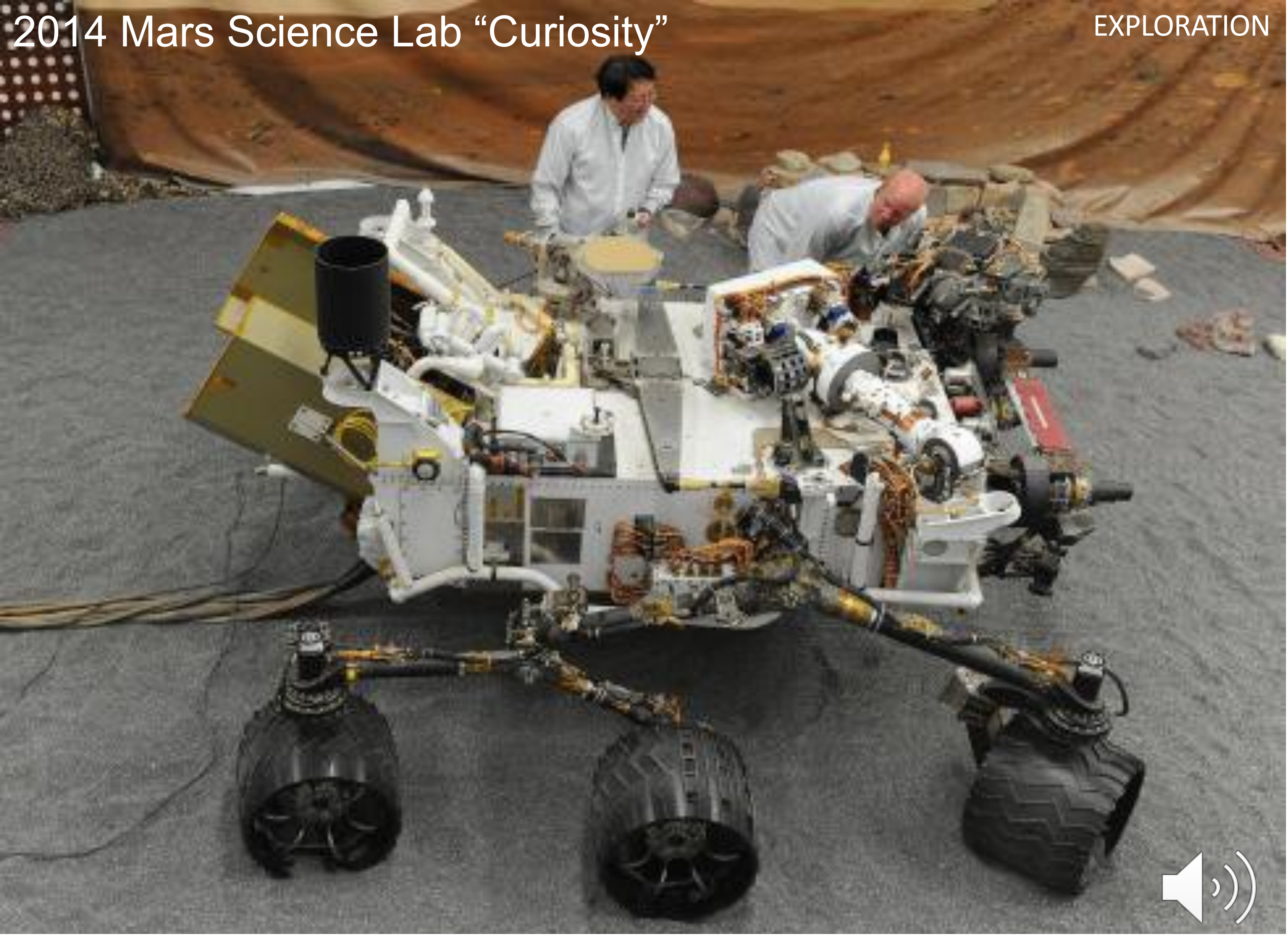


Image from: http://i.usatoday.net/tech/_photos/2012/08/04/Mars-rover-to-explore-intriguing-giant-crater-I020IN68-x-large.jpg

2014 Mars Science Lab "Curiosity"

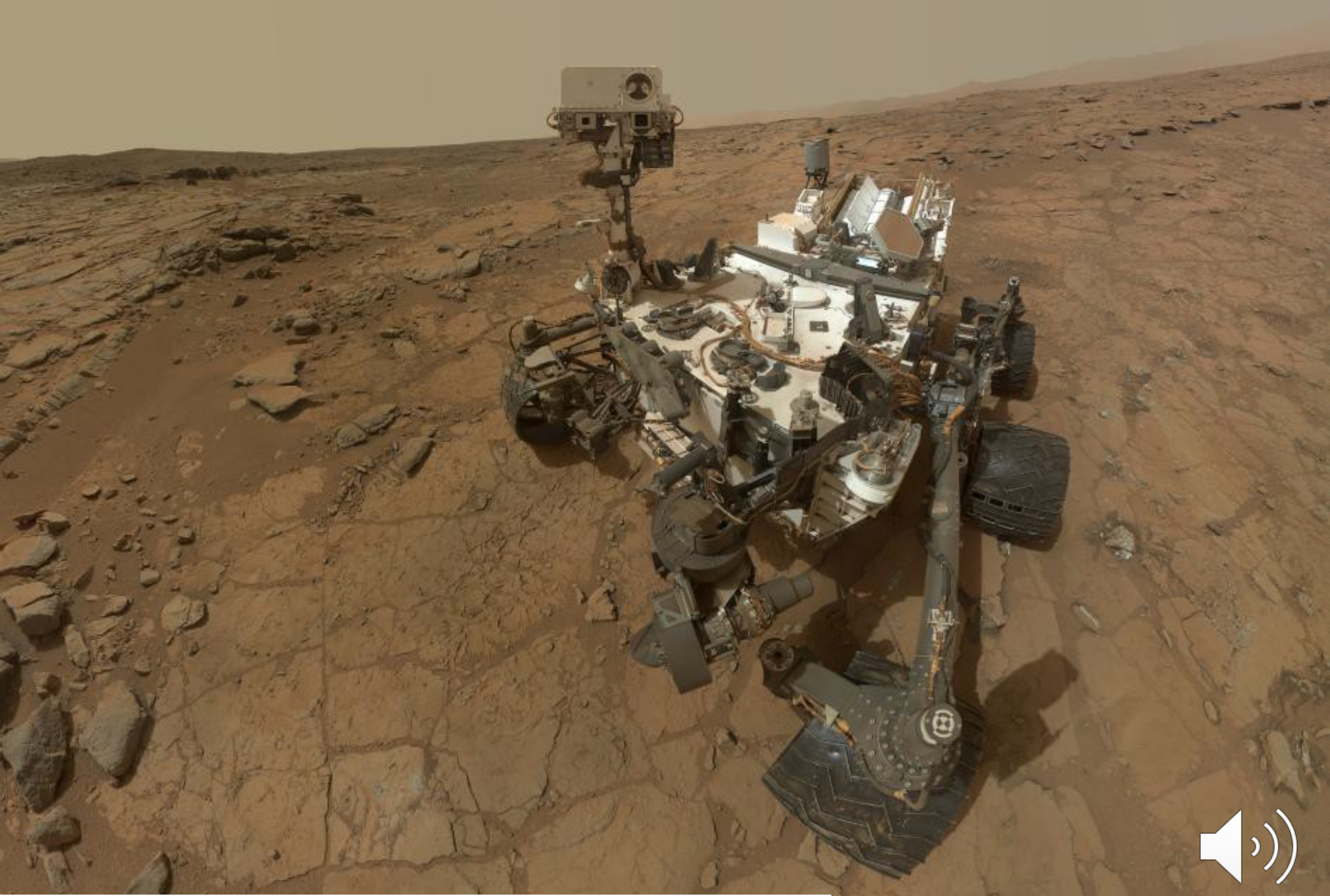


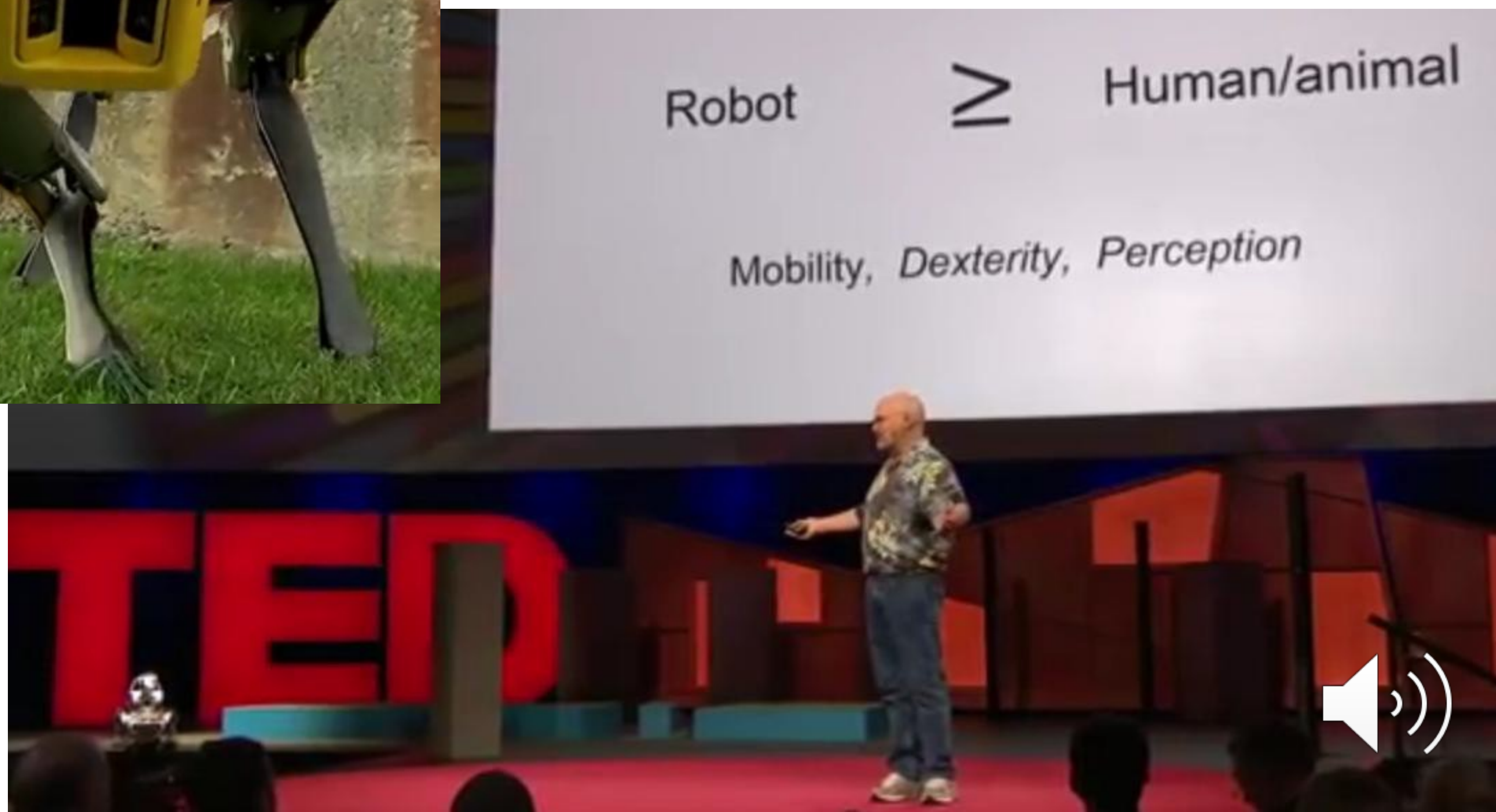
Image from: http://www.nasa.gov/images/content/725557main_pia16764-43_946-710.jpg

2017 Boston Dynamics

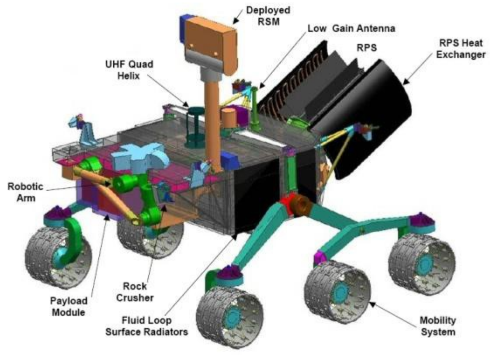
VIDEO of "SPOT MINI": https://www.youtube.com/watch?v=3aJ6n1WrT0o

2017 TED TALK::

s://www.youtube.com/watch?v=AO4In7d6X-c

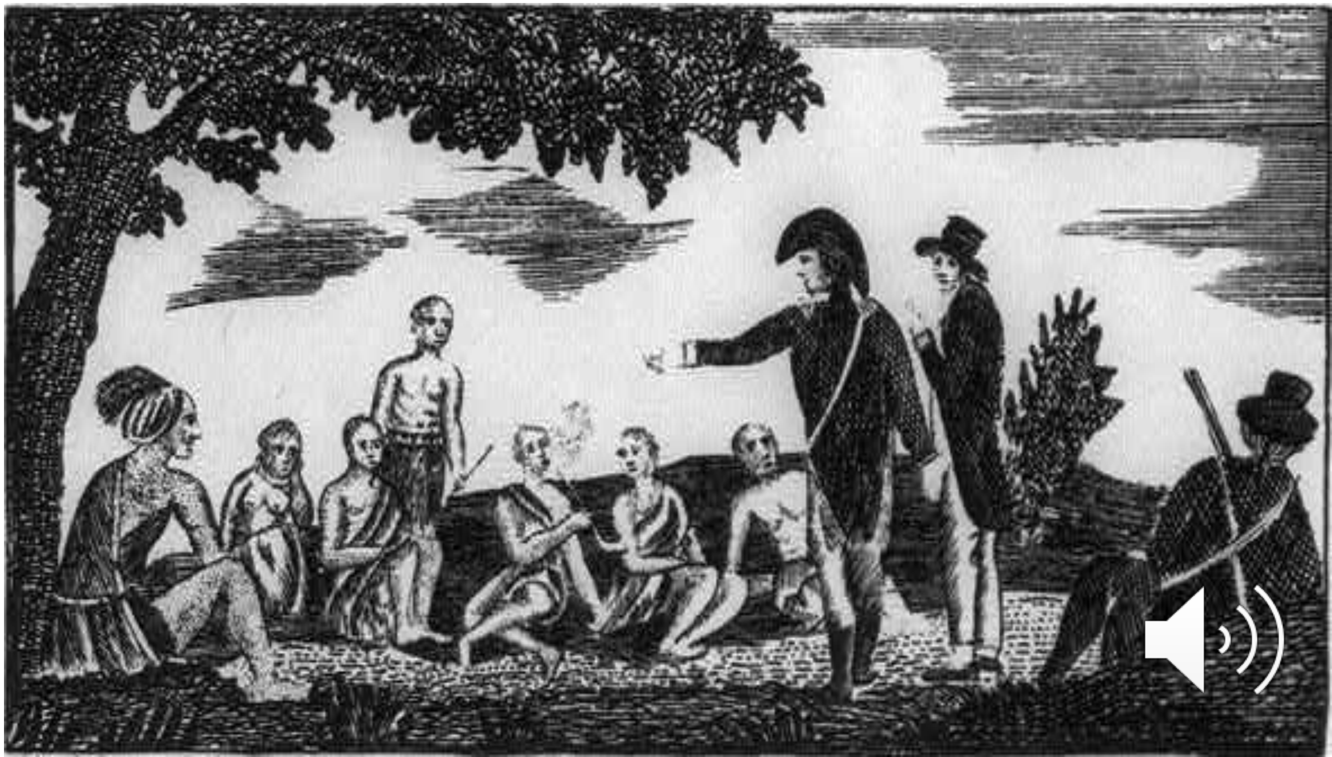


New-School



Old-School qualities lost?

Human-to-human first-contact, and general **diplomacy,** could diminish



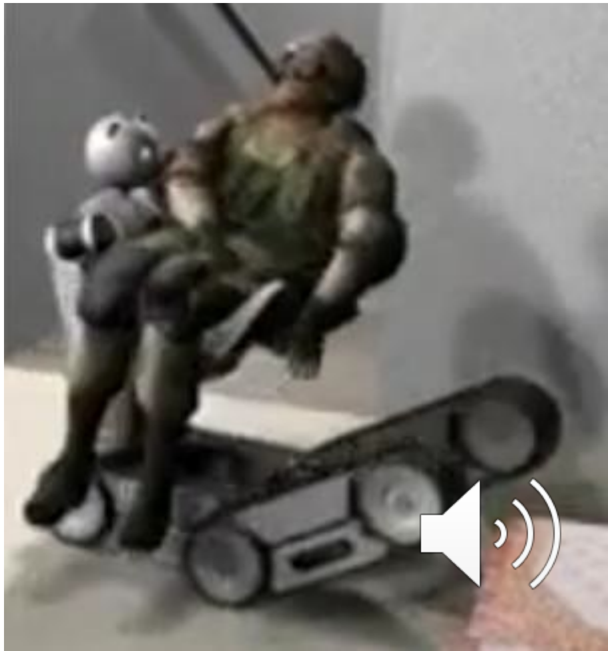
2014 “BEAR” (Battlefield Extract Assist Robot)

Image from: : http://www.pirotechnologies.com/wp-content/uploads/2014/11/military_battlefieldbear_800_070623.jpg

Image from: : http://www.pouted.com/wp-content/uploads/2013/02/bear-robot.jpg

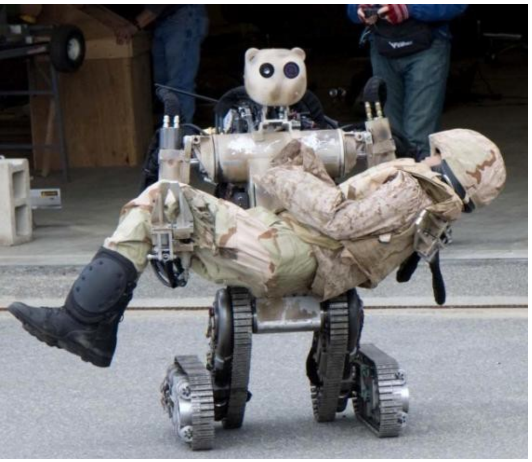
2015 “BEAR” (Battlefield Extract Assist Robot)

ttps://www.youtube.com/watch?v=8Nv6GGNA3Z4



New-School

Great for battlefield extraction of wounded soldiers !



Old-School qualities lost?

Maybe not ?

TEDIOUS TASKS

Image from: http://robohub.org/wp-content/uploads/2013/12/Amazon_PrimeAir.jpg

Image from: http://theguycornernyc.files.wordpress.com/2013/12/amazon-prime-air.jpg

New-School

Old-School qualities lost?

Home delivery **installation** disappearing

Package- delivery **accountability** disappearing

Customer Service
VIDEO: https://www.youtube.com/watch?v=QBU2GYxs1uc

2017 Humanoids, Boston Dynamics

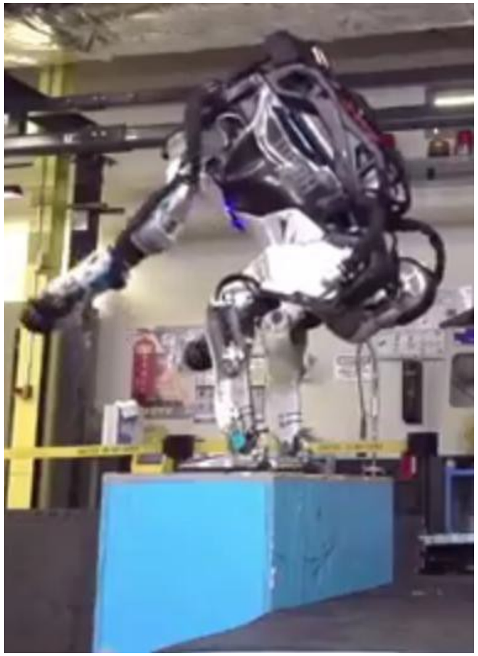
TEDIOUS TASKS

Laborer

2017Boston Dynamics "Atlas"

VIDEO:

https://www.youtube.com/watch?v=fRj34o4hN4I



Laborer?

New-School

Old-School qualities lost?

Human-interaction disappearing

ACTROIDS

*“**Repliee Q2** can mimic such human functions as blinking, breathing and speaking, with the ability to recognize and process speech and touch, and then respond in kind.”*

VIDEO:
http://www.youtube.com/watch?v=rOqfrM8aiOQ

ACTROIDS

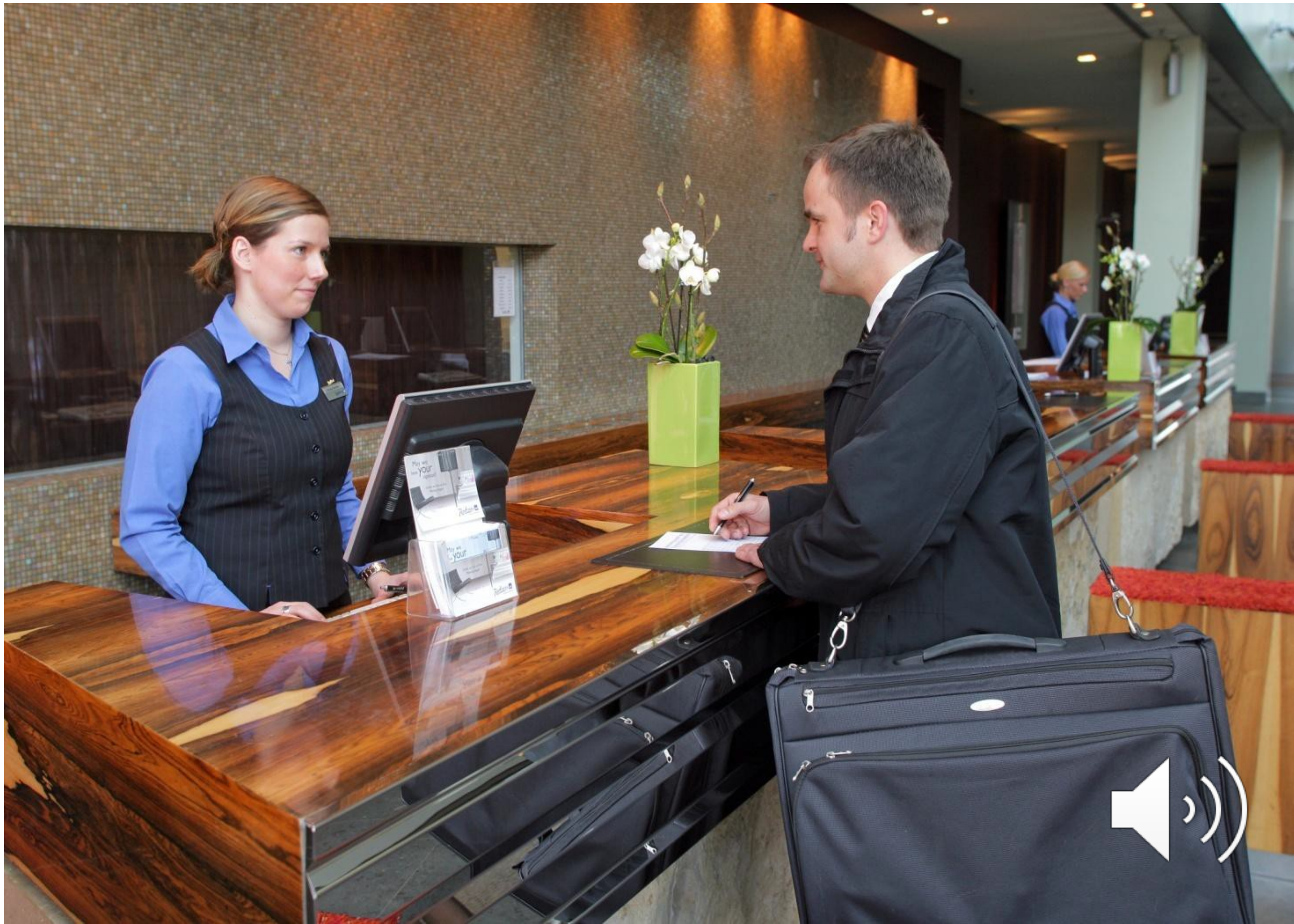
2015 Japanese hotel staffed by robots

Image from: http://www.cnn.com/2015/02/04/travel/japan-hotel-robots/

New-School

Old-School qualities lost?

Sincere **Hospitality (genuine empathy)** could disappear



2011 Companion NAO Next Gen

2014 **VIDEO** *(NAO and Asimo in first 12 minutes):* https://www.youtube.com/watch?v=S5AnWzjHtWA

2014 Companion Jibo

VIDEO: https://www.youtube.com/watch?v=UKERTiraS08

2017 HONDA ASIMO

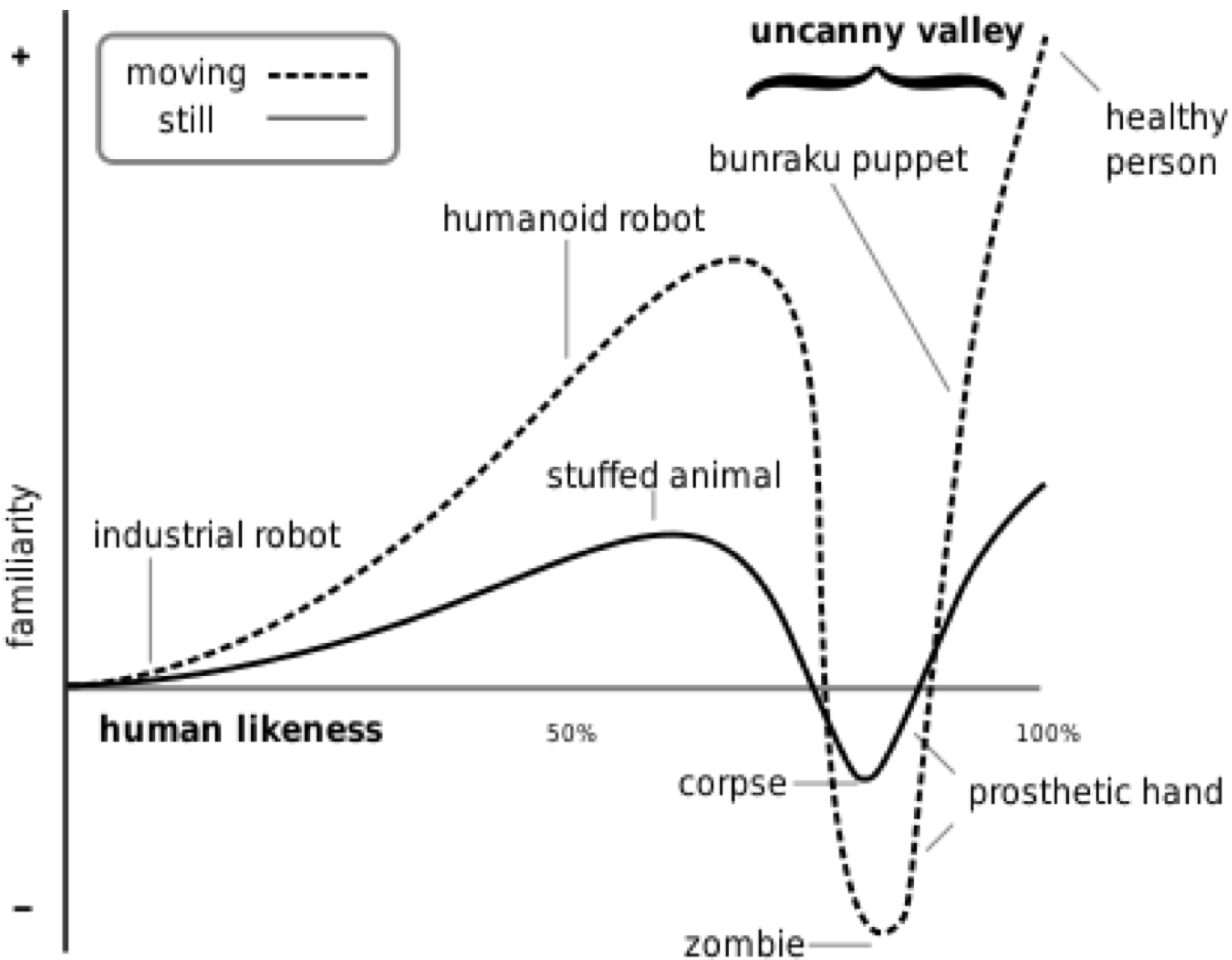
First edition in 2000

“Advanced Step in Innovative Mobility”

https://www.youtube.com/watch?v=QdQL11uWWcI

2017 VIDEO:
https://www.youtube.com/watch?v=fQ3EHtEl_NY

“Uncanny Valley” **frightens humans**



Honda’s “Asimo”

Bunraku Puppet

Zombie

Image from: http://upload.wikimedia.org/wikipedia/commons/thumb/f/f0/Mori_Uncanny_Valley.svg/450px-Mori_Uncanny_Valley.svg.png

Image from: http://www.21stcentury.co.uk/robotics/honda_asimo_robot.asp Image from: http://www.21stcentury.co.uk/robotics/honda_asimo_robot.asp

New-School

Old-School qualities lost?

Less **human relationships ?**

UBIQUITOUS COMPUTING

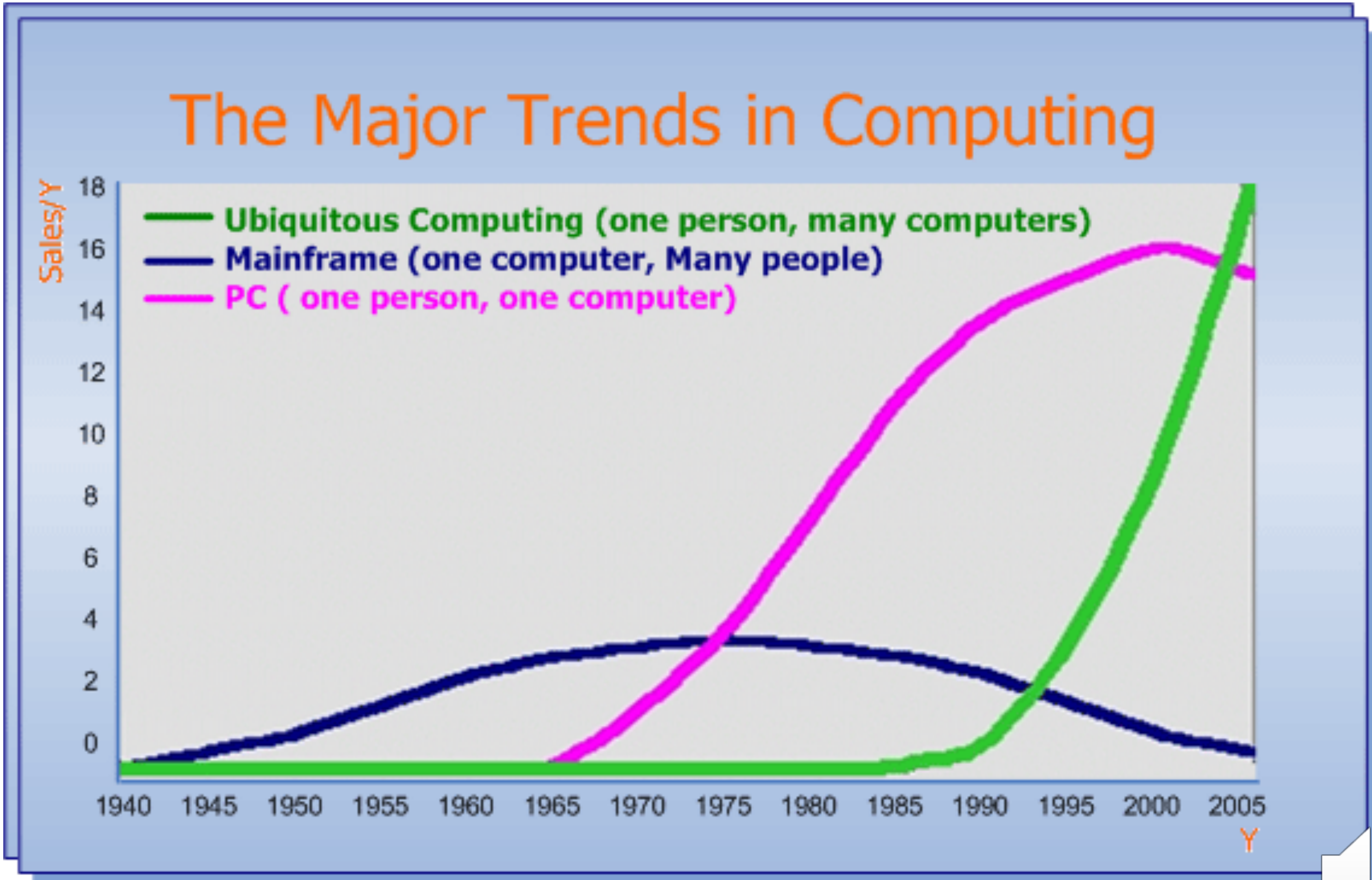


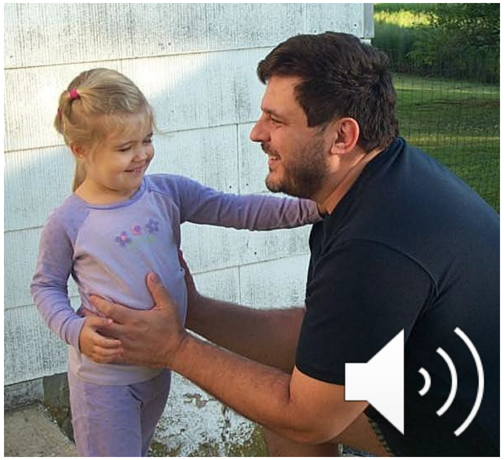
Image from: http://www.ubiq.com/hypertext/weiser/majortrends.gif

Image from: http://www.visualphotos.com/photo/2x4176453/a_girl_with_a_pacifier_sitting_at_the_computer_1832372.jpg

New-School

Old-School qualities lost?

Face-to-Face with people is diminishing



2015 drones

Northrop Grumman Corp.

Image from: http://www.emporia.edu/earthsci/student/graves1/project.html   mage from: http://geographicalimaginations.com/tag/global-hawk/

MILITARY

New-School

Old-School qualities lost?

"Rules of Engagement" could be diminished

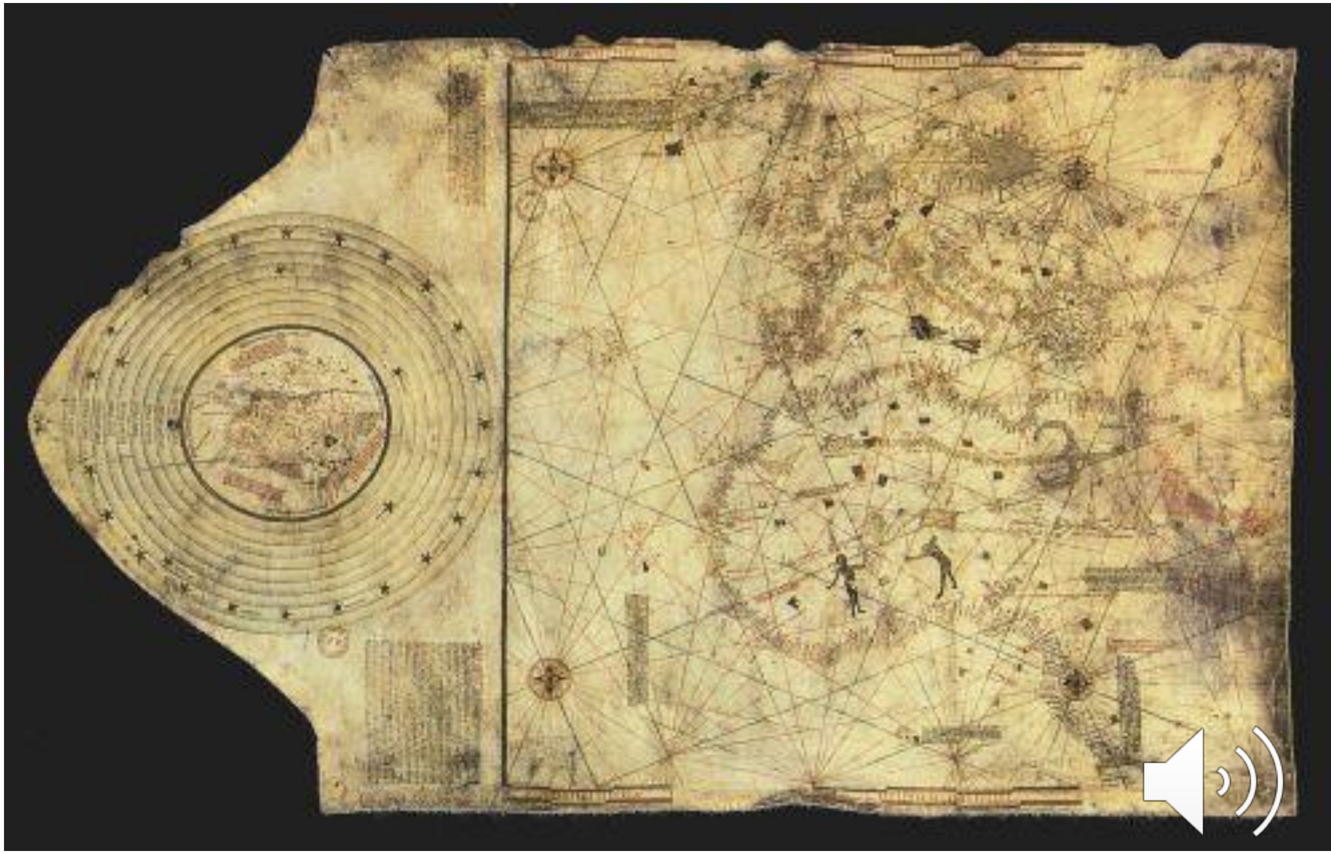
GPS Navigation

New-School

Old-School qualities lost?

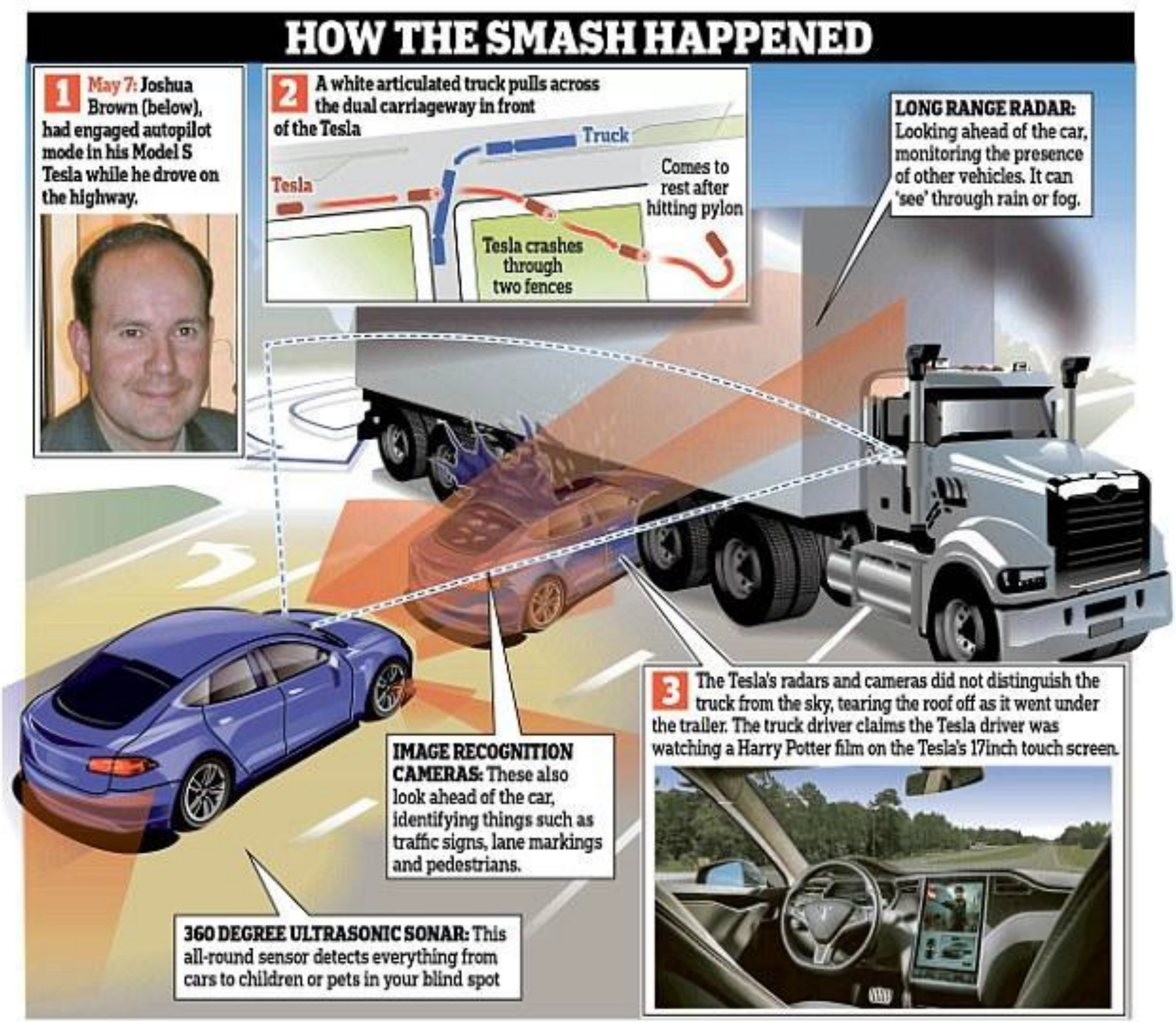
Loose ability to navigate without technology ?

Christopher Columbus's Map of the World:



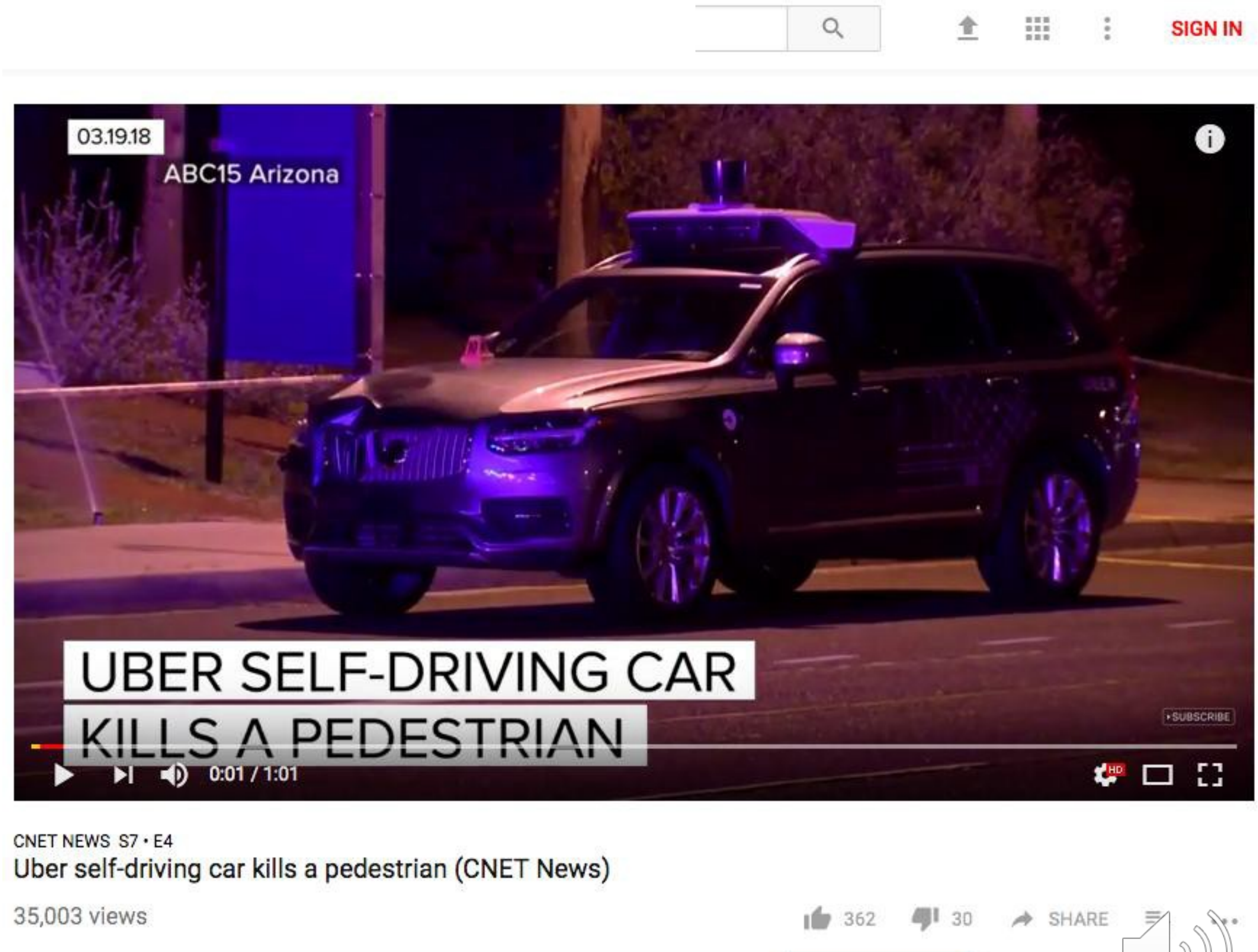
https://www.researchgate.net/figure/Christopher-Columbus-map-of-the-world_fig2_29540182

2017 Driverless Vehicles - Tesla



http://spendergast.blogspot.com/2016/07/tesla-looking-at-autopilot-florida.html

2018 Driverless Vehicles



VIDEO: https://www.youtube.com/watch?v=kKiKgQIXWAA

2018 Driverless Vehicles

Tech Alert

IEEE SPECTRUM

JOIN IEEE

22 March 2018

Uber Robocar Kills Pedestrian, Despite Presence of Safety Driver

Earlier this week, the world was presented with the latest evidence that artificial intelligence might never fully overcome humans' unpredictability. A self-driving Uber vehicle reportedly killed someone in Tempe, Ariz., on 19 March. A pedestrian stepped out into the car's path at an instant when it was too late for either the car or the safety driver to react. In response, Uber has suspended its robocar testing efforts.

2018 Driverless Vehicles

2018 MIT media lab: Moral Machine

http://moralmachine.mit.edu/

"Should a Self-Driving Car kill two jaywalkers

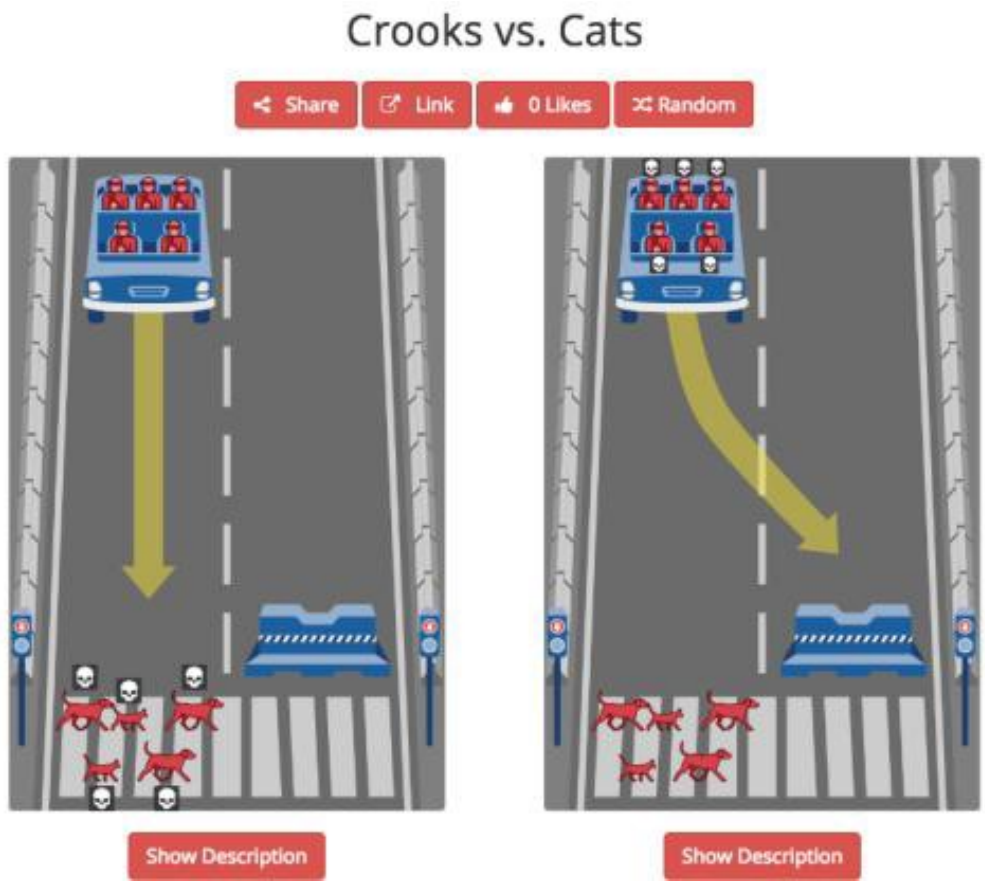
or one law-abiding citizen?"

2018 Driverless Vehicles

2018 MIT media lab: Moral Machine

http://moralmachine.mit.edu/

“Should a Self-Driving Car kill jaywalking pets or all of the passengers, which are known to be hardened criminals?”



2018 Vehicles Driverless

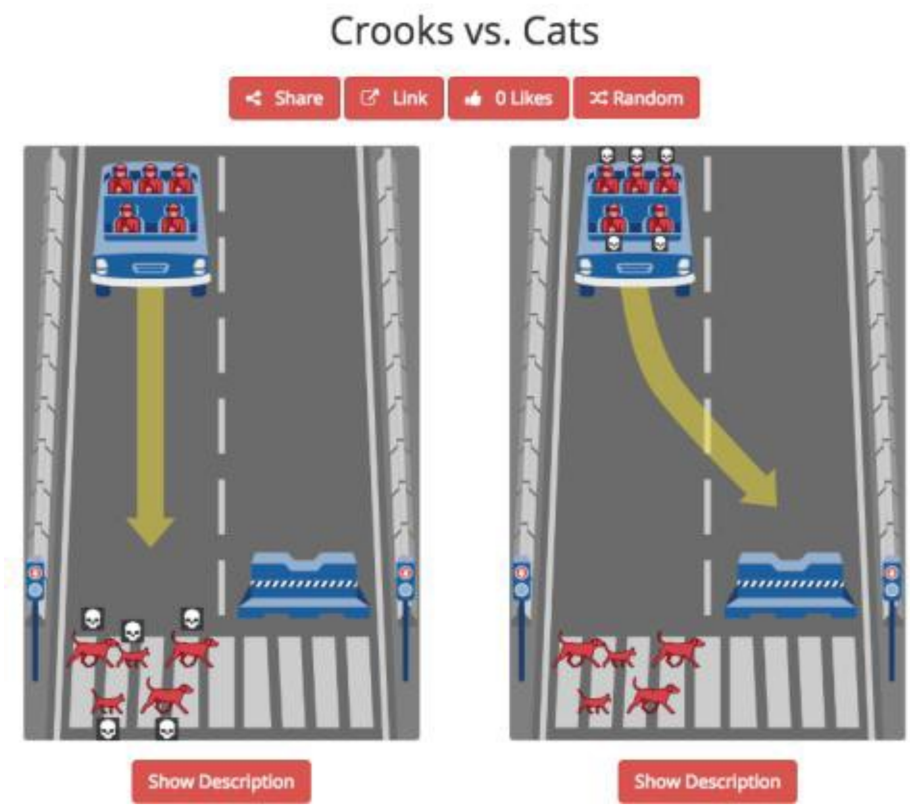
You ready for flying taxis from Uber? | Engadget Today

VIDEO: https://www.youtube.com/watch?v=3V-Q2URwIuU

New-School

Old-School qualities lost?

Human Driver's alertness and discretion lost !



Advanced Robots driven by Robot Autonomy

Robots are mobile, dexterous, and/or sensory extensions of Machine Intelligence

Human Mind

↓

Human appendages and senses

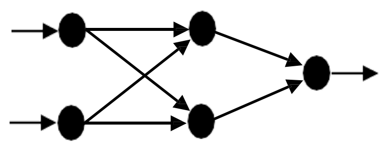
Machine Learning and Autonomy

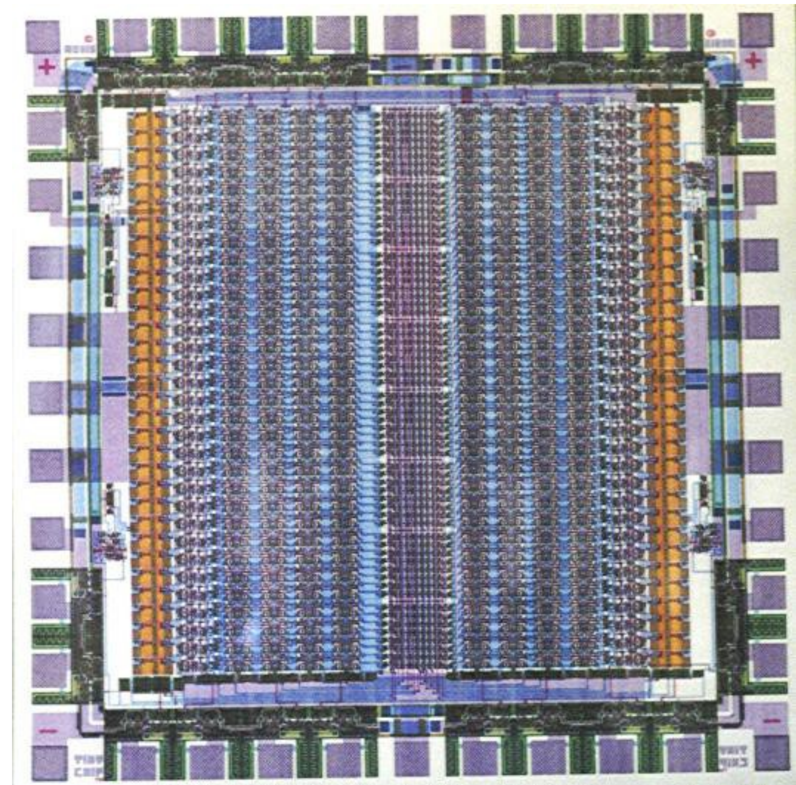
↓

Robotic mechanisms and sensors

Two major Machine Intelligence fields

- Artificial **Neural Networks**
  - Connectionist architectures
  - Hardware or Software
  - *Similar* to a biological brain's reasoning and/or Physiology
  - Various types
  - LEARNS !
  - **NOT TRACEABLE**





1992 Neural Network Chip
Wunderlich, et al.

- **Symbolic AI** programs
  - Heuristics, inference, hypothesis-testing, and forms of knowledge representation
  - "Expert Systems"
  - Predicate Calculus, PROLOG, LISP
  - **Confidence Factors ("Values"), Probability Theory**

	Wunderlich 2002++ Research	**Can human do?**	Can bug do? (spider)	Can Conventional Computer Program do?	Can Symbolic AI Program do?	Can Artificial Neural Network do?	Comments
	BASIC ANIMAL ABILITIES:						
1	Acquire and retain knowledge	yes	yes	yes	yes	yes	
2	Solve problems	yes	yes	yes	yes	yes	
3	**LEARN** and adapt	yes	yes	no	somewhat	**yes**	Evolution
4	Motor coordination	yes	yes	somewhat	somewhat	somewhat	Survival
5	Acquire energy	yes	yes	somewhat	somewhat	somewhat	Survival
6	Protect self	yes	yes	somewhat	somewhat	somewhat	Survival
7	Sensory processing	yes	yes	yes	yes	yes	
8	Real-time thought	yes	yes	yes	yes	yes	
9	React instinctively	yes	yes	no	not yet	not yet	
10	Anticipate	yes	yes	yes	yes	yes	
11	Predict	yes	yes	yes	yes	yes	
12	Communicate	yes	yes	yes	yes	yes	
13	Generalize	yes	yes	no	somewhat	yes	
14	Associate	yes	yes	somewhat	somewhat	yes	
15	Recognition patterns	yes	yes	somewhat	somewhat	yes	
16	**Robust** under partial failure	yes	yes	no	no	yes	
17	**AUTONOMOUS thought**	yes	yes	no	somewhat	somewhat	
18	Drive to reproduce	yes	yes	no	not yet	not yet	
19	**STABILITY**, repeatability, **predictability**	somewha t	somewha t	yes	yes	somewhat	Uncertainty
20	Multitask	yes	yes	yes	no	yes	

	Wunderlich 2002++ Research	Can human do?	Can bug do? (spider)	Can Conventional Computer Program do?	Can Symbolic AI Program do?	Can Artificial Neural Network do?	Comments
	COMPLEX ABILITIES:						
21	Abstraction	yes	unlikely	no	no	somewhat	
22	Intuition	yes	unlikely	no	not yet	not yet	
23	Common sense	yes	yes	no	not yet	not yet	
24	Manipulate tools	yes	no	yes	yes	yes	Evolution
25	Heuristics	yes	yes	somewhat	yes	no	
26	Inference	yes	yes	somewhat	yes	somewhat	
27	Hypothesis testing	yes	somewhat	somewhat	yes	no	
28	Self-discipline, impulse-control	yes	unlikely	no	somewhat	no	
29	Ethical behavior	yes	unlikely	somewhat	somewhat	somewhat	coded/trained
30	Selective awareness (filtering)	yes	yes	yes	yes	yes	
31	**OPEN TO INSPECTION**	somewhat	somewhat	YES	YES	NO !	
32	**EMOTIONS**	yes	unlikely	no	not yet	not yet	
33	Imagination	yes	unlikely	no	not yet	not yet	
34	Creativity	yes	unlikely	no	not yet	not yet	
35	Passion	yes	unlikely	no	not yet	not yet	
36	Playfulness	yes	unlikely	no	not yet	not yet	Evolution
37	Empathy	yes	unlikely	no	not yet	not yet	
38	Courage	yes	unlikely	no	not yet	not yet	
39	Leadership	yes	unlikely	no	not yet	not yet	
40	Self awareness	yes	unlikely	no	not yet	not yet	
41	Awareness of mortality	yes	unlikely	immortal?	immortal?	immortal?	Replace parts

	Wunderlich 2010++ Research	Can human do?	Can bug do? (spider)	Can Conventional Computer Program do?	Can Symbolic AI Program do?	Can Artificial Neural Network do?	Comments
	***COMPLEX ABILITIES*:**						
42	Group psychology	yes	unlikely	somewhat	somewhat	somewhat	Networking
43	Social Networking	yes	Maybe?	somewhat	yes	yes	Humanity?

2010-2015 +: Virtual worlds created, including worlds for survival, creativity, factions, Freshman FYS green towns , FYS Japanese villages, and digital circuit designs

http://users.etown.edu/w/wunderjt/TSOJIN_ranks.pdf

VIDEO: https://www.youtube.com/watch?v=wSNo8dHpBOU

VIDEO: https://www.youtube.com/watch?v=S94apibblwY

	Wunderlich Research **2018**	Can human do?	Can bug do? (spider)	Can Conventional Computer Program do?	Can Symbolic AI Program do?	Can Artificial Neural Network do?	Comments
	***COMPLEX ABILITIES*:**						
44	**Undetected Bias**	yes	no	somewhat	somewhat	**YES !!**	Hidden?!?
45	**Disinformation**	yes	somewhat	somewhat	**YES**	**YES**	
46	Choosing “lesser?” **evil**	yes	yes	yes	yes	yes	**Driverless death**
47	Sensor Fusion and Integration of Processing	yes	yes	somewhat	somewhat	yes	

2018 #44 Undetected Bias

Example: Employee hiring systems **unintentionally incorporating undetected bias hidden in statistical data** used for machine learning (e.g., past hiring data representing decisions made by previous biased humans)

And new machine intelligence *could* detect an individual's **propensity towards illness or disability over time**; From hand-writing analysis? Facial expressions,? Voice patterns? etc. (i.e., Even if medical records and other private data excluded)

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)

J. Wunderlich, 1991

AI program to help pick a toy for a child

NOTE: Unlike Probability Theory, Confidence Factors do not need to add up to 100

User input:

1. Child's Age?
   - Program automatically assigns a CNF Confidence factor = 100
2. Do you want to spend more or less than $25?
   - Input CNF Confidence factor (e.g. CNF=65 for less than $25)
3. Child's gender?
   - Program automatically assigns a CNF Confidence factor = 100
4. Preference for type of toy? (Action, Cuddly, or Creative)
   - Input CNF Confidence factor s for each

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)
J. Wunderlich, 1991

```
ASSUMPTIONS:
        1) Gender is not relevant for children younger than the age of one.
        2) Children younger than the age of one cannot have a known preference for toys.
        3) Children between the ages of one and three cannot have a known preference for toys.

CONTROL OF SEARCH SPACE:
    As a result of the above assumptions, the rules have been ordered so that:
        A) child_age is the first variable in the premise of every rule.
        B) gender and child_preference questions are not asked when child_age = under_1
        C) The child_preference question is not asked when child_age = one_to_three

TESTING OF EXPERT SYSTEM:
    The expert system was tested under the three scenarios listed in the table below.
    The resulting output is shown in the last column with the calculated confidence factors.
    These confidence factors were calculated by VP-EXPERT using the following standard laws of Certainty:
        A) CNF(P1 and P2) = MIN(CNF(P1), CNF(P2))
        B) CNF(P1 or P2) = MAX(CNF(P1), CNF(P2))
    And when two or more rules support the same result R:
        C) CNF(R1) + CNF(R2) - (CNF(R1) * CNF(R2))  when CNF(R1) and CNF(R2) are positive
        D) CNF(R1) + CNF(R2) + (CNF(R1) * CNF(R2))  when CNF(R1) and CNF(R2) are negative
        E) (CNF(R1) + CNF(R2))/(1-MIN(|CNF(R1)|,|CNF(R2)|) otherwise
```

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)

J. Wunderlich, 1991

... one solution is scale by 1/100:

```
The example below shows the CNF calculations for suggestedd_toy = dress_up_doll
    For the premise of RULE 12:
    [(child_age=four_to_six) AND (price=under_25) AND (gender=female) AND (child_preference=cuddly_toy)]
            CNF=1            AND     CNF=0.65     AND      CNF=1      AND           CNF=0.55
    Using law #A above; CFN(premise) = MIN(1,0.65,1,0.55) = 0.55
    Using law #C above; [CFN(conclusion) = CFN(premise) * CFN(RULE 12)] = [0.55 * 0.9] = 0.49     see NOTE 7
    Laws #C,#D, or #E are not used here because only RULE 12 fires to support the goal (suggested_toy=dress_up_doll)
```

TEST TRACE #	INPUT: child_age (see NOTE 1)	INPUT: price (see NOTE 2)	INPUT: gender (seeNOTE 3)	INPUT: chid_preference (see NOTE 4)	RULE FIRED AND ITS CNF (see NOTE 7)	OUTPUT: suggested_toy
1	under_1	under_25 (CNF=65)	N.A.	N.A.	CNF(R1)=95	teething_toy (CNF=61)
		over_25 (CNF=20)			CNF(R2)=90	mobile_for_crib (CNF=58)
					CNF(R3)=95	plastic_rattle (CNF=61)
					CNF(R4)=75	sterling_silver_rattle (CNF=15)
2	one_to_three	under_25 (CNF=65)	male	N.A.	CNF(R5)=90	roly_poly (CNF=58)
		over_25 (CNF=20)			CNF(R6)=90	tricycle (CNF=18)
					CNF(R7)=85	hammer_and_pegs_game (CNF=55)
3	four_to_six CNF=100	under_25 (CNF=65)	female CNF=100	action_toys (CNF=25)	CNF(R9)=95	lincoln_logs (CNF=61)
		over_25 (CNF=20)		cuddly_toys (CNF=55)	CNF(R11)=95	doll_house (CNF=18)
				creative_toys (CNF=75)	CNF(R12)=90	dress_up_doll (CNF=49)
					CNF(R14)=85	toy_tea_set (CNF=55)

Note 7: CFN's for RULES were assigned by J. Wunderlich Typically these will be assigned by the "Knowledge Engineer" after consultation with the "Domain Expert"

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)

J. Wunderlich, 1991

CFN's for RULES were assigned by J. Wunderlich Typically these will be assigned by the "Knowledge Engineer" after consultation with the "Domain Expert"

```
RULE 1
IF child_age = under_one AND
price = under_25
THEN suggested_toy = teething_toy CNF 95;

RULE 2
IF child_age = under_one AND
price = under_25
THEN suggested_toy = mobile_for_crib CNF 90;

RULE 3
IF child_age = under_one AND
price = under_25
THEN suggested_toy = plastic_rattle CNF 95;

RULE 4
IF child_age = under_one AND
price = over_25
THEN suggested_toy = sterling_silver_rattle CNF 75;


RULE 5
IF child_age = one_to_three AND
price = under_25
THEN suggested_toy = roly_poly CNF 90;

RULE 6
IF child_age = one_to_three AND
price = over_25
THEN suggested_toy = tricycle CNF 90;

RULE 7
IF child_age = one_to_three AND
price = under_25 AND
gender = male
THEN suggested_toy = hammer_and_pegs_game CNF 85;
```

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)

J. Wunderlich, 1991

CFN's for RULES were assigned by J. Wunderlich Typically these will be assigned by the "Knowledge Engineer" after consultation with the "Domain Expert"

```
RULE 9
IF child_age = four_to_six AND
price = under_25 AND
child_preference = creative_toys
THEN suggested_toy = lincoln_logs CNF 95;

RULE 10
IF child_age = four_to_six AND
price = over_25 AND
gender =  male AND
child_preference = action_toys
THEN suggested_toy = go_cart CNF 85;

RULE 11
IF child_age = four_to_six AND
price = over_25 AND
gender = female AND
child_preference = creative_toys
THEN suggested_toy = doll_house CNF 90;

RULE 12
IF child_age = four_to_six AND
price = under_25 AND
gender = female AND
child_preference = cuddly_toys
THEN suggested_toy = dress_up_doll CNF 90;

RULE 13
IF child_age = four_to_six AND
price = over_25 AND
gender = male AND
child_preference = action_toys
THEN suggested_toy = hot_wheels_set CNF 95;

RULE 14
IF child_age = four_to_six AND
price = under_25 AND
gender = female AND
child_preference = creative_toys
THEN suggested_toy = toy_tea_set CNF 85;

RULE 15
IF child_age = four_to_six AND
price = under_25 AND
gender = male AND
child_preference = creative_toys
THEN suggested_toy = army_men CNF 90;
```

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)
J. Wunderlich, 1991

TEST TRACE #	INPUT: child_age (see NOTE 1)	INPUT: price (see NOTE 2)	INPUT: gender (seeNOTE 3)	INPUT: chid_preference (see NOTE 4)	RULE FIRED AND ITS CNF (see NOTE 7)	OUTPUT: suggested_toy
1	under_1	under_25 (CNF=65)	N.A.	N.A.	CNF(R1)=95	teething_toy (CNF=61)
		over_25 (CNF=20)			CNF(R2)=90	mobile_for_crib (CNF=58)
					CNF(R3)=95	plastic_rattle (CNF=61)
					CNF(R4)=75	sterling_silver_rattle_(CNF

Test-trace #1 →

```
suggested_toy
!    Testing 1
!    !    child_age
!    !    !    (= under_one CNF 100 )
!    !    price
!    !    !    (= under_25 CNF 65 )
!    !    !    (= over_25 CNF 20 )
!    (= teething_toy CNF 61 )
!    Testing 2
!    (= mobile_for_crib CNF 58 )
!    Testing 3
!    (= plastic_rattle CNF 61 )
!    Testing 4
!    (= sterling_silver_rattle CNF 15 )
!    Testing 5
!    Testing 6
!    Testing 7
!    Testing 8
!    Testing 9
!    Testing 10
!    Testing 11
!    Testing 12
!    Testing 13
!    Testing 14
!    Testing 15
```

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)

J. Wunderlich, 1991

TEST TRACE #	INPUT: child_age (see NOTE 1)	INPUT: price (see NOTE 2)	INPUT: gender (seeNOTE 3)	INPUT: chid_preference (see NOTE 4)	RULE FIRED AND ITS CNF (see NOTE 7)	OUTPUT: suggested_toy
2	one_to_three	under_25 (CNF=65)	male	N.A.	CNF(R5)=90	roly_poly (CNF=58)
		over_25 (CNF=20)			CNF(R6)=90	tricycle (CNF=18)
					CNF(R7)=85	hammer_and_pegs_game (CNF=5

Test-trace #2 →

```
gested_toy
 Testing 1
 !   child_age
 !   !   (= one_to_three CNF 100 )
 Testing 2
 Testing 3
 Testing 4
 Testing 5
 !   price
 !   !   (= under_25 CNF 65 )
 !   !   (= over_25 CNF 20 )
 (= roly_poly CNF 58 )
 Testing 6
!  (= tricycle CNF 18 )
!  Testing 7
!  !   gender
!  !   !   (= male CNF 100 )
!  (= hammer_and_pegs_game CNF 55 )
!  Testing 8
!  Testing 9
!  Testing 10
!  Testing 11
!  Testing 12
!  Testing 13
!  Testing 14
!  Testing 15
```

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)

J. Wunderlich, 1991

TEST TRACE #	INPUT: child_age (see NOTE 1)	INPUT: price (see NOTE 2)	INPUT: gender (seeNOTE 3)	INPUT: chid_preference (see NOTE 4)	RULE FIRED AND ITS CNF (see NOTE 7)	OUTPUT: suggested_toy
3	four_to_six CNF=100	under_25 (CNF=65)	female CNF=100	action_toys (CNF=25)	CNF(R9)=95	lincoln_logs (CNF=61)
		over_25 (CNF=20)		cuddly_toys (CNF=55)	CNF(R11)=95	doll_house (CNF=18)
				creative_toys (CNF=75)	CNF(R12)=90	dress_up_doll (CNF=49)
					CNF(R14)=85	toy_tea_set (CNF=55)

MODIFIED Test-trace #3

with age changed to one_to_three, and

gender changed to male

This changed OUTPUT to:

roly_poly (CNF 58)

tricycle (CNF 18)

hammer_and_pegs_game (CNF 55)

```
suggested_toy
!    Testing 1
!    !    child_age
!    !    !    (= one_to_three CNF 100 )
!    Testing 2
!    Testing 3
!    Testing 4
!    Testing 5
!    !    price
!    !    !    (= under_25 CNF 65 )
!    !    !    (= over_25 CNF 20 )
!    (= roly_poly CNF 58 )
!    Testing 6
!    (= tricycle CNF 18 )
!    Testing 7
!    !    gender
!    !    !    (= male CNF 100 )
!    (= hammer_and_pegs_game CNF 55 )
!    Testing 8
!    Testing 9
!    Testing 10
!    Testing 11
!    Testing 12
!    Testing 13
!    Testing 14
!    Testing 15
```

Perhaps unintended 1991 gender-bias in RULES and /or in CNF's of RULES should be adjusted

Example **Symbolic AI** rule-based Expert System with Confidence Factors (CNF's)

J. Wunderlich, 1991

Perhaps unintended 1991 gender-bias in RULES and/or in CNF's of RULES should be adjusted

```
RULE 7
IF child_age = one_to_three AND
price = under_25 AND
gender = male
THEN suggested_toy = hammer_and_pegs_game CNF 85;

RULE 10
IF child_age = four_to_six AND
price = over_25 AND
gender = male AND
child_preference = action_toys
THEN suggested_toy = go_cart CNF 85;

RULE 11
IF child_age = four_to_six AND
price = over_25 AND
gender = female AND
child_preference = creative_toys
THEN suggested_toy = doll_house CNF 90;

RULE 12
IF child_age = four_to_six AND
price = under_25 AND
gender = female AND
child_preference = cuddly_toys
THEN suggested_toy = dress_up_doll CNF 90;

RULE 13
IF child_age = four_to_six AND
price = over_25 AND
gender = male AND
child_preference = action_toys
THEN suggested_toy = hot_wheels_set CNF 95;

RULE 14
IF child_age = four_to_six AND
price = under_25 AND
gender = female AND
child_preference = creative_toys
THEN suggested_toy = toy_tea_set CNF 85;

RULE 15
IF child_age = four_to_six AND
price = under_25 AND
gender = male AND
child_preference = creative_toys
THEN suggested_toy = army_men CNF 90;
```

Anna Elizabeth Wunderlich, born June15th, 2002

	Wunderlich Research 2018	Can human do?	Can bug do? (spider)	Can Conventional Computer Program do?	Can Symbolic AI Program do?	Can Artificial Neural Network do?	Comments
	***COMPLEX ABILITIES*:**						
44	**Undetected Bias**	yes	no	somewhat	somewhat	**YES !!**	Hidden?!?
45	**Disinformation**	yes	somewhat	somewhat	**YES**	**YES**	
46	Choosing “lesser?” evil	yes	yes	yes	yes	yes	**Driverless death**
47	Sensor Fusion and Integration of Processing	yes	yes	somewhat	somewhat	yes	

2018 #45 Disinformation

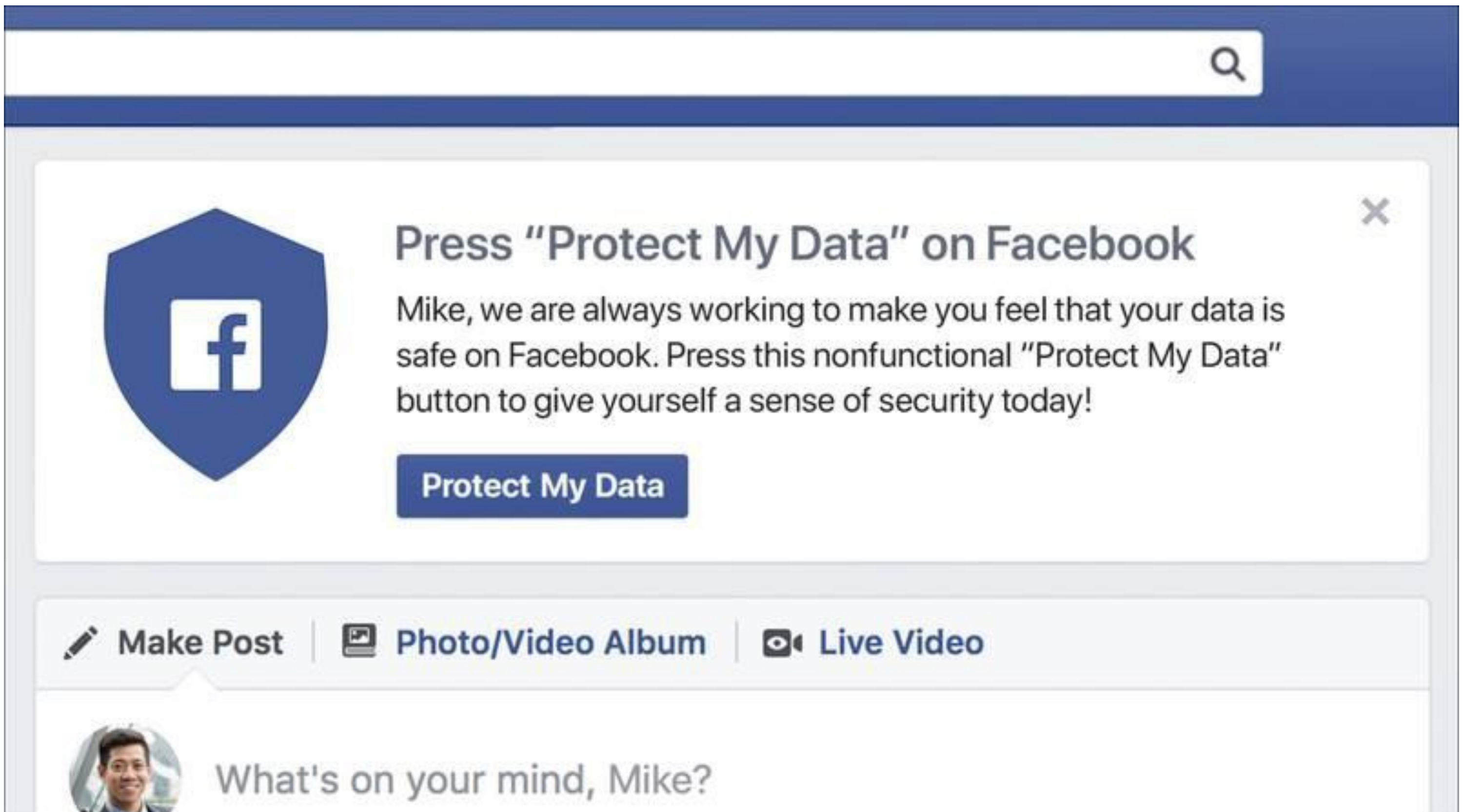
Has been happening for a very long time, and doesn't require a computer

		Can human do?
45	Disinformation	yes

Unbalancing **(Destabilizing !)** your opponent is called "Kuzushi" in Judo

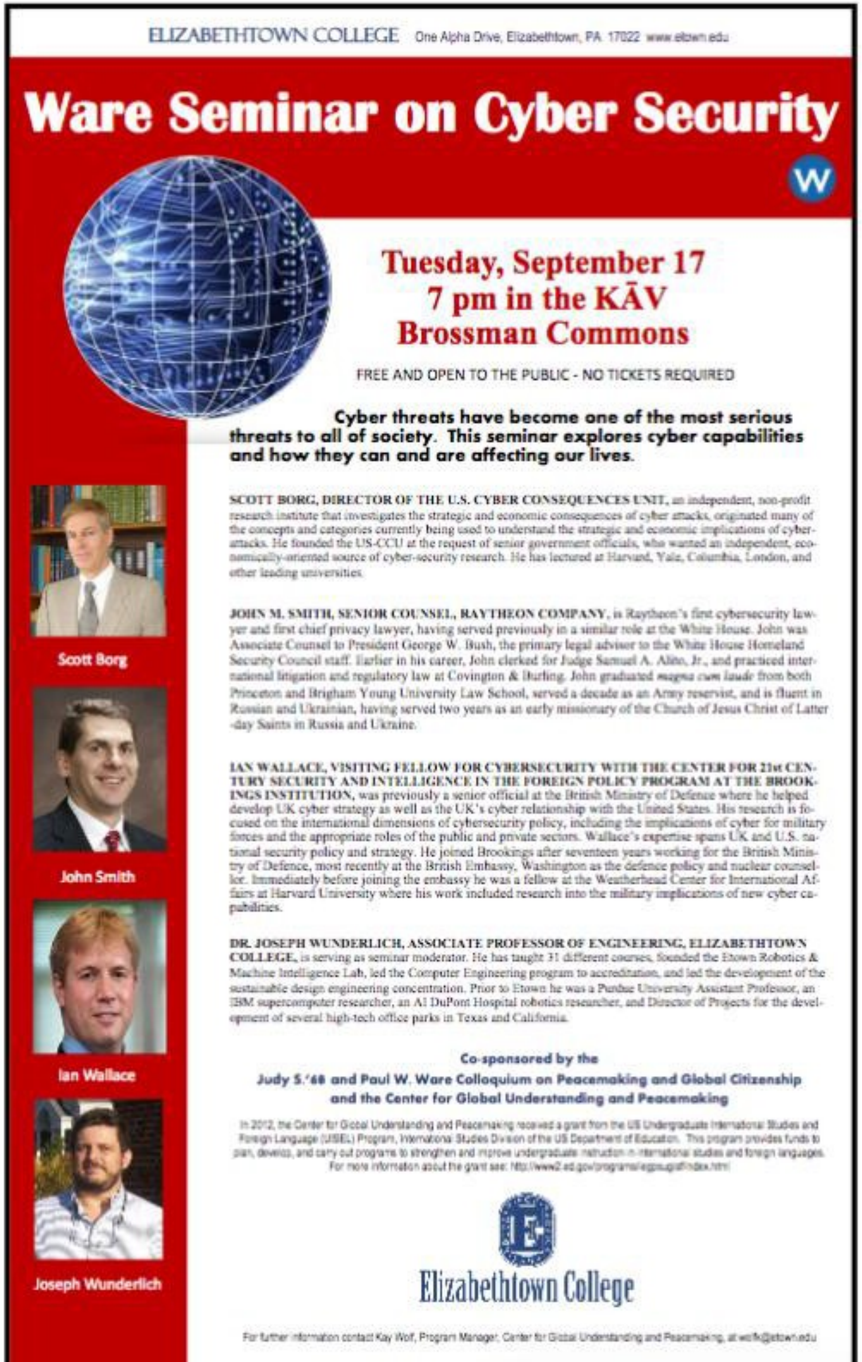

会议室
402
2016 G20 HANGZHOU SUMMIT

					Can Symbolic AI Program do?	Can Artificial Neural Network do?	
45	Disinformation				YES	YES	



http://www.clickhole.com/article/privacy-win-facebook-adding-protect-my-data-button-7587?utm_content=Main&utm_campaign=SF&utm_source=Facebook&utm_medium=SocialMarketing

2013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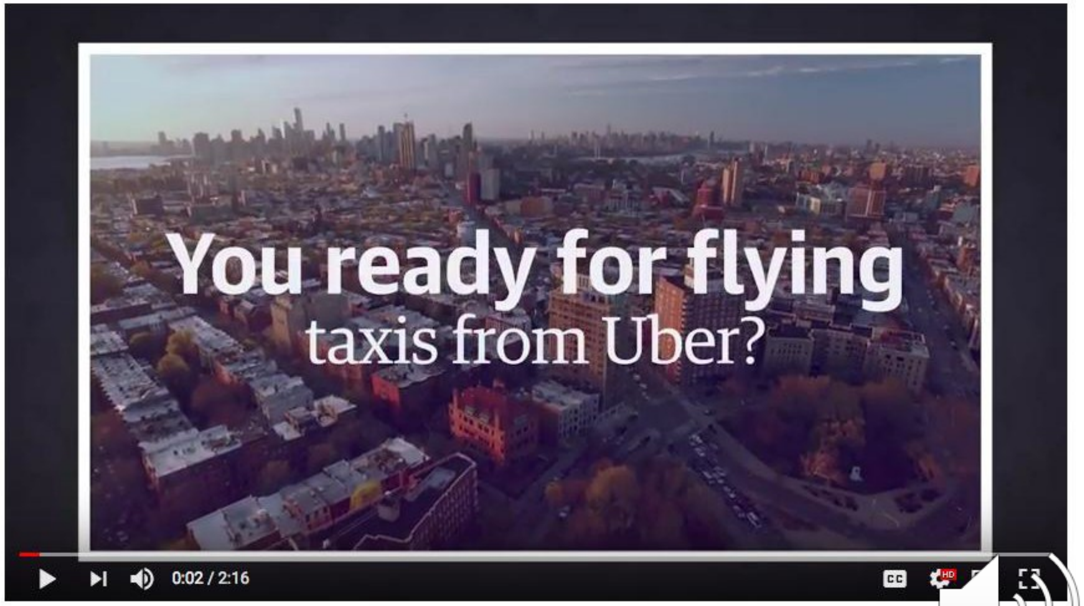
Ware Seminar on Cyber Security
W
Tuesday, September 17
7 pm in the KĀV
Brossman Commons
FREE AND OPEN TO THE PUBLIC - NO TICKETS REQUIRED
Cyber threats have become one of the most serious threats to all of society. This seminar explores cyber capabilities and how they can and are affecting our lives.
SCOTT BORG, DIRECTOR OF THE U.S. CYBER CONSEQUENCES UNIT, an independent, non-profit research institute that investigates the strategic and economic consequences of cyber attacks, originated many of the concepts and categories currently being used to understand the strategic and economic implications of cyber-attacks. He founded the US-CCU at the request of senior government officials, who wanted an independent, economically-oriented source of cyber-security research. He has lectured at Harvard, Yale, Columbia, London, and other leading universities.
JOHN M. SMITH, SENIOR COUNSEL, RAYTHEON COMPANY, is Raytheon's first cybersecurity lawyer and first chief privacy lawyer, having served previously in a similar role at the White House. John was Associate Counsel to President George W. Bush, the primary legal advisor to the White House Homeland Security Council staff. Earlier in his career, John clerked for Judge Samuel A. Alito, Jr., and practiced international litigation and regulatory law at Covington & Burling. John graduated magna cum laude from both Princeton and Brigham Young University Law School, served a decade as an Army reservist, and is fluent in Russian and Ukrainian, having served two years as an early missionary of the Church of Jesus Christ of Latter-day Saints in Russia and Ukraine.
IAN WALLACE, VISITING FELLOW FOR CYBERSECURITY WITH THE CENTER FOR 21st CENTURY SECURITY AND INTELLIGENCE IN THE FOREIGN POLICY PROGRAM AT THE BROOKINGS INSTITUTION, was previously a senior official at the British Ministry of Defence where he helped develop UK cyber strategy as well as the UK's cyber relationship with the United States. His research is focused on the international dimensions of cybersecurity policy, including the implications of cyber for military forces and the appropriate roles of the public and private sectors. Wallace's expertise spans UK and U.S. national security policy and strategy. He joined Brookings after seventeen years working for the British Ministry of Defence, most recently at the British Embassy, Washington as the defence policy and nuclear counsellor. Immediately before joining the embassy he was a fellow at the Weatherhead Center for International Affairs at Harvard University where his work included research into the military implications of new cyber capabilities.
DR. JOSEPH WUNDERLICH, ASSOCIATE PROFESSOR OF ENGINEERING, ELIZABETHTOWN COLLEGE, is serving as seminar moderator. He has taught 31 different courses, founded the Etown Robotics & Machine Intelligence Lab, led the Computer Engineering program to accreditation, and led the development of the sustainable design engineering concentration. Prior to Etown he was a Purdue University Assistant Professor, an IBM supercomputer researcher, an AI DuPont Hospital robotics researcher, and Director of Projects for the development of several high-tech office parks in Texas and California.
Scott Borg
John Smith
Ian Wallace
Joseph Wunderlich
Co-sponsored by the
Judy S.'68 and Paul W. Ware Colloquium on Peacemaking and Global Citizenship
and the Center for Global Understanding and Peacemaking
In 2012, the Center for Global Understanding and Peacemaking received a grant from the US Undergraduate International Studies and Foreign Language (UISFL) Program, International Studies Division of the US Department of Education. This program provides funds to plan, develop, and carry out programs to strengthen and improve undergraduate instruction in international studies and foreign languages. For more information about the grant see:
Elizabethtown College
For further information contact Kay Wolf, Program Manager, Center for Global Understanding and Peacemaking, at wolfk@etown.edu

	Wunderlich Research 2018	Can human do?	Can bug do? (spider)	Can Conventional Computer Program do?	Can Symbolic AI Program do?	Can Artificial Neural Network do?	Comments
	***COMPLEX ABILITIES*:**						
44	**Undetected Bias**	yes	no	somewhat	somewhat	**YES !!**	Hidden?!?
45	**Disinformation**	yes	somewhat	somewhat	**YES**	**YES**	
46	Choosing "lesser?" evil	yes	yes	yes	yes	yes	**Driverless death**
47	Sensor Fusion and Integration of Processing	yes	yes	somewhat	somewhat	yes	

2018 #46
Choosing "lesser?" evil

Driverless death

What could possibly go wrong?



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	Wunderlich Research **2018**	Can human do?	Can bug do? (spider)	Can Conventional Computer Program do?	Can Symbolic AI Program do?	Can Artificial Neural Network do?	Comments
	***COMPLEX ABILITIES*:**						
44	**Undetected Bias**	yes	no	somewhat	somewhat	**YES !!**	Hidden?!?
45	**Disinformation**	yes	somewhat	somewhat	**YES**	**YES**	
46	Choosing “lesser?” evil	yes	yes	yes	yes	yes	**Driverless death**
47	Sensor Fusion and Integration of Processing	yes	yes	somewhat	somewhat	yes	

2018 #47

Sensor Fusion

(Vision, hearing, brainwaves,
GPS, Laser-Range-Finders, Ultrasound, etc)

and

Integration of Processing

including combining **Symbolic AI** and **Neural Networks**

2011 IBM Watson

Video: https://www.youtube.com/watch?v=WFR3lOm_xhE

J. Wunderlich related IBM Research, mid-1990's

IBM S/390 supercomputers (New York) ported to IBM RS6000 workstations (Austin, Texas) – predecessor to POWER7 that **Watson** runs on

Supervised an Austin Texas Engineer via IBM Intranet

In 2011 Watson was a Special-Purpose Machine to play **Jeopardy**

Like **IBM "Deep-Blue" --** Special-Purpose Machine to play **Chess** that beat world-champion Garry Kasparov in 1996

An IBM SP2 MPP Supercomputer by IBM "Power- Parallel" group in the same center as IBM S/390 SMP Supercomputer Development Lab

Present applications for Watson include Cloud computing, Healthcare, Education, and Weather Foresting

2011 IBM Watson

Natural Language Processing

- Understanding Context
  - **Disambiguating language** (understanding *which* meaning of a word in a sentence)
- Somewhat understanding puns and wordplay

Knowledge Representation

- Problem Definition
- **Pattern Matching**

Data Mining

Confidence and Probability Theory

Machine Learning (adaptability)

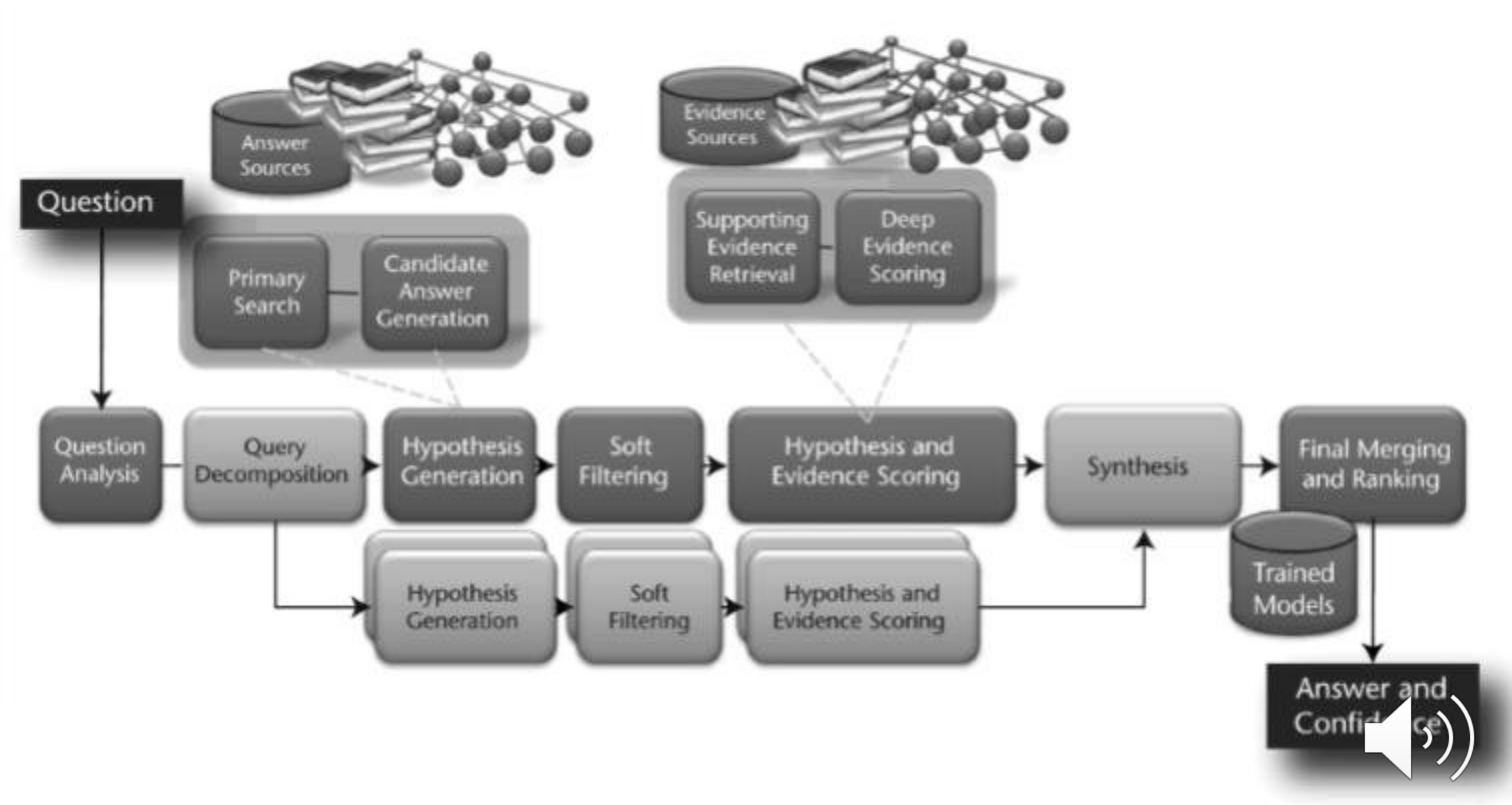
MPP (Massively Parallel Processing) hardware

In 2011 Watson **not connected to the Internet**. But it had 200 million pages of documents on four terabytes of disc space including an entire copy of Wikipedia; and for a short time the “Urban Dictionary” (removed because Watson was cursing)

2011 IBM Watson

From 2010 AI Magazine "*Building Watson: An Overview of the DeepQA Project*"

http://www.aaai.org/ojs/index.php/aimagazine/article/view/2303/2165



2011 IBM Watson

From 2010 AI Magazine "*Building Watson: An Overview of the DeepQA Project*"
http://www.aaai.org/ojs/index.php/aimagazine/article/view/2303/2165

Excluded Question Types.

The *Jeopardy* quiz show ordinarily admits two kinds of questions that IBM and Jeopardy Productions, Inc., agreed to exclude from the computer contest: audiovisual (A/V) questions and Special Instructions questions. A/V questions require listening to or watching some sort of audio, image, or video segment to determine a correct answer. For example:

Category: Picture This
(Contestants are shown a picture of a B-52 bomber)
Clue: Alphanumeric name of the fearsome machine seen here.
Answer: B-52

Special instruction questions are those that are not "self-explanatory" but rather require a verbal explanation describing how the question should be interpreted and solved. For example:

Category: Decode the Postal Codes
Verbal instruction from host: We're going to give you a word comprising two postal abbreviations; you have to identify the states.
Clue: Vain
Answer: Virginia and Indiana

2011 IBM Watson

From 2010 AI Magazine "*Building Watson: An Overview of the DeepQA Project*"
http://www.aaai.org/ojs/index.php/aimagazine/article/view/2303/2165

The Domain

As a measure of the *Jeopardy* Challenge's breadth of domain, we analyzed a random sample of 20,000 questions extracting the lexical answer type (LAT) when present. We define a LAT to be a word in the clue that indicates the type of the answer, independent of assigning semantics to that word. For example in the following clue, the LAT is the string "maneuver."

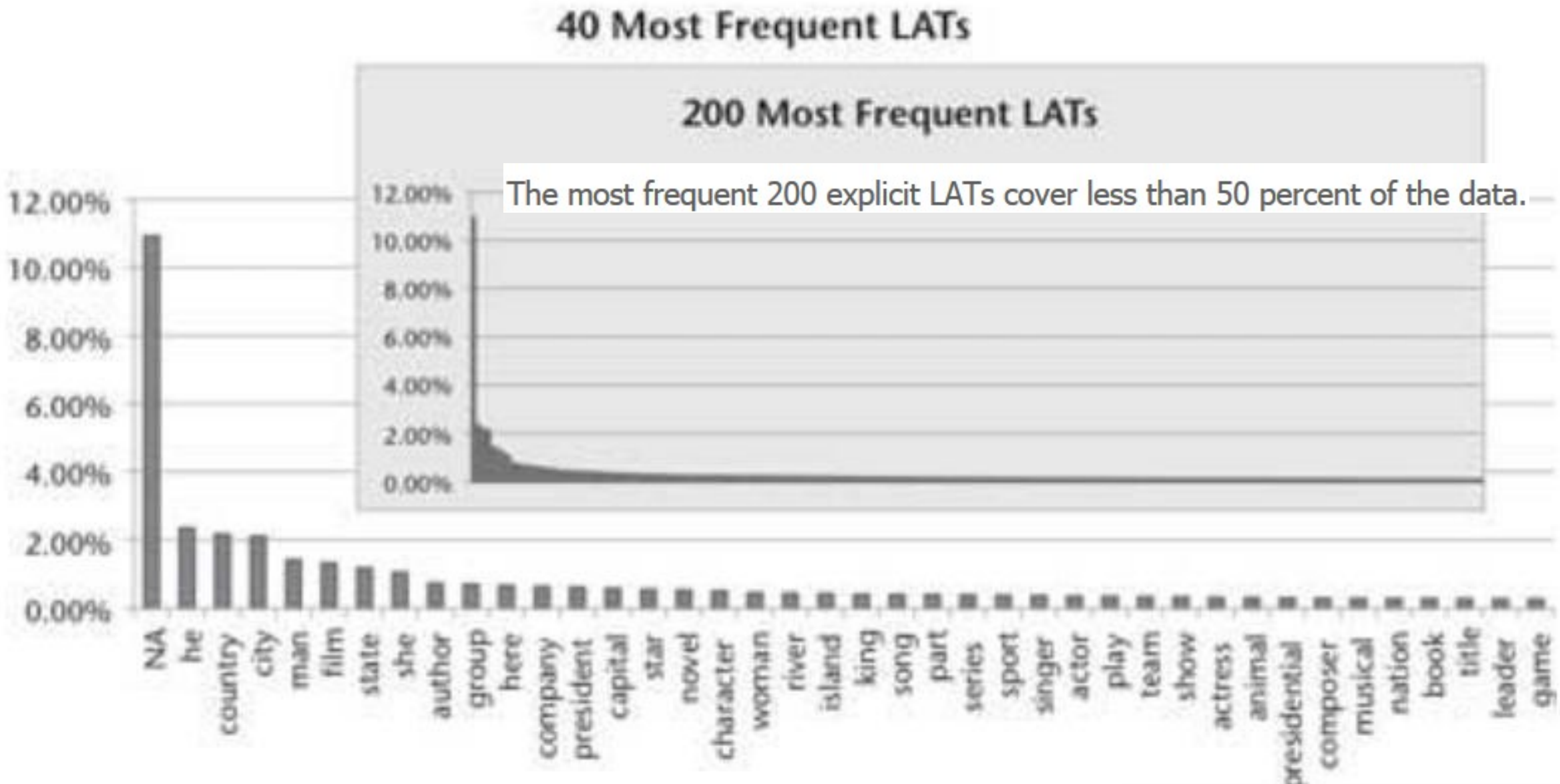
Category: Oooh….Chess
Clue: Invented in the 1500s to speed up the game, this maneuver involves two pieces of the same color.
7 *Answer:* Castling

About 12 percent of the clues do not indicate an explicit lexical answer type but may refer to the answer with pronouns like "it," "these," or "this" or not refer to it at all. In these cases the type of answer must be inferred by the context. Here's an example:

Category: Decorating
Clue: Though it sounds "harsh," it's just embroidery, often in a floral pattern, done with yarn on cotton cloth.
Answer: crewel

2011 IBM Watson

From 2010 AI Magazine "*Building Watson: An Overview of the DeepQA Project*"
http://www.aaai.org/ojs/index.php/aimagazine/article/view/2303/2165



Designer's ***trying*** to make Watson not so Application Specific.

. Our clear technical bias for both business and scientific motivations is to create general-purpose, reusable natural language processing (NLP) and knowledge representation and reasoning (KRR) technology that can exploit as-is natural language resources and as-is structured knowledge rather than to curate task-specific knowledge resources.

2011 IBM Watson

From 2010 AI Magazine "*Building Watson: An Overview of the **DeepQA** Project*"
http://www.aaai.org/ojs/index.php/aimagazine/article/view/2303/2165

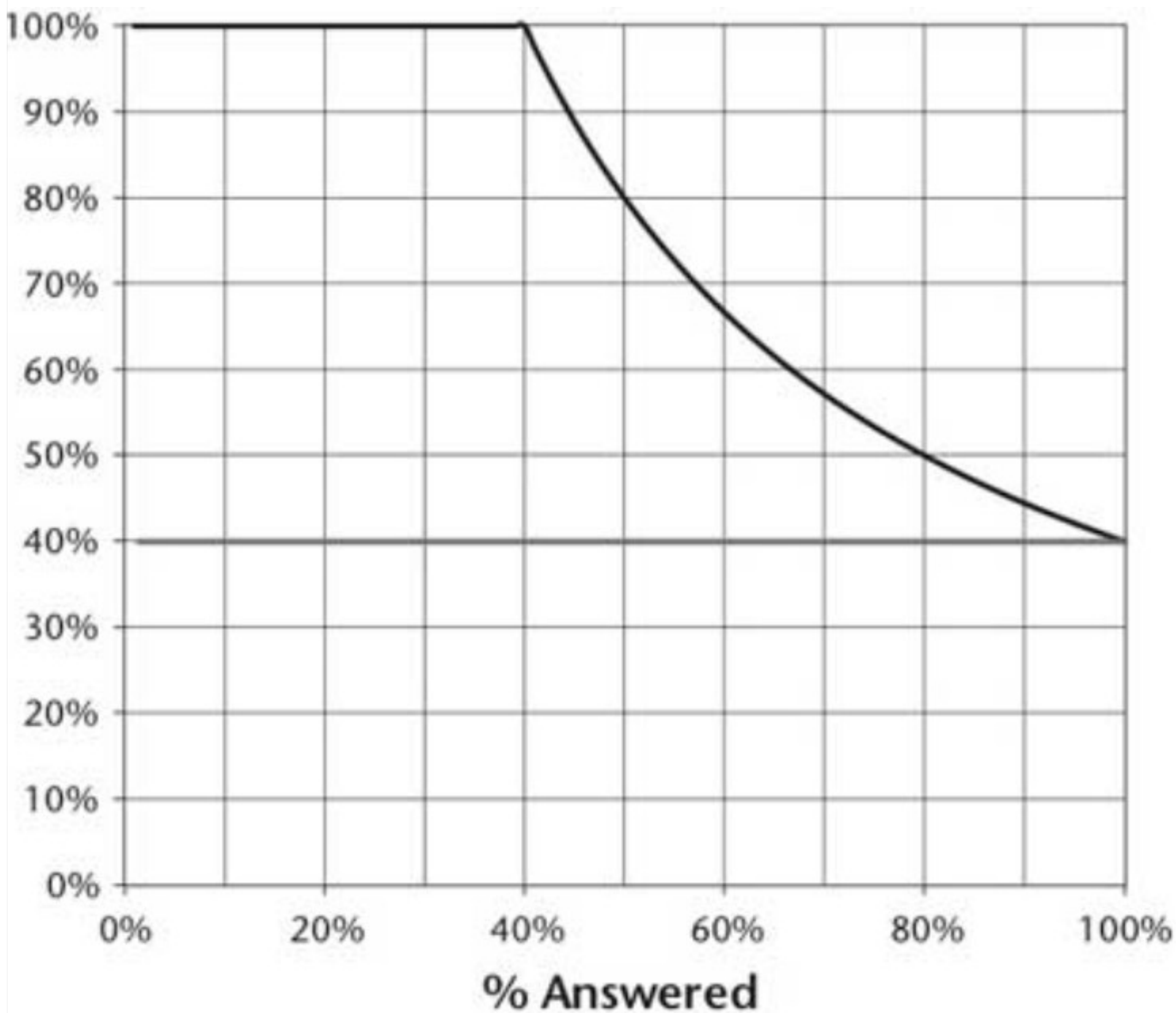


Figure 2. Precision Versus Percentage Attempted.
Perfect confidence estimation (upper line) and no confidence estimation (lower line).

*Programmers could "**Tune**" this to be more or less Aggressive in % attempted vs Precision to compete with the known ratio for best Jeopardy players*

Watson would eventually TUNE ITSELF

2011 IBM Watson

From 2010 AI Magazine "*Building Watson: An Overview of the DeepQA Project*"
http://www.aaai.org/ojs/index.php/aimagazine/article/view/2303/2165

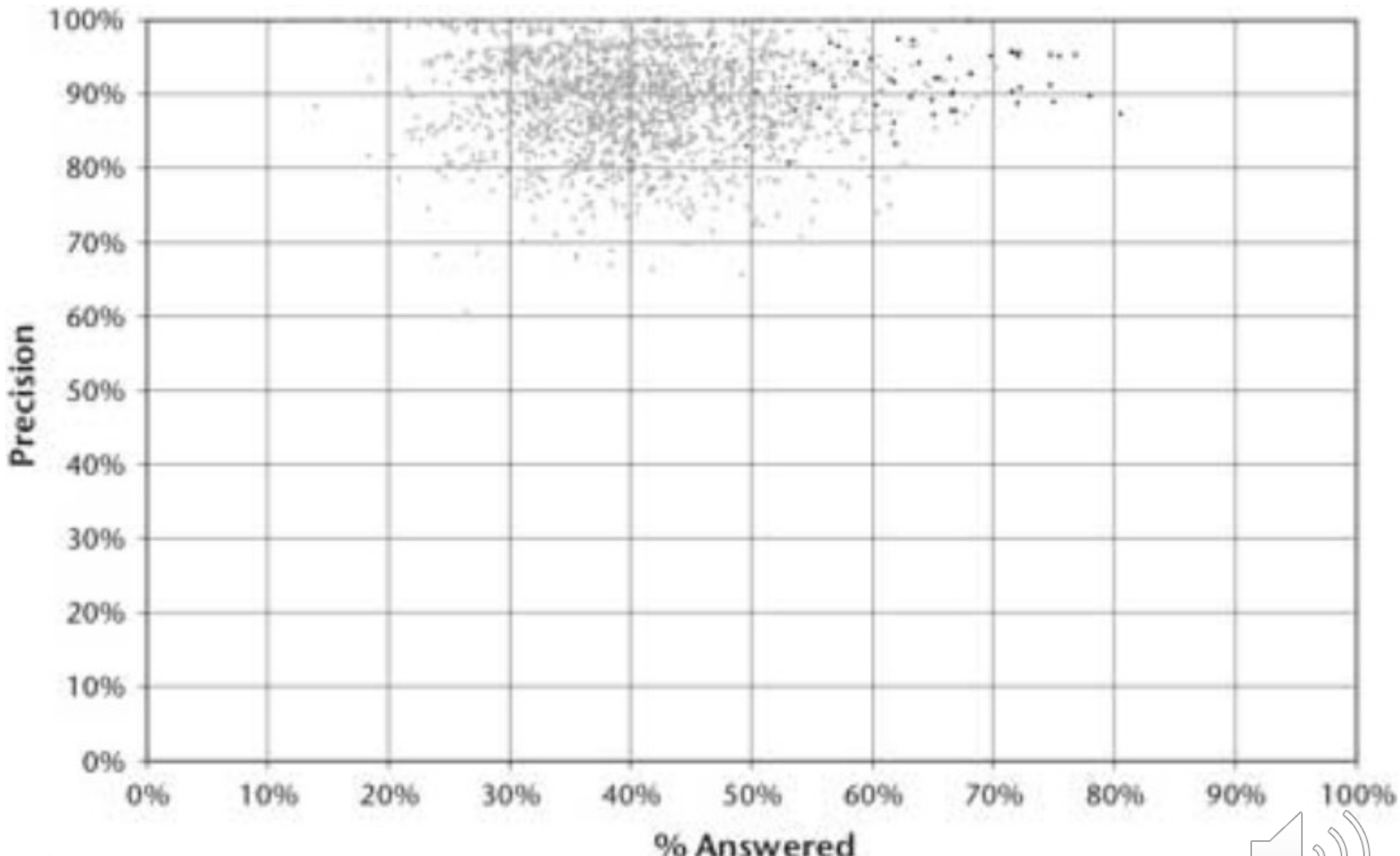
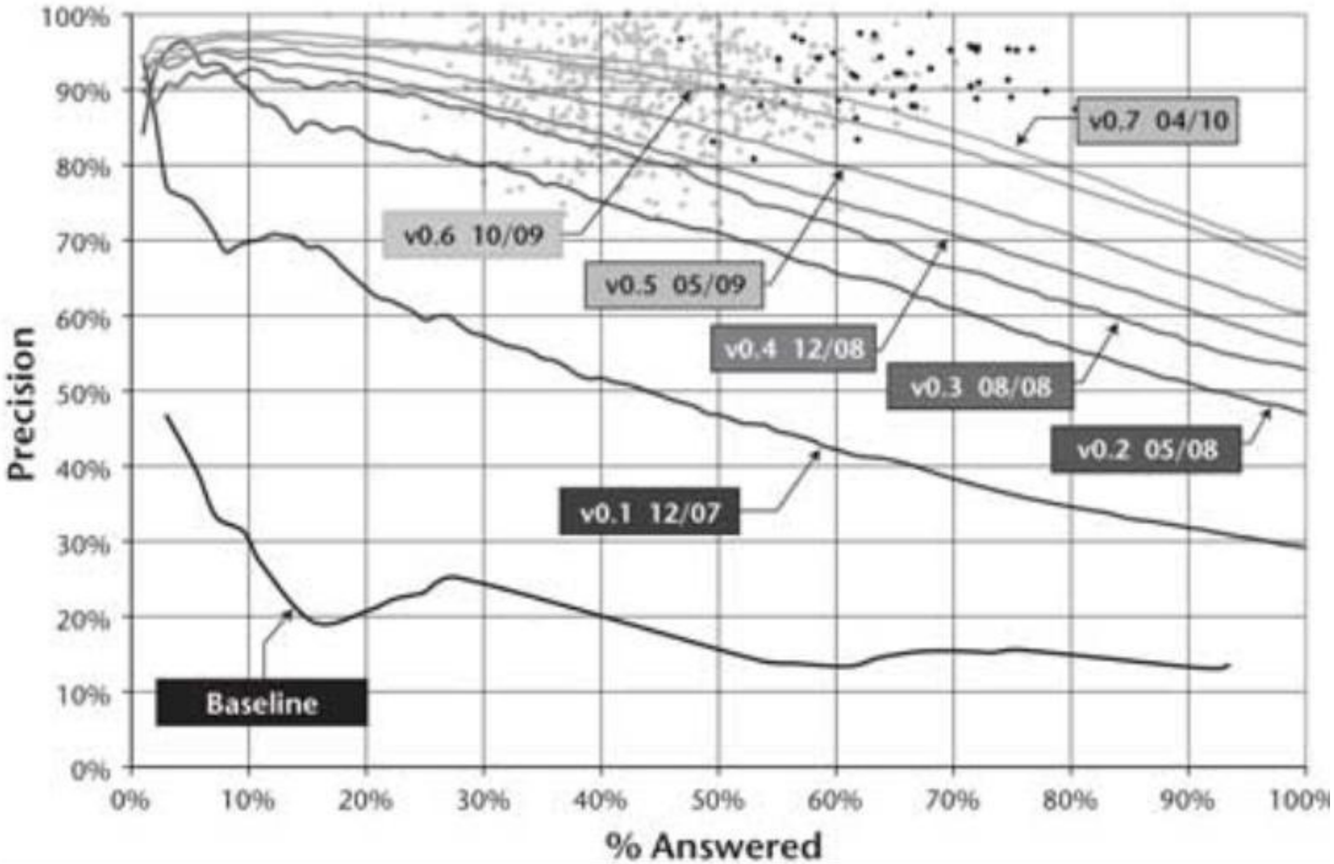


Figure 3. Champion Human Performance at Jeopardy.

2011 IBM Watson

From 2010 AI Magazine "*Building Watson: An Overview of the DeepQA Project*"

http://www.aaai.org/ojs/index.php/aimagazine/article/view/2303/2165



*Watson's performance, and therefore "**Confidences**" increased over time*

After approximately 3 years of effort by a core algorithmic team composed of 20 researchers and software engineers with a range of backgrounds in natural language processing, information retrieval, machine learning, computational linguistics, and knowledge representation and reasoning, we have driven the performance of DeepQA to operate within the winner's cloud on the *Jeopardy* task, as shown in figure 9. Watson's results illustrated in this figure were measured over blind test sets containing more than 2000 *Jeopardy* questions.

2011 IBM Watson

From ***"Final Jeopardy,"*** by Stephen Baker, **2012**, Mariner Books Publishing:

- Initial problems:
  - Developed **speech defect** -- adding "D' to words ending in "N"; like "What is Pakistan**d**"
  - **No-common-sense wagering** on "Daily Double" e.g., it bet only $5, when it was loosing $12,400 to $6,700, because one heuristics (rule) told it to not bet much if it had close to only half as much as opponent; The reasoning of the rule was to have enough to catch up in "Final Jeopardy" where contestants wager before given a final question
- Watson **built confidence** *(and therefore increase it's aggressiveness of play)* if it had just raced through a category
- Watson best with hard-facts unencumbered by **humor, slang, or cultural references**
- Watson, like Google search, **can't make inductive leaps** like Charles Darwin

2011 IBM Watson

From *"Smart Machines, IBM's Watson and the Era of Cognitive Computing,"*

by John E. Kelly III and Steve Hamm **2013**, Columbia University Press:

- Watson will eventually interpret **images**, numbers (it had problems with Roman Numerals), **voices**, and other **sensory information**
  - ***Neural Networks well-suited for this***
    - ***Do preprocessing, then feed to a cognitive core-brain***

- **Big Data"**

  The digital Universe is growing ~60% per year with **social media**, **sensor networks, and huge warehouses of business, scientific, and government records on-line**
  - **Coevolution of Computer Science and Medicine**
    - Billions of combinations of variables in **human genome** results in **15 to 20% of medical diagnoses inaccurate or incomplete**
  - **Urban Design & Planning**
    - Requires understanding inner workings of a city
    - **Human navigation**: At a busy intersection we instantly identify people, vehicles, buildings, streets, and sidewalks; and see how they interrelate . . . . . . ***difficult for driverless cars***

2011 IBM Watson

From ***"The Second Machine Age,"*** by Erik Brynjolfsson and Andrew McAfee **2014**, W Norton & Son Publishing:

- **Dr. Watson**" **matches** peer-reviewed medical literature to **patient symptoms, medical histories, and test results to formulate diagnosis and treatment**
  - Would take human 160 hours/week to do Watson's reading of Medical literature
  - IBM partnered with Memorial Sloan-Kettering Cancer Center
  - Watson **augments a physician's clinical expertise and judgment**
- Watson **not good at "Thinking outside the Box"** (**Ideation**, **Creativity**, **Innovation**)
- **Humans needed for idiosyncrasies and special cases** .. ***think about the risks of driverless cars***

2011 IBM Watson

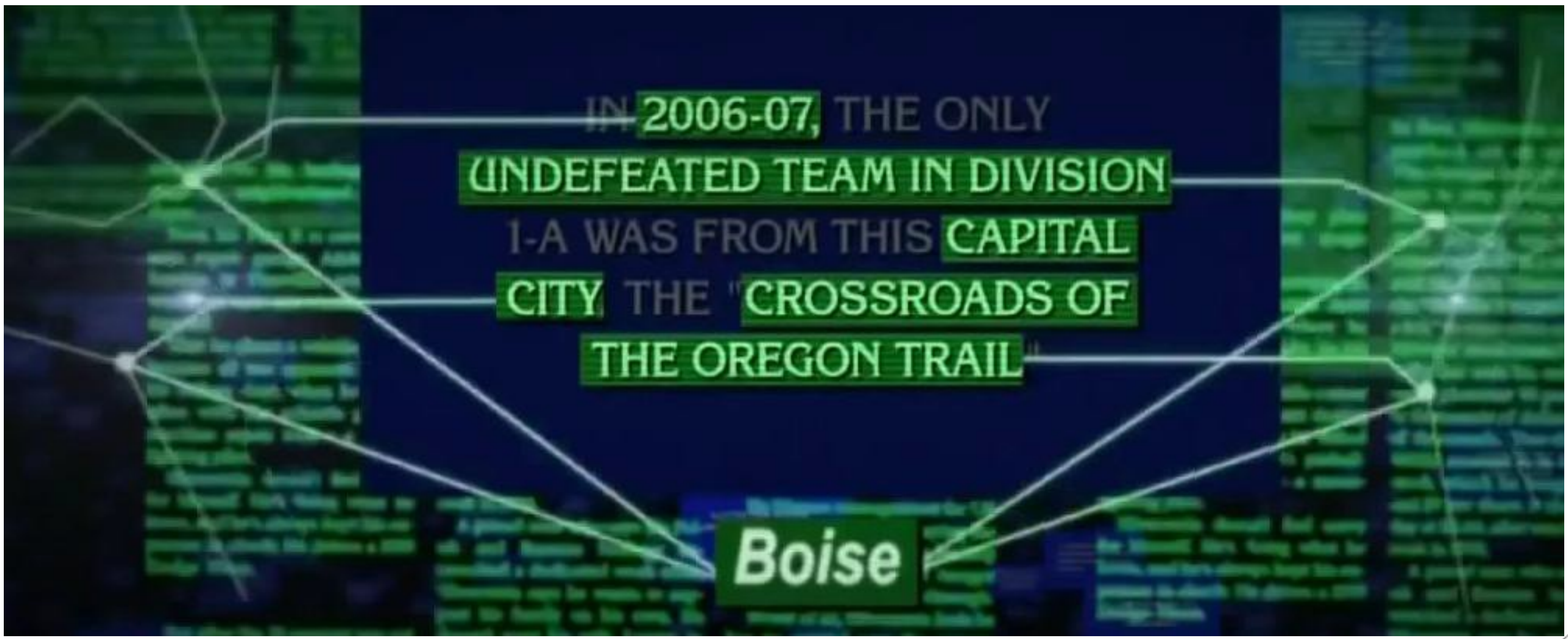
From: ***"IBM Watson: Smartest machine ever built,"*** **2015, PBS NOVA episode,**
https://www.youtube.com/watch?v=3zQI-LMcDnA

- Understanding jeopardy questions is difficult (also understanding categories)
- HCI **H**uman **C**ompute **I**nteraction is difficult **!!**
  - 100's of practice games with humans
- Parsing sentences to find correct meaning of a **double-meaning** sentence
- Jeopardy different than **well-defined rules of Chess**; also:
  - **Humans play chess more conceptually** (Control center, flank opponent)
  - IBM Deep Blue just did exhaustive search of all possibilities
- Compared to six million rules for human **Common Sense** in the software "Psych," IBM wanted Watson to be more flexible
- **2800 CPU's**
- **Disc Storage** included Bible, World Book Encyclopedia, all of Wikipedia, much of New York Times archive, the internet movie database, many books, plays, etc
- Since deaf (receives questions by text), **couldn't initially hear other answers**
- Unlikely to understand **overall meaning** in plays, parables, etc

2011 IBM Watson

From: ***"IBM Watson: Smartest machine ever built,"*** **2015**, PBS NOVA episode, https://www.youtube.com/watch?v=3zQI-LMcDnA

- Watson giving 10's of thousands of old jeopardy questions with correct answers
  - Watson looks for patterns
  - Then Watson looks for supporting evidence



2011 IBM Watson

From: ***"IBM Watson: Smartest machine ever built,"*** **2015**, PBS NOVA episode,
https://www.youtube.com/watch?v=3zQI-LMcDnA

- **Then weigh the evidence, on average, and calculate a <u>confidence</u> for all possible answers**

This original version of Watson was an advanced example of:

1) ***Natural Language Processing***
2) ***Statistical Analysis***

Watson, competing on the game show Jeopardy. The bars at the bottom show its confidence in each answer. If no answer passes the confidence threshold (the white line), Watson doesn't respond.

From 2015 ARS TECHNICA: "***Debugging the Myths about Artificial Intelligence***"
http://arstechnica.com/information-technology/2015/12/demystifying-artificial-intelligence-no-the-singularity-is-not-just-around-the-corner/

2014 IBM Watson

VIDEO: “**IBM Watson: How it Works,**” IBM: https://www.youtube.com/watch?v=_Xcmh1LQB9I

CONCEPTS:

- Observation/Evaluation/Decision-Making
- Unstructured Data (80% of the current Data on Earth)
- Natural Language Processing
- Context
- Intent
- Inferences

METHODOLOGY:

- “Corpos” body of relevant literature
- Curate Content
- “Ingestion” preprocessing (indexing & organizing)
- Machine Learning
    - “QuestionAnswer” pairs (by experts) for “Ground Truth”
- Continuous learning
- Evidence-based recommendations
- Yield of new inferences and patterns
- Hypothesis’ generation / evidence search / confidence
    - From weighted evidence scores Data
- Analytics to glean insights
    - Create inspirations for Human Experts to augment their decisions

2015 IBM Watson

Reference: ***"IBM Pushes Deep Learning with a Watson Upgrade,"*** **2015**, MIT Technology Review, https://www.technologyreview.com/s/539226/ibm-pushes-deep-learning-with-a-watson-upgrade/

"Deep learning involves training a computer to recognize often complex and abstract patterns by feeding large amounts of data through successive networks of artificial neurons, and refining the way those networks respond to the input"

"Combining disparate strands of AI research could become an important trend in coming years"

"Applying learning from one area, such as vision, to another, such as speech, is known as a multimodal approach. It could make future AI systems far more useful and could yield fundamental insights into the nature of intelligence."

2016 IBM Watson

Watch all of this Oxford University Video:

https://www.youtube.com/watch?v=rXVoRyIGGhU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