



National Aeronautics and Space Administration

Astronauts and IoT: Toward True Human-Autonomy Teaming

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Nordic Digital Business Summit 2016

Helsinki, Finland

22 September 2016



Overview

Three Themes

- Robotics and human interfaces progressing quickly but real AI not so much
- Human intelligence will remain unique and of great value for decades
- Not designing autonomous systems to interact with humans increases costs



Machine Intelligence

We appear to be at an exciting time with respect intelligent machines (again).

- **Four Related Areas of Development**
 1. Big Data - volume, velocity and variety
 2. Deep Learning
 3. Networked operations and cyber-physical systems
 4. Moore's Law (exponential growth, doubling of components on an integrated circuit every two years): faster, bigger computers driving change with increasing velocity
- **Stephen Hawking, Bill Gates and Elon Musk have all recently warned about the potential dangers of AI.**
- **Also interesting time in terms of self-driving cars and companies with robotic operations/factories like Amazon, Tesla and Toyota**
- **Big Blue, Watson, Pokerbot**
- **Google DeepMind AI Division beats human at GO (Jan 2016)**
- **First AI investment software hits Wall St. (Feb 2016)**



Manpower Reduction: Start with the Human (Not the Technology)

The Autonomy Paradox

(Blackhurst, Gresham & Stone, 2011)

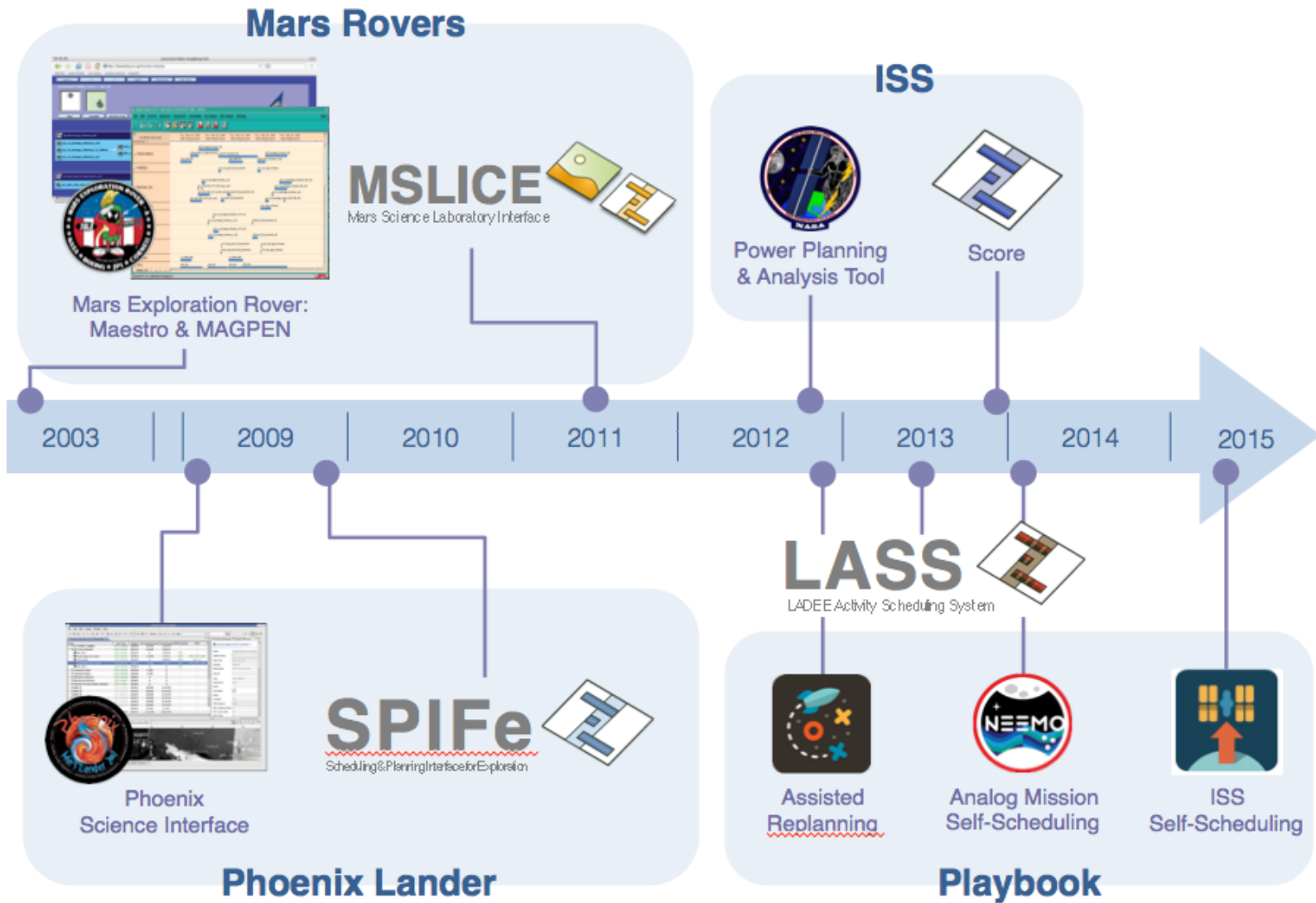
- Autonomy doesn't get rid of humans, it changes their roles
- DoD has shifted from Levels-of-Automation to Cognitive Echelons
- As machine intelligence advances, the need for better human interfaces increases



The Littoral Combat Ship
Built to be operated by 45 sailors



Path to Collaborative, Human-in-the-Loop Planning Systems





Toward Human-Autonomy Teaming?



Caged Robots



Domesticated Robots





Robots Designed for Teaming



...but still mostly caged *autonomy*



Generative, Adaptive Expertise

**Toyota replacing
some robots on the
factory floor with
humans**



**Rio Tinto working to
integrate humans in
with robotic mining
systems**



- When a robot is doing the work, the process stops improving.
- Improvement in non-deterministic environments requires adaptive expertise



Self-Driving Cars

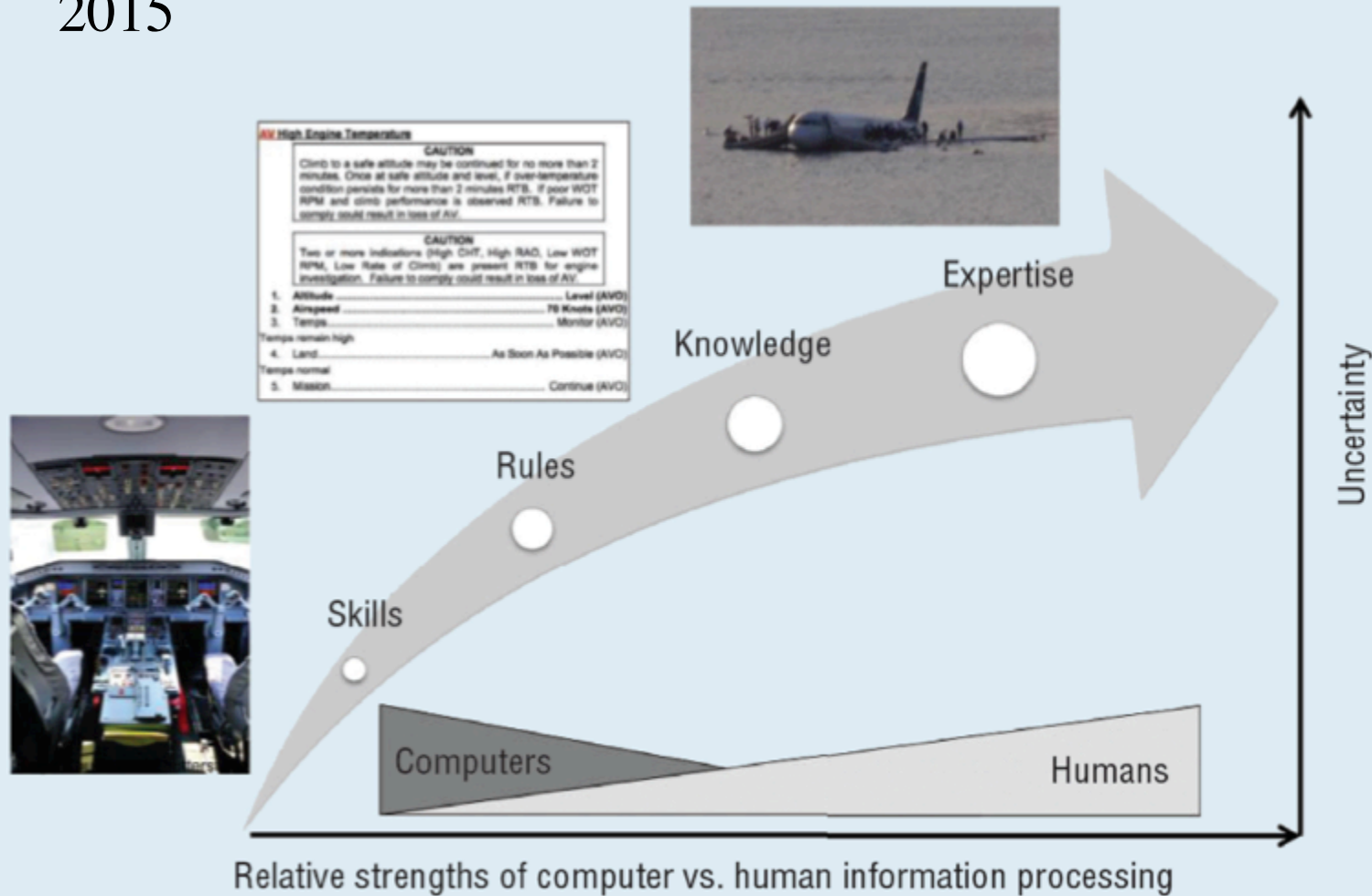
Driving: Low Cognitive Demand Task

- Does not necessarily indicate progress in machine intelligence relevant to performance in more complex decision-making and reasoning along the lines of expert humans.
- Last 5% challenge
- Control room v. return of control





2015



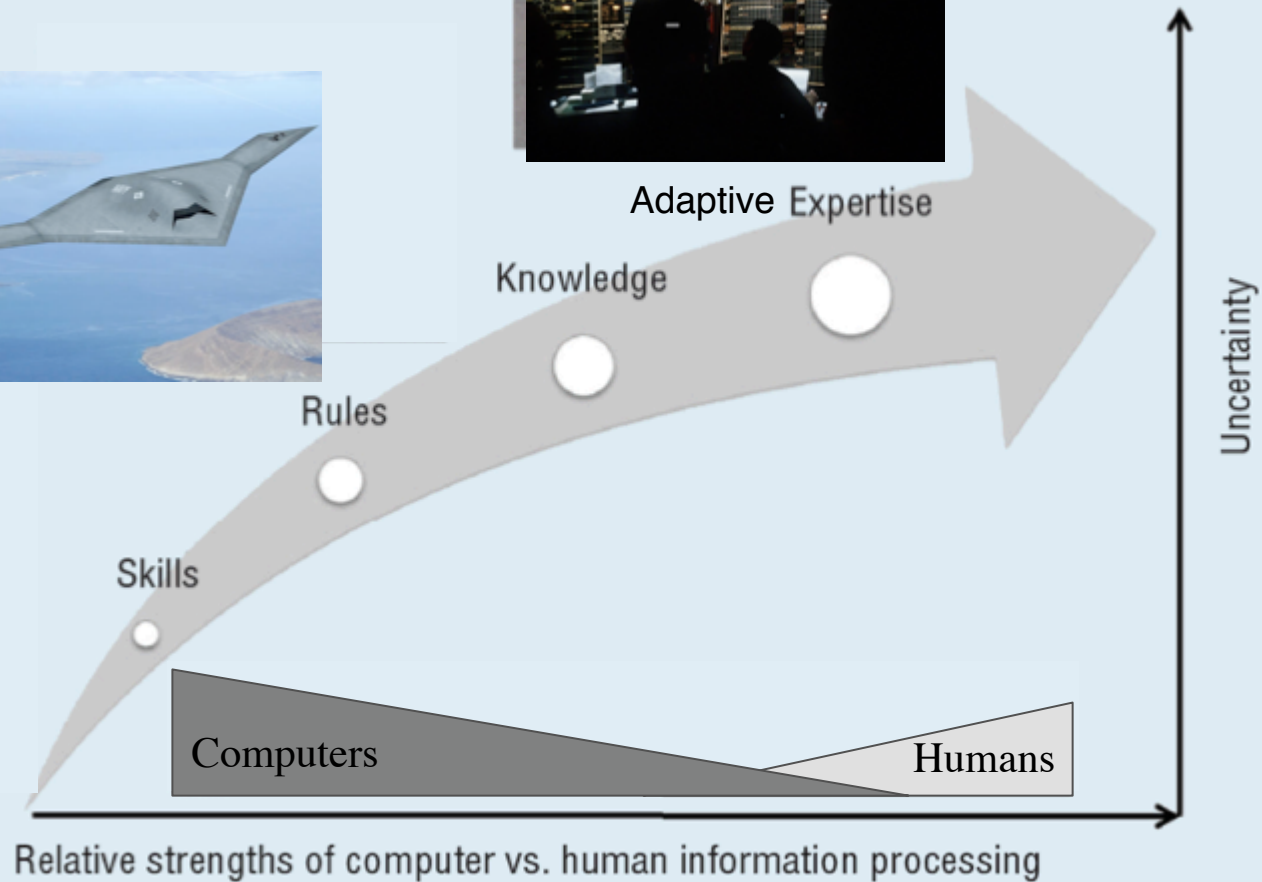
From Cummings, M.L., "[Man vs. Machine or Man + Machine?](#)" *IEEE Intelligent Systems*, (2014) 29(5), p. 62-69.



2035



e.g, current HITL
for ATM Next-Gen
research



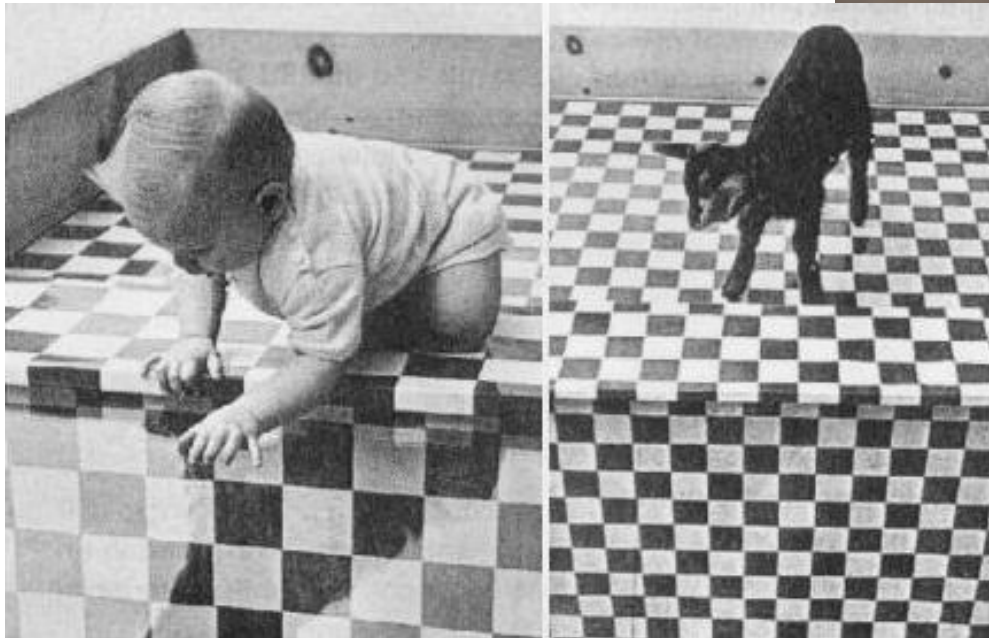
Architecture based on autonomy performing all skill and rule-based roles, as well as most knowledge-based roles. Manpower reduced by two orders of magnitude with remaining expert humans teaming with machine intelligence to solve complex problem solving under uncertainty. Machine intelligence for airspace management evolves from the outset to support teaming with small set of expert humans to support cooperative problem-solving.



Tabula Rasa?

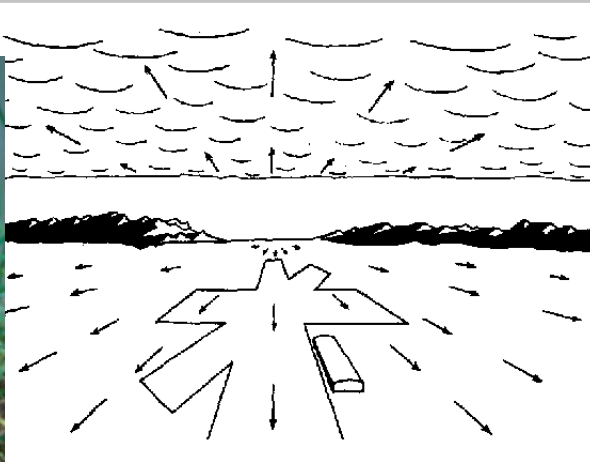
- **Animal perceptual systems attend to specific information from the visual environment**

www.mauromedia.com





Affordances from the Environment



idealised flowfield (after Gibson, 1950)





Human Cognitive Architecture not Tabula Rasa nor Randomly Constrained

- **Key characteristics of human problem solving:**
“Why did this happen?”
and “Can this be done better?”
 - Induction rather than deduction
 - More than knowing the answer to a question: what is the right question
- **Heuristics and biases**



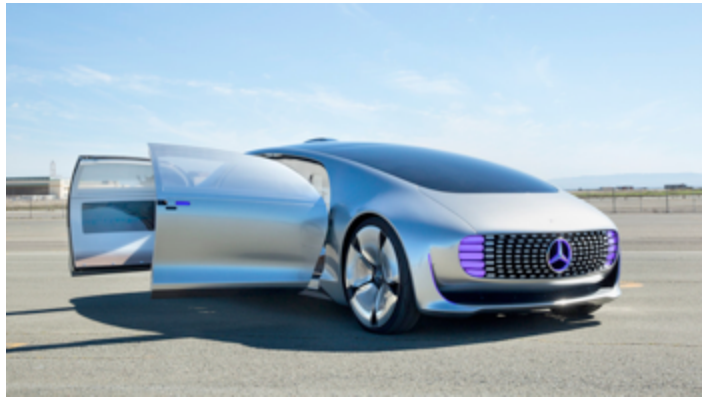
80 billion neurons



100,000
neurons



Using Affordances



- **Application of Gibsons' Ecological Psychology**
 - Alternatives to using human central attention resource
 - A car more like a horse



Big Data

Natural Language translation

- “Will Big Data spell the end of Theory?”

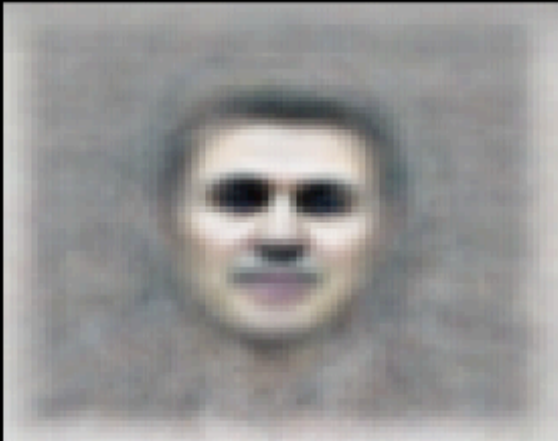


NASA has big data on the science side. Unfortunately, on engineering side, NASA has a big problem with data but not a big data problem.



Deep Learning

Neural Nets plus big data



Face detector



Human body detector



Cat detector

**Google Deep Learning Experiment: emergent images from
YouTube image analysis**



Deep Learning for Pattern Recognition

From Jeremy Howard's
TED Talk in Dec. 2014



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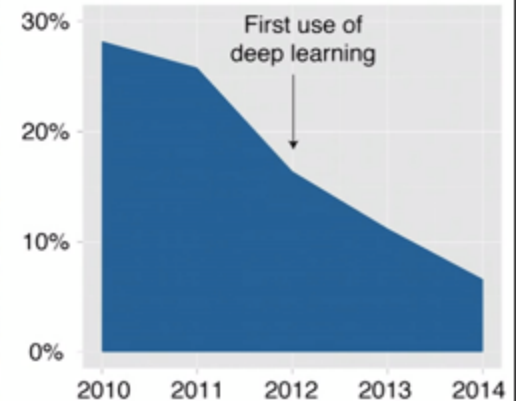
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ImageNet examples



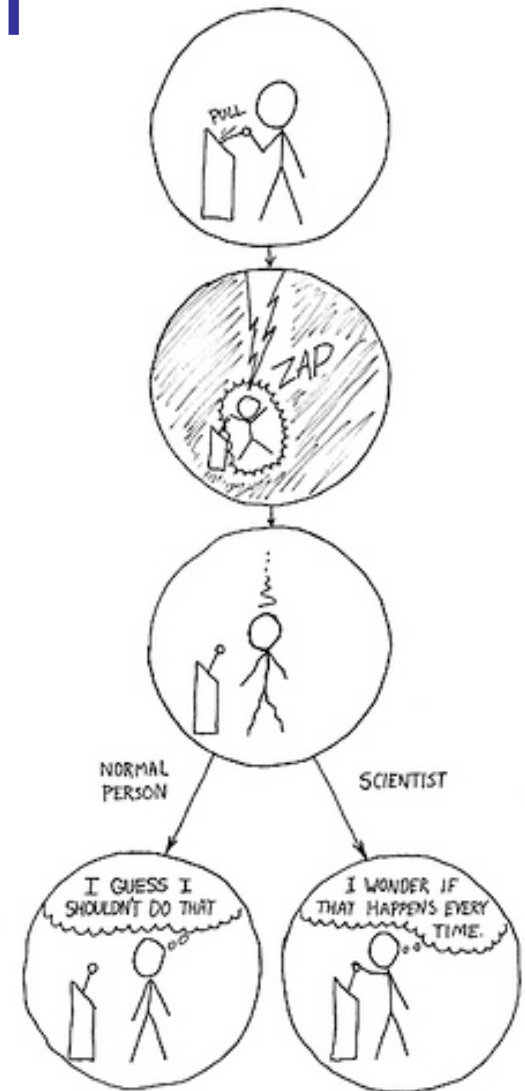
Object classification error rate





Correlation v. Causation

- **Humans: Causal reasoners based on contentful understading**
- **Machines: Correlational reasoners (a lot of data really helps)**
- **Human are poor at fast, systematic assessment of large data sets**
- **Humans are good at solving slow (hours to days) complex problems under uncertainty, where the outcome is based on successfully generating and evaluating causal explanations**
- **For humans, remarkably little exposure to data is needed to learn language in the first two years**
 - Internet of Things, Cyber-Physical Systems

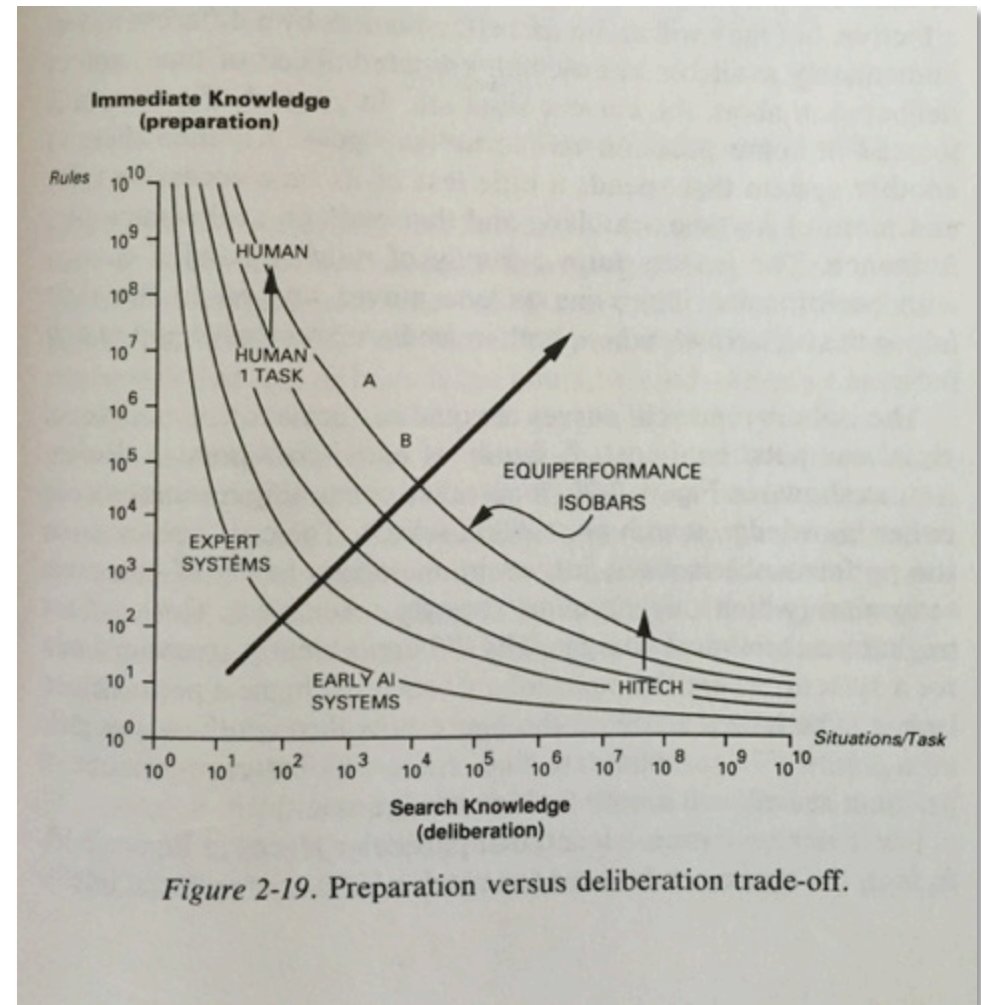




Adaptive v. Associative Expertise

From Newell, 1990

- Human and machine intelligence can arrive at equivalent solutions via different paths for certain classes of problems





Skills, Rules, Knowledge and Expertise

Adaptive Expertise: Problem Solving under uncertainty

- **Differentiate skill-based expertise, like driving and chess from adaptive expertise like innovative engineering or real-time control of complex systems.**
- **Using schemas, selective attention, chunking information, automaticity and more reliance on top-down information.**
- **10,000-20,000 hours on task**
 - This is one reason we start driving at 14-15 years old
- **Expertise in the performance of complex, knowledge rich tasks under a great deal of uncertainty not well understood. We know some humans do it well some of the time, but not how or why.**



Teaming of Human and Machine Intelligence

- Even as computers get very “intelligent”, it is very likely that the nature of their intelligence will be different than that of humans (unless they become omniscient or we program them to function just like humans)
- Humans are particularly good at adaptive problem-solving and discovery, areas where there has been little machine intelligence progress
- Successful efforts going forward will be those that wrap new machine intelligence capabilities around human competencies in order to get the most out of each

Goal: Design the human into the process. Focus on how the system will communicate its state to the human so that the human can help in un-anticipated situations.

What data and how it is presented such that you can impose human intuition on it.



Expertise and Big Data

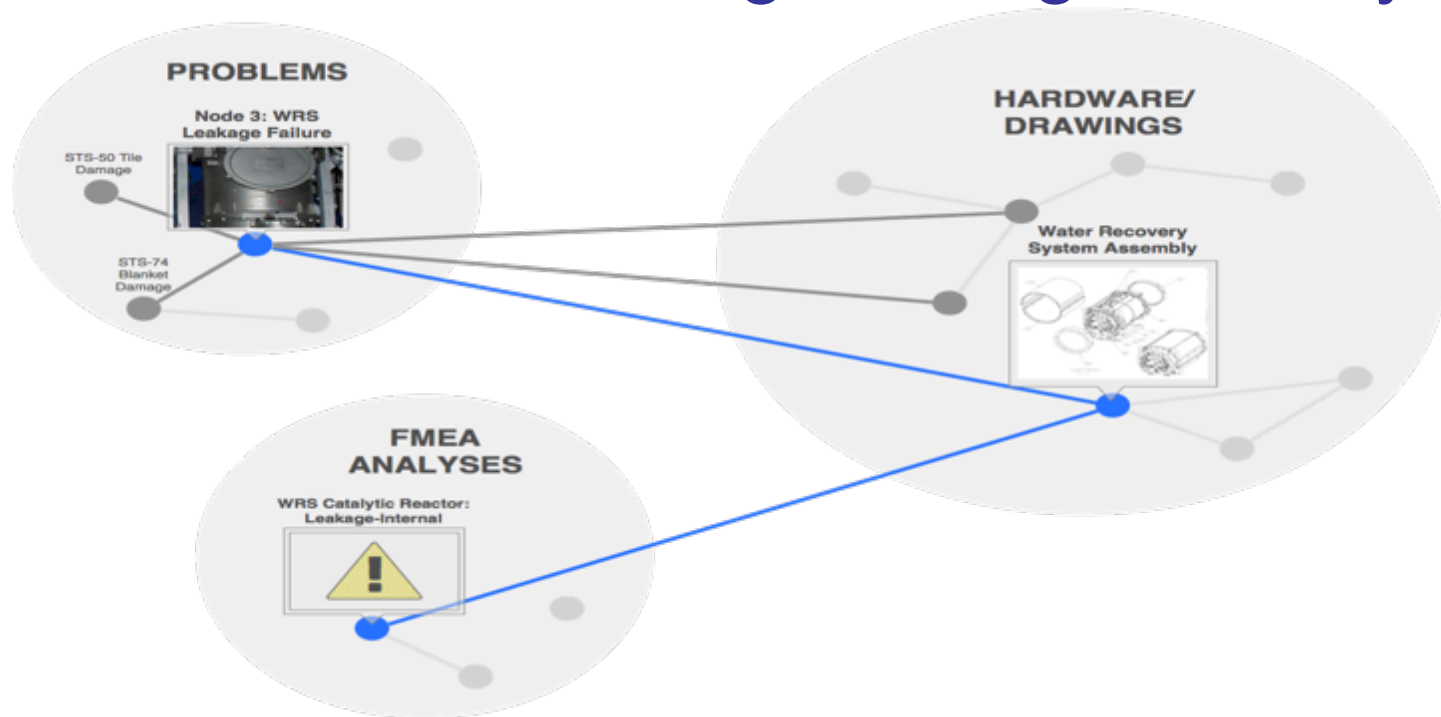
Endorsements on LinkedIn:

- From free text string skills “HCI” to a structured taxonomy of skills and suggestion capability
- To more consistently define skills across users and set up the infrastructure to support endorsements

The screenshot shows a LinkedIn profile's 'Skills & Endorsements' section. The top bar includes the LinkedIn logo, a search bar, and notification counts (37, 10, 135). Below the header, a 'Notify your network?' dialog box is visible, with a 'No' button selected. The main section lists 'Top Skills' with corresponding endorsement counts and a list of endorsing members' profile pictures. The skills listed are: Human Computer... (39), Artificial Intelligence (23), Human Systems... (22), Machine Learning (17), Simulations (14), Computer Science (13), Software Engineering (10), Cognitive Modeling (8), Human Factors (7), and User-centered Design (7). A pop-up window for 'Bonnie John' (1st) is overlaid, showing her profile picture, name, title 'Director of Computation and Innovation at...', and buttons for 'Send a message' and 'View Profile'. Below the skills list, a section titled 'Also knows about...' shows additional skills: Project Management (6), Algorithms (6), Science (6), and Research Design (6).



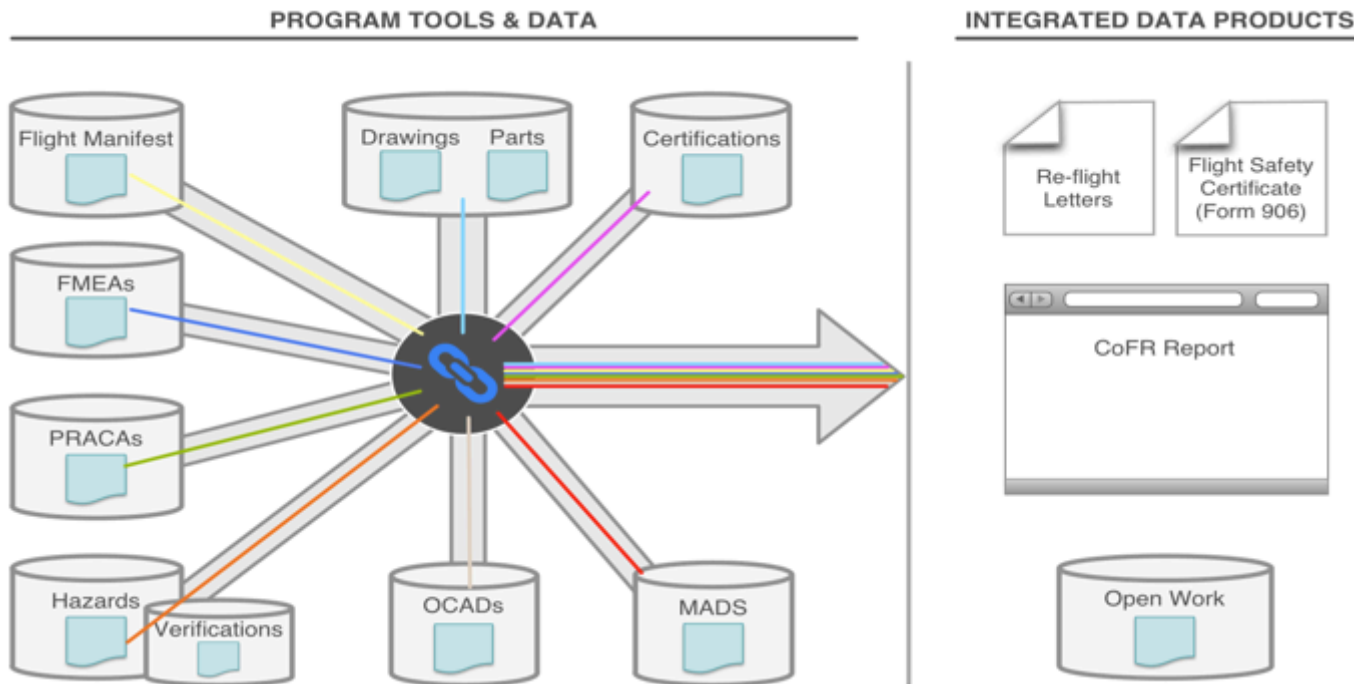
NASA's Small Data: Engineering & Safety



- If a failure occurs on a piece of hardware, what similar PRACAs have been filed in the past? What FMEAs and Hazards were related to that hardware — why were they not successful in mitigating the failure?*



NASA's Small Data: Engineering & Safety



- Enabling application and capture of human expertise to NASA's systems engineering processes
 - Structuring data and creating *persistent* links **as part of existing engineering processes**
 - Providing efficient access to data and knowledge over mission lifecycle, enabling **reuse** of output of ongoing engineering processes



The Economics of Human-Centered Automation

- **For lower costs, higher efficiencies and overall improved system performance:**
 - Characterize nature of human roles (skills, rules, knowledge, expertise) and tasks (e.g., proportion of hard and soft constraints)
 - Wrap autonomy around remaining human roles from the beginning

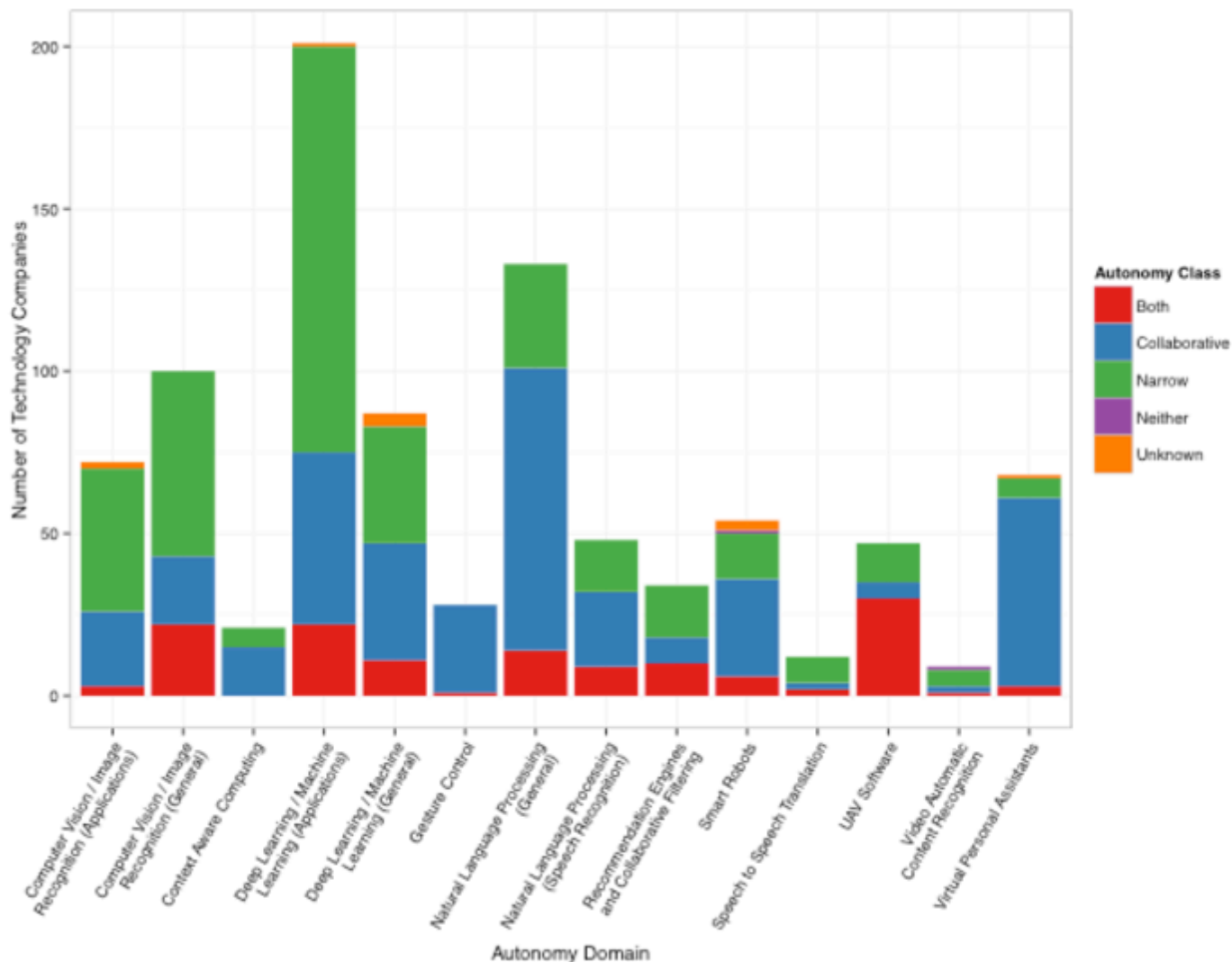
Critical to shape the autonomy industry

- e.g., *Apple v. Littoral Combat Ship*





Investment in Artificial Intelligence





Autonomy in Non-Deterministic Environments

- **Mars Rovers 5-25 meters**
- **Challenges for self-driving cars: the last 5%**
 - What is the role of humans in control centers and what information do they need to have?
- **Communicating with humans**
- **Putting humans in the context**
 - “Most of the information pilots have comes from their rear end”
- **Keeping humans in the loop**



Final Thoughts

- **Humans will remain important components of complex systems**
- **Use human adaptive expertise as much as possible**
- **Use human perceptual system as much as possible in interactions with big data sets**
- **Robotics progressing faster than AI**
- **Be aware of areas where you don't have big data**
 - Not all problems are associative in nature
- **Don't assume search will solve all problems**



Ames Research Center



Thank you