

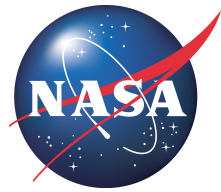


# Multiple Views on Safety-Critical Automation: Aircraft, Autonomous Vehicles, Air Traffic Management and Satellite Ground Segments Perspectives

Special Interest Group

5/9/2016

# Engineering Automation in Interactive Critical Systems



## Similarities:

- Automation behavior is not well understood
- Environment is not well understood
- Evaluation is very expensive

## Differences:

“Failure isn’t an option” – Apollo 13

- very small beta test community
- Tightly coupled, highly dynamic, - perrow



# 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



# 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



## **The Littoral Combat Ship**

**Built to be operated by 45 sailors**

Dr. Larry Shattuck, NPS (pg. 13-15)

<http://human-factors.arc.nasa.gov/workshop/autonomy/download/presentations/Shaddock%20.pdf>



# 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**



# 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



20 billion neurons



100,000 neurons





# Self-Driving Cars

- **Driving: Low Cognitive Demand Task**

- Does not necessarily mean 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

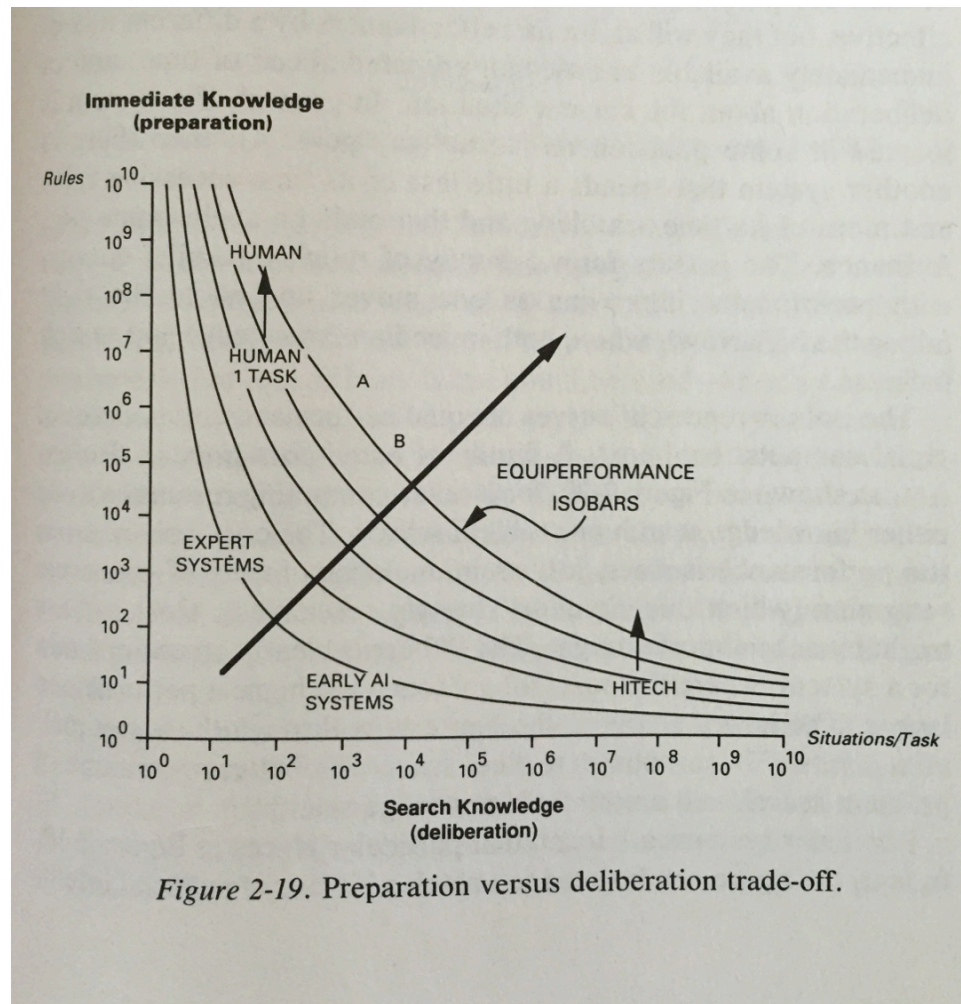






# Adaptive v. Associative Expertise

- 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.

# Defining the Mission



## How well can we describe the work?

- **Background:**
  - Difficult problem (CTA 15+ year history)
  - Time with domain experts is expensive and limited
  - Accurate task descriptions are critical
  - Current task analysis methods request detailed action sequence information, which is time consuming, and problematic
- **Focus Issues:**
  - How can we involve domain experts in the task analysis process most efficiently?
  - How can identify work structures and prioritize important work themes?
  - What level of description detail is necessary?
    - Need performance metrics/utility functions



# 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)

# High – Level Problem Areas in Human Automation



**Research Objective I.** *Determination of the Relative Abilities of Humans and Machines to Perform Critical Functions...*

**Research Objective II.** *Determination of the Capacities of Human Operators for Handling Information in a Communication System.*

**Research Objective III.** *Determination of the Essential Information Required at every -Stage in the Operation of an Air-Navigation and Traffic-Control System.*

**Research Objective IV.** *Establishment of Criteria and "Indices-of-Merit" for Human-Operator and Human-Machine Performance.*

**Research Objective V.** *Determination of Principles Governing the Efficient Visual Display of Information.*

**Research Objective VI.** *Determination of Optimum Conditions for the Use of Direct Vision.*

**Research Objective VII.** *Determination of the Psychological Requirements for Communication Systems.*

**Research Objective VIII.** *Optimum Human-Machine Systems Engineering.*

**Research Objective IX.** *Maximum Application of Existing Human-Engineering Information.*



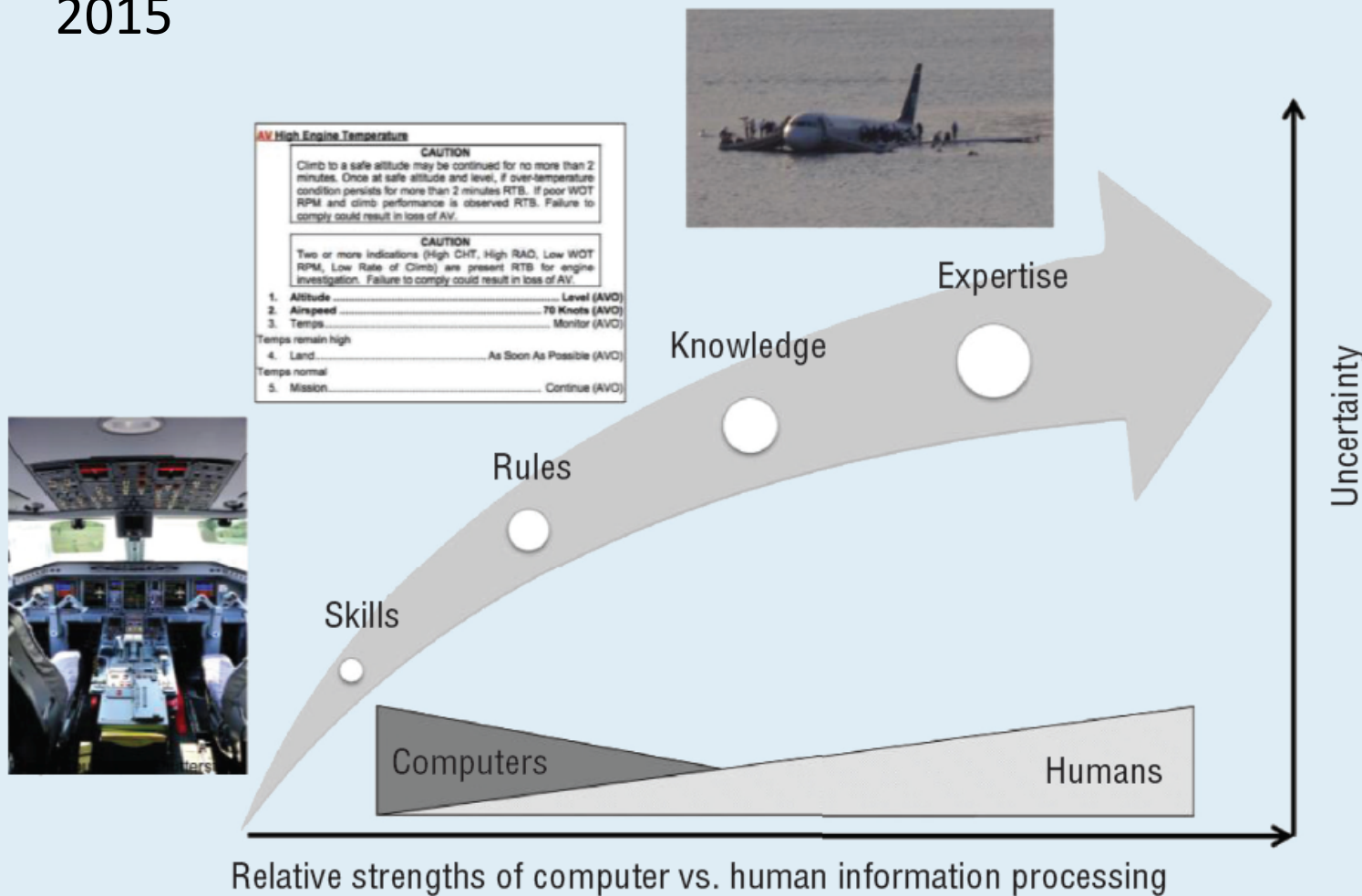
# Teaming of Human and Machine Intelligence

- 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 it’s 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.*

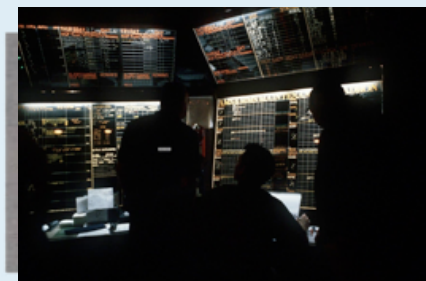
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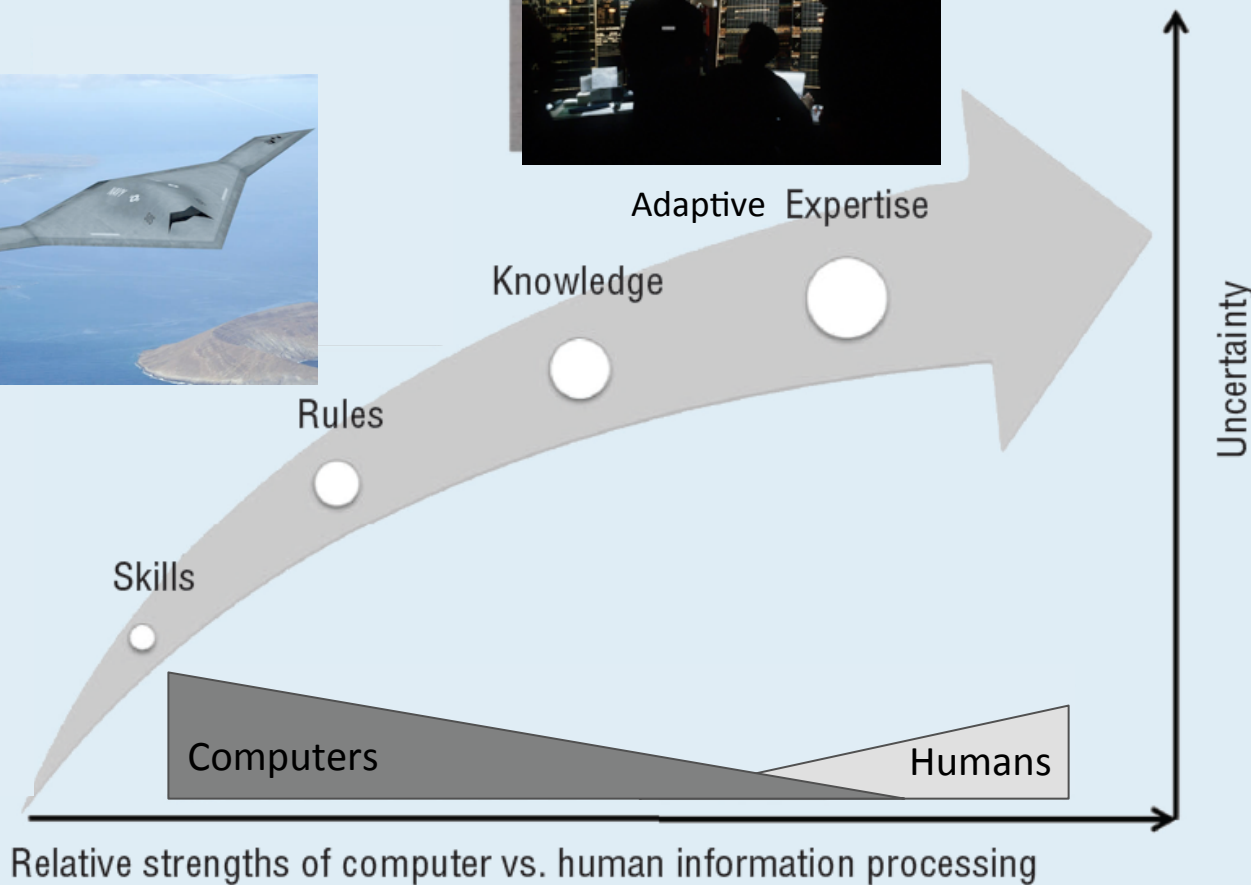




2035



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.

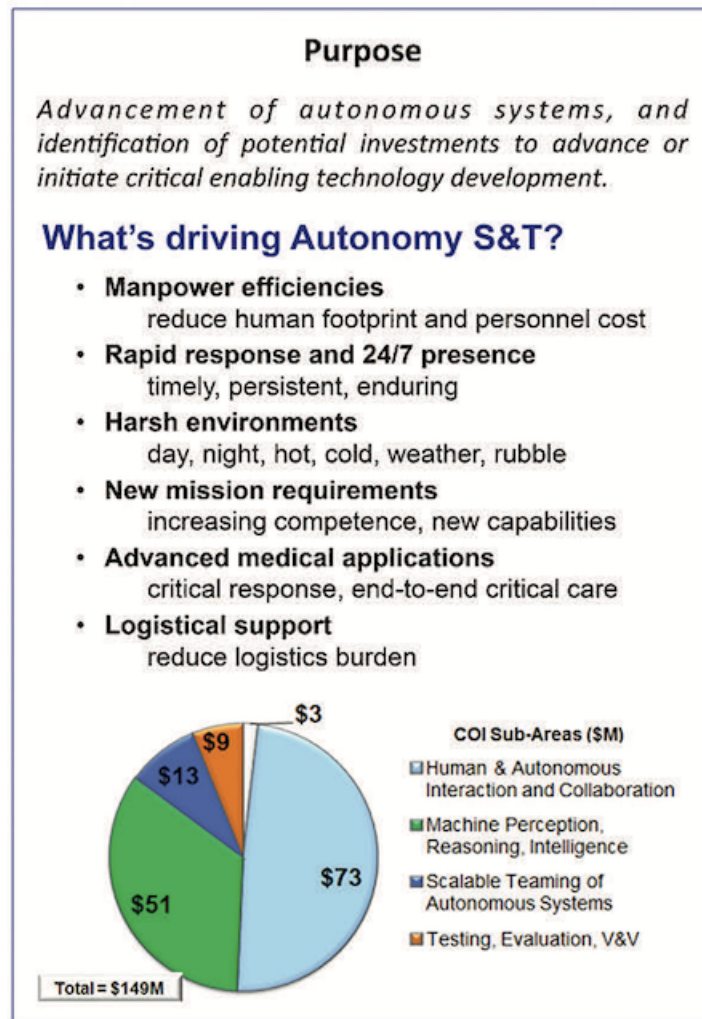


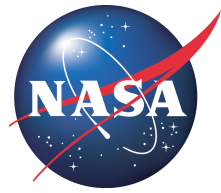
# The Economics of Human-Centered Automation

- 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*





# Autonomy in Non-Deterministic Environments

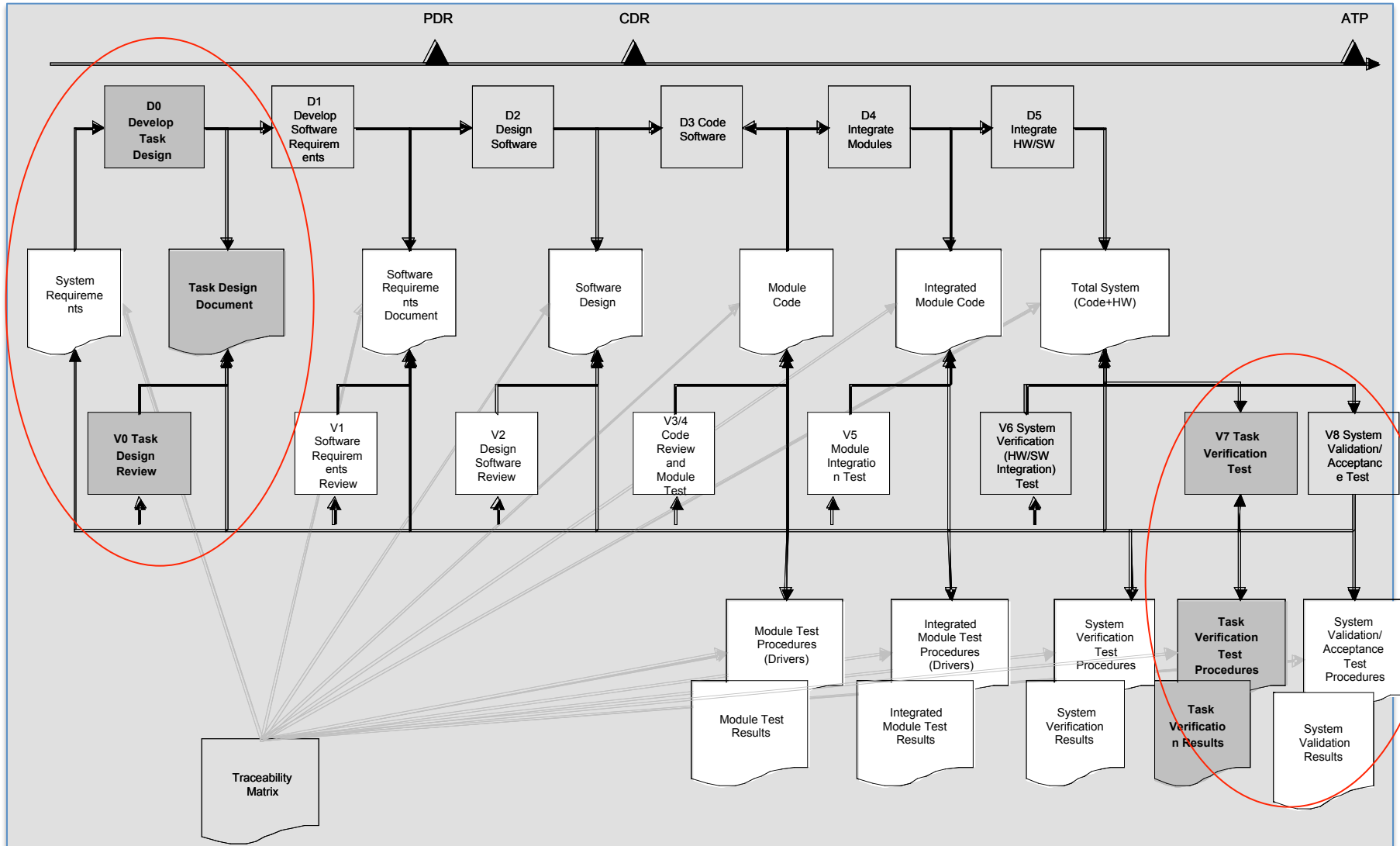
- - Mars Rovers 5-25 meters
- Challenges for self-driving cars: the last 5%
  - What is the role of humans in control centers and what information do they have?
    - Questions from recent Nissan work
- Communicating with humans
- Putting humans in the context
  - Most of a pilots information comes from his 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

# Automation Task Design and Verification



(Sherry, Feary)



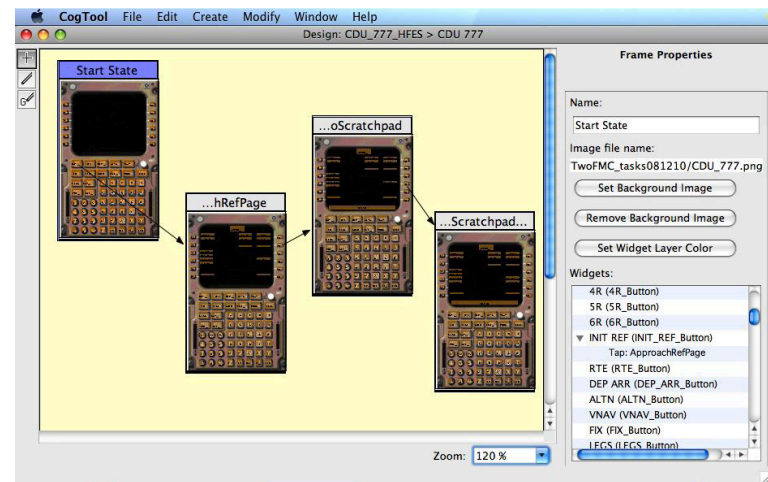
# Making Analysis Affordable

## Aviation Cogtool Explorer with Semantic Analysis (Carnegie-Mellon Univ.)

- Combined a tool that allows a designer to quickly build a representation of a procedure, then analyze it with multiple techniques including:

- Information foraging analysis for pilot attention

- Latent semantic analysis for pilot cognition, based on an aviation “corpus” database that simulates the knowledge of typical airline pilots



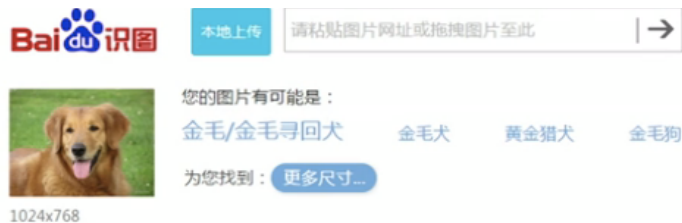
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Mode Keys	mode keys init	0.18	Heading	mode keys init
Keyboard alphanumeric	keyboard alph	0.14	Heading	keyboard alpha
Function Keys	function keys	0.11	Heading	function keys
2R Flaps 30 degree	2R Flaps 30 de	0.49	Link	LCD screen display
1R Flaps 25 degree	1R Flaps 25 de	0.47	Link	LCD screen display
4R Flap Speed Enter	4R Flap Speed	0.39	Link	LCD screen display
INIT REF Initialization	INIT REF Initia	0.32	Link	Mode Keys
3L Landing Ref reference	3L Landing Re	0.27	Link	LCD screen display
6L Index IDENT identifier	6L Index IDEN	0.21	Link	LCD screen display
4L EGLL27R 12108	4L EGLL27R 1	0.18	Link	LCD screen display
A B C D E F G H I J	A B C D E F G	0.14	Link	Keyboard alpha
FMC COMM Flight Management	FMC COMM Fli	0.12	Link	Mode Keys
MENU aircraft subsystem	MENU aircraft	0.09	Link	Mode Keys
CLR clear from screen	CLR clear from	0.09	Link	Function Keys



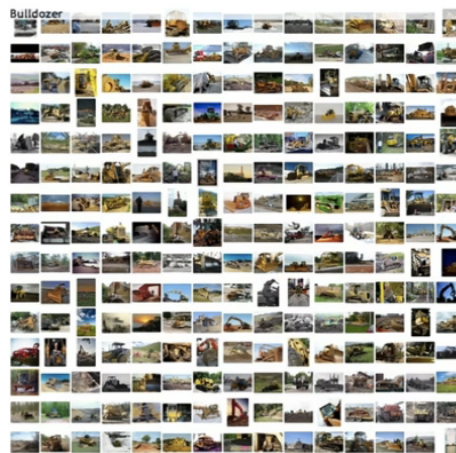


# Deep Learning for Pattern Recognition

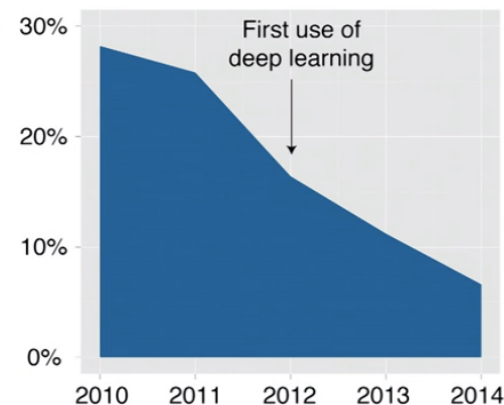
- From Jeremy Howard's TED Talk in Dec. 2014



ImageNet examples



Object classification error rate



相似图片

全部相似图片





# Thank You

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