Human-computer sensemaking models and the challenges of incorporating artificial intelligence

Peter Pirolli
Institute for Human and Machine Cognition

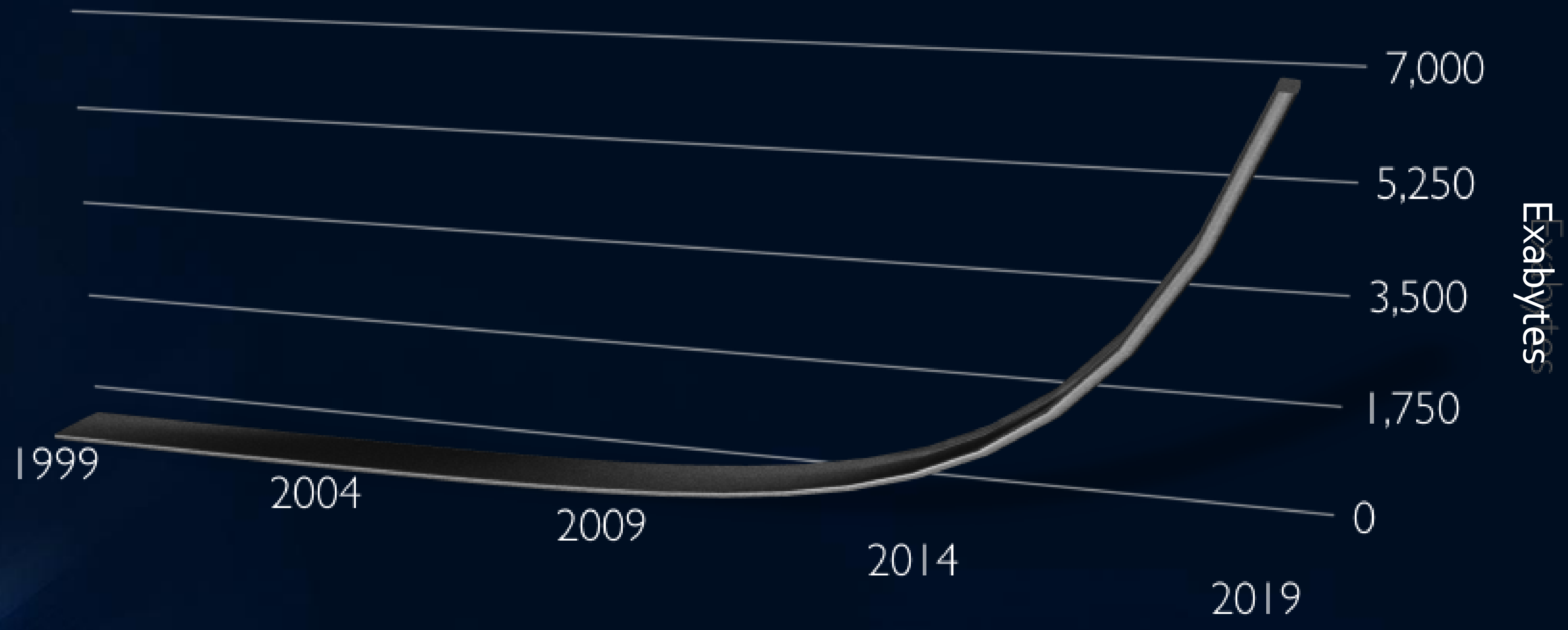
Overview

- Multi-level models of sensemaking
  - Computational models that predict the cognition and performance of users of sensemaking systems
- Augment the intelligence of humans engaged in sensemaking
  - By increasing the rate of gain of knowledge from information systems
- Challenges of artificial intelligence

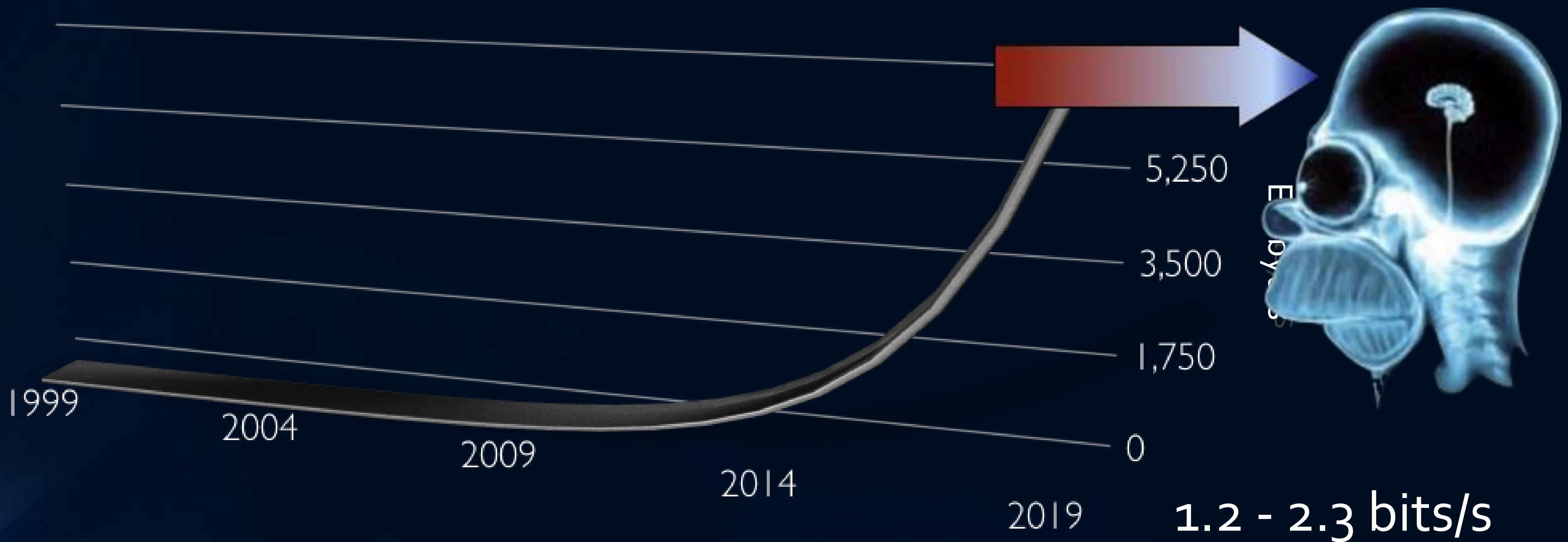
Human-Computer Interaction + Cognitive science

- New computer applications benefit from sound cognitive science.
- Interactive digital systems are a testbed for advanced theories of human cognition.

Challenge:
Adaptation to the Volume of Information



Challenge:
Adaptation to the Volume of Information

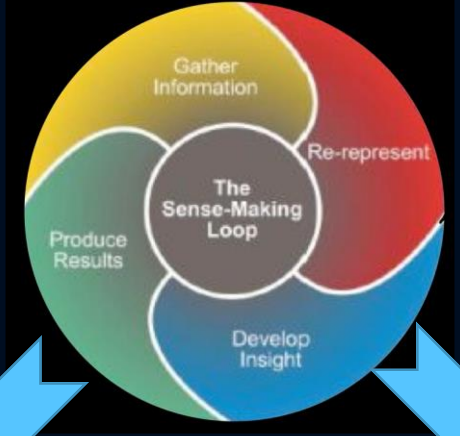


1.2 - 2.3 bits/s

Sensemaking

- Characteristics
  - Massive amounts of data
  - Ill-structured task
  - Organization, interpretation, insight needed
  - Output, decision, solution required
- Examples
  - Understanding a health problem and making a medical decision
  - Buying a new laptop
  - Weather forecasting
  - Producing an intelligence report

Image source: http://www.cs.stonybrook.edu/~mueller/teaching/cse591_visAnalytics/



Augmented Human Intellect

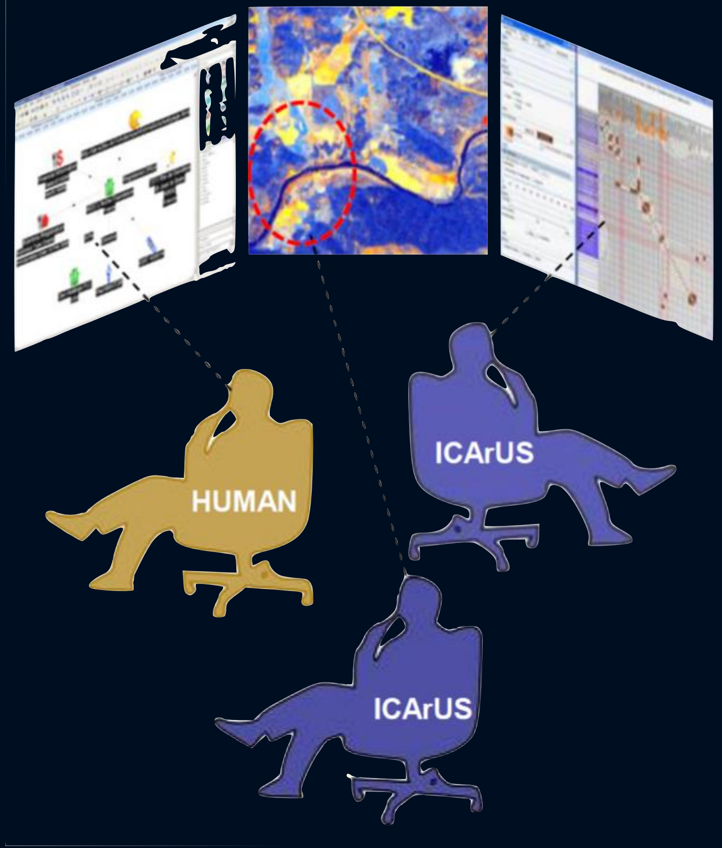
New information technologies to augment human intelligence

Cognitive Science

Rigorous scientific & engineering models of human sensemaking

- *Useful (valuable) knowledge* improves the utility of an inference, decision, action, problem solution…
- We can improve human intelligence by *increasing the rate of useful knowledge gained* as a function of interaction time
- Not just "more information" or more data
- Often may include system improvements that reduce cognitive *bias*, increase *accuracy* of assessments of system/source capabilities, *trustworthiness*, and *credibility*

Example:
Geospatial Intelligence Analysis



IARPA
BE THE FUTURE

Example:
Geospatial Intelligence Analysis

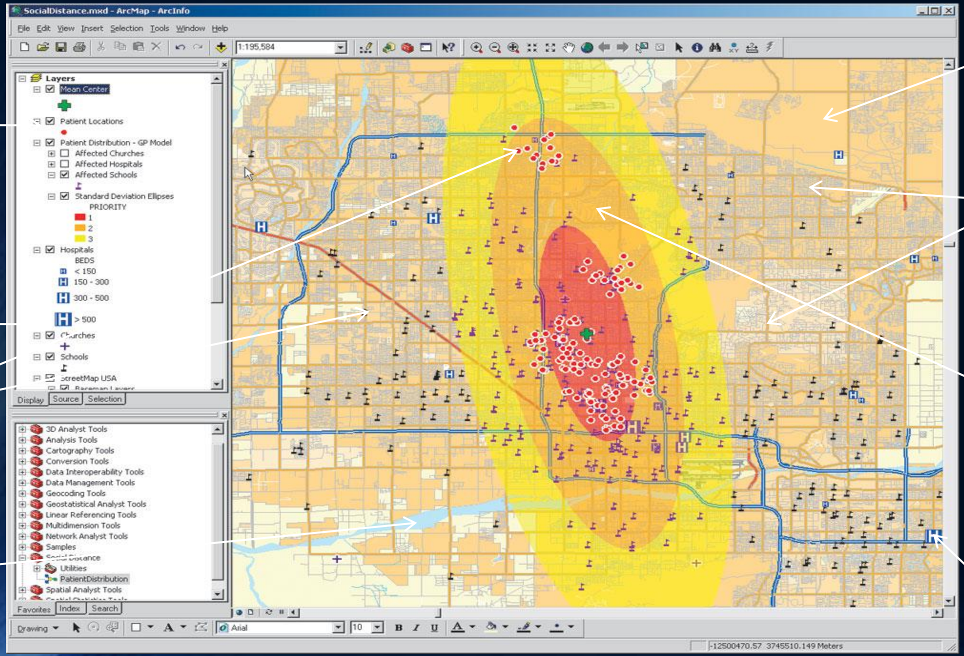
- Forage for information
- Choose layers, filter information, etc.…

Typical GIS display for geospatial analysis

Multiple data layers (for individual or composite viewing)

Significant incidents and activities

Natural objects (e.g. rivers)



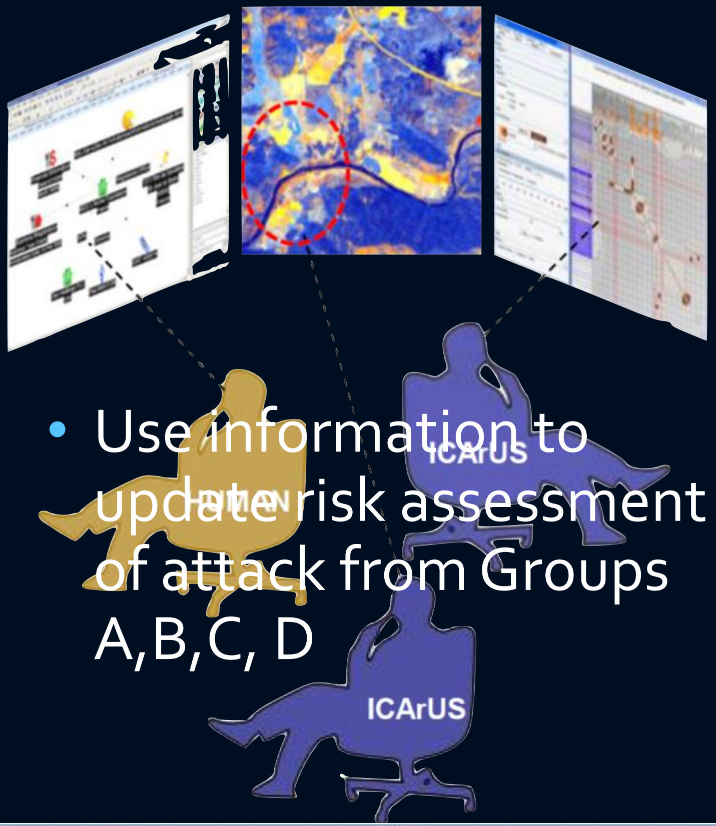
Terrain features (physical, socio-cultural, other)

Built environment (e.g., buildings and roads)

Probabilistic representations / standard deviation ellipses (e.g. location of signal source)

Significant objects / structures

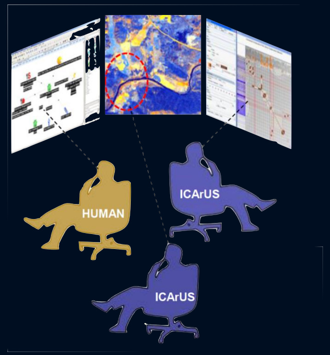
http://get4share.com/forum/free-download-esri-arcgis-desktop-v9-2-a-2516.html



- Use information to update risk assessment of attack from Groups A,B,C, D

INTs	Description
IMINT	If A or B attack then the attack is four times as likely to occur on a *Government* vs. *Military* building If C or D attack then vice versa
MOVINT	If A or C attack then the attack is four times as likely to occur on a *Major* vs. *Minor* road If B or D attack then vice versa
SIGINT	If SIGINT on a group reports *chatter*, then attack by that group is seven times as likely as attack by each other group If SIGINT on a group reports *silent*, then attack by that group is one-third as likely as attack by each other group
SOCINT	If a group attacks then that group is twice as likely to attack in tis *own* vs. *other* region

Levels of Information Interaction



Scale	Time Unit	Band
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10^6 s	Weeks	Social/Organizational
10^5 s	Days	
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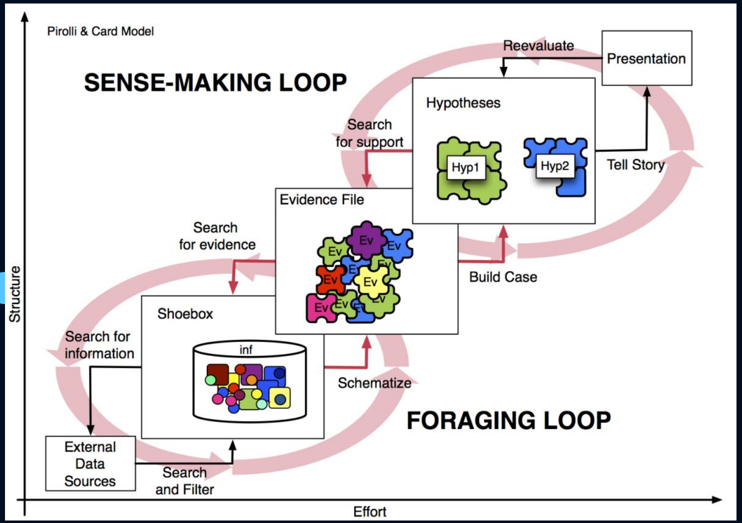
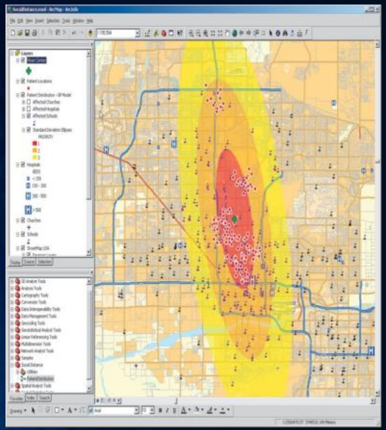
Macrocognitive Model
Information Foraging Theory

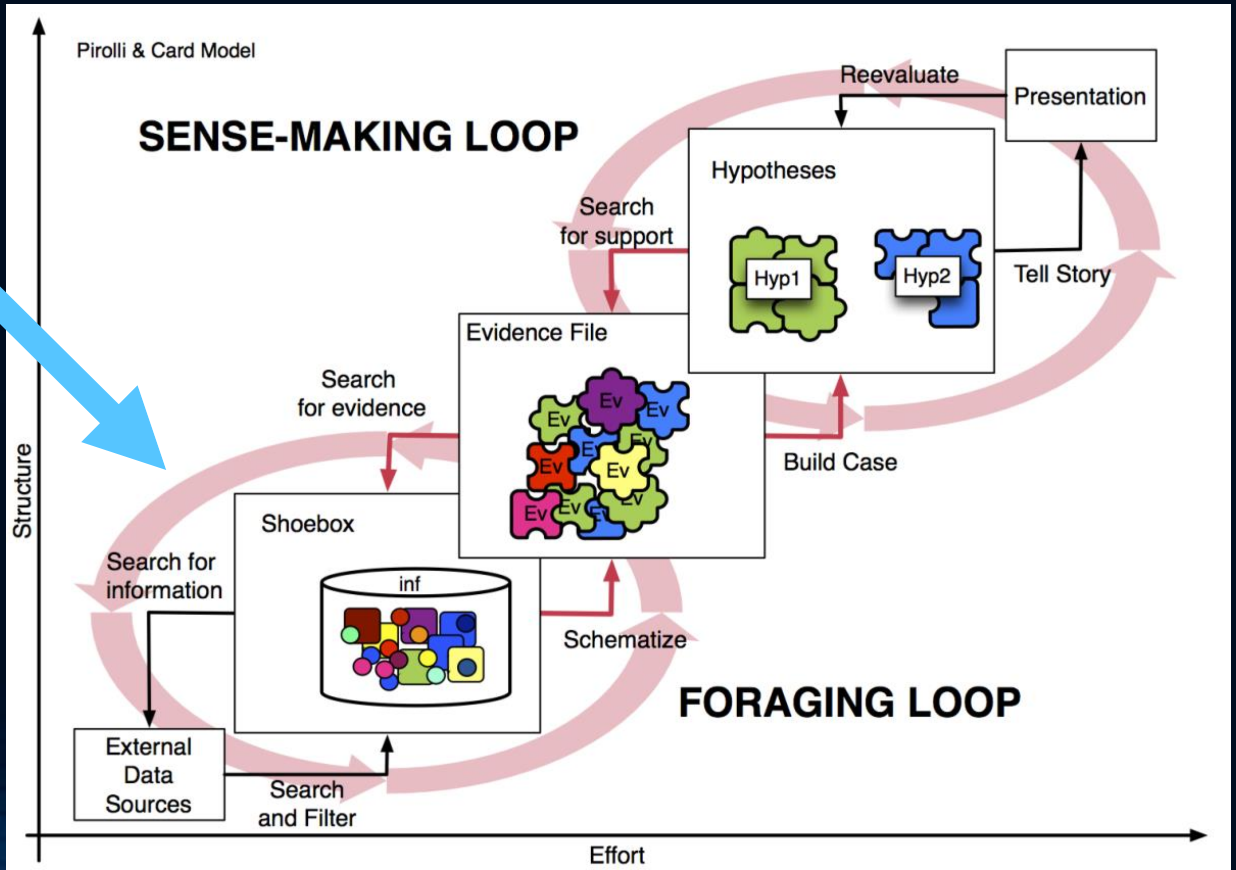


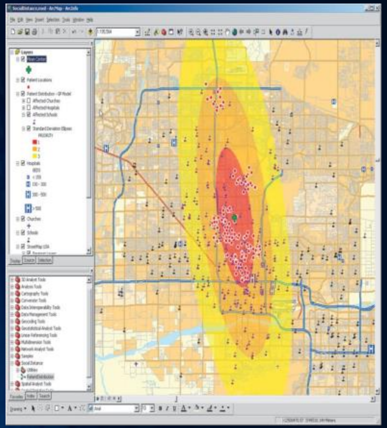


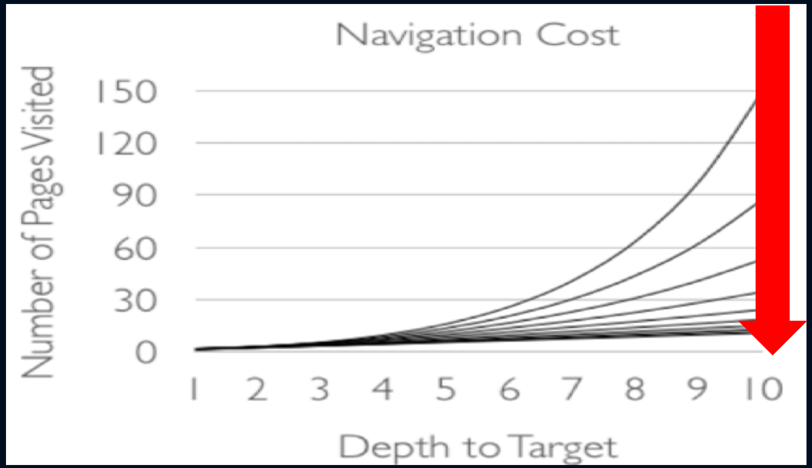
What information should I seek?

Rational Level Analysis

- Information Foraging:

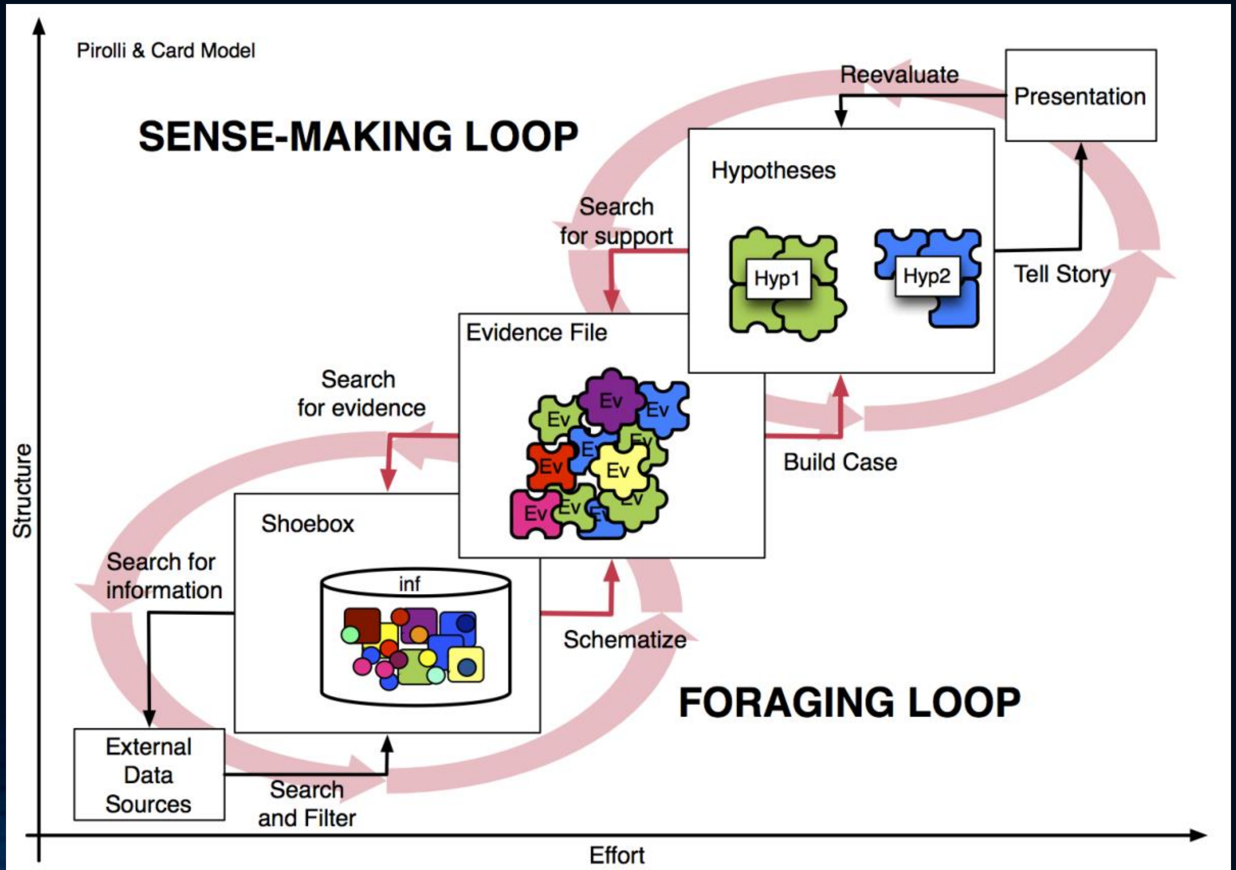


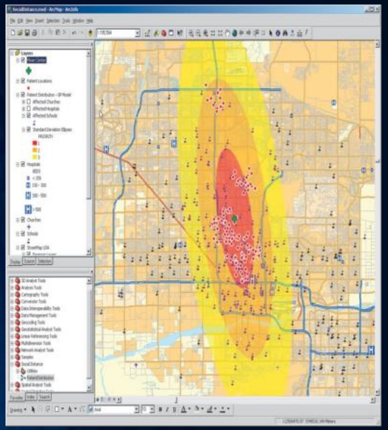




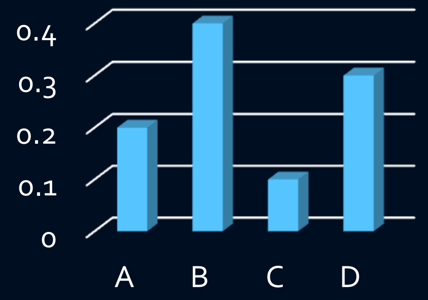
Rational Level Analysis

- Information Foraging:
  - Humans optimize their information foraging to increase knowledge gained and reduce interaction costs





What is the risk of attack from Group A, B, C, D?



Rational Level Analysis

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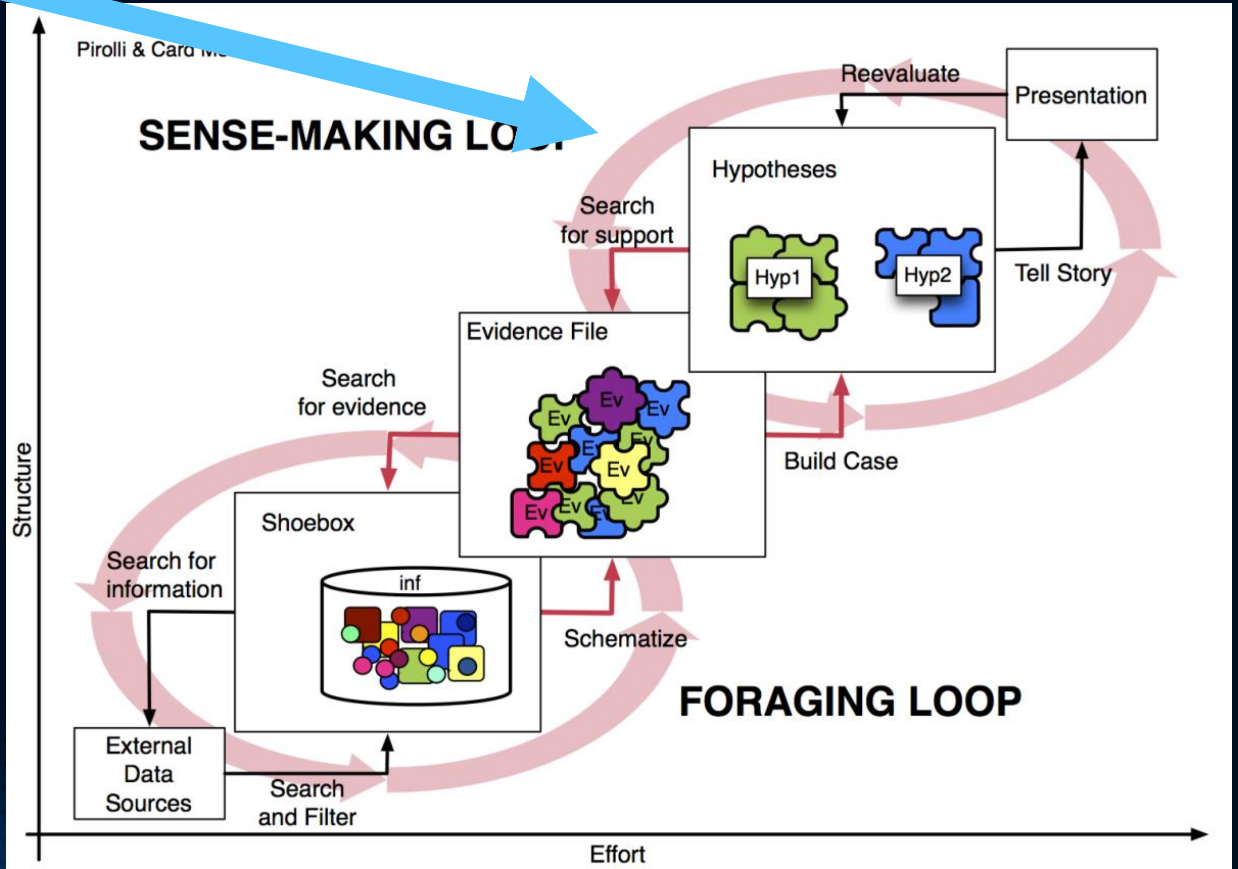
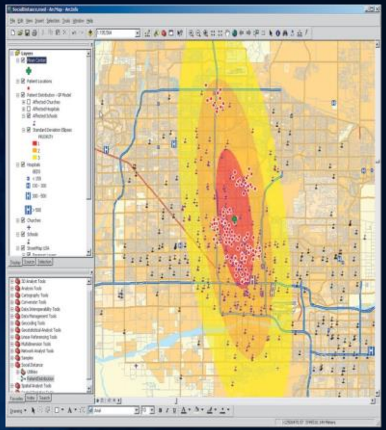
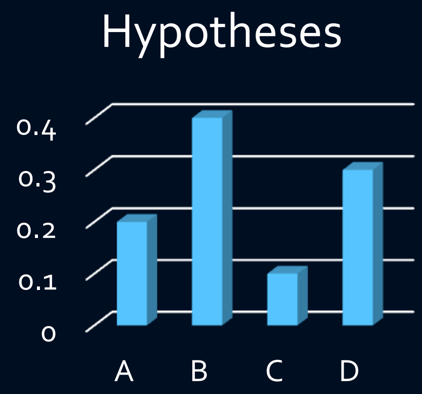
- Sensemaking:



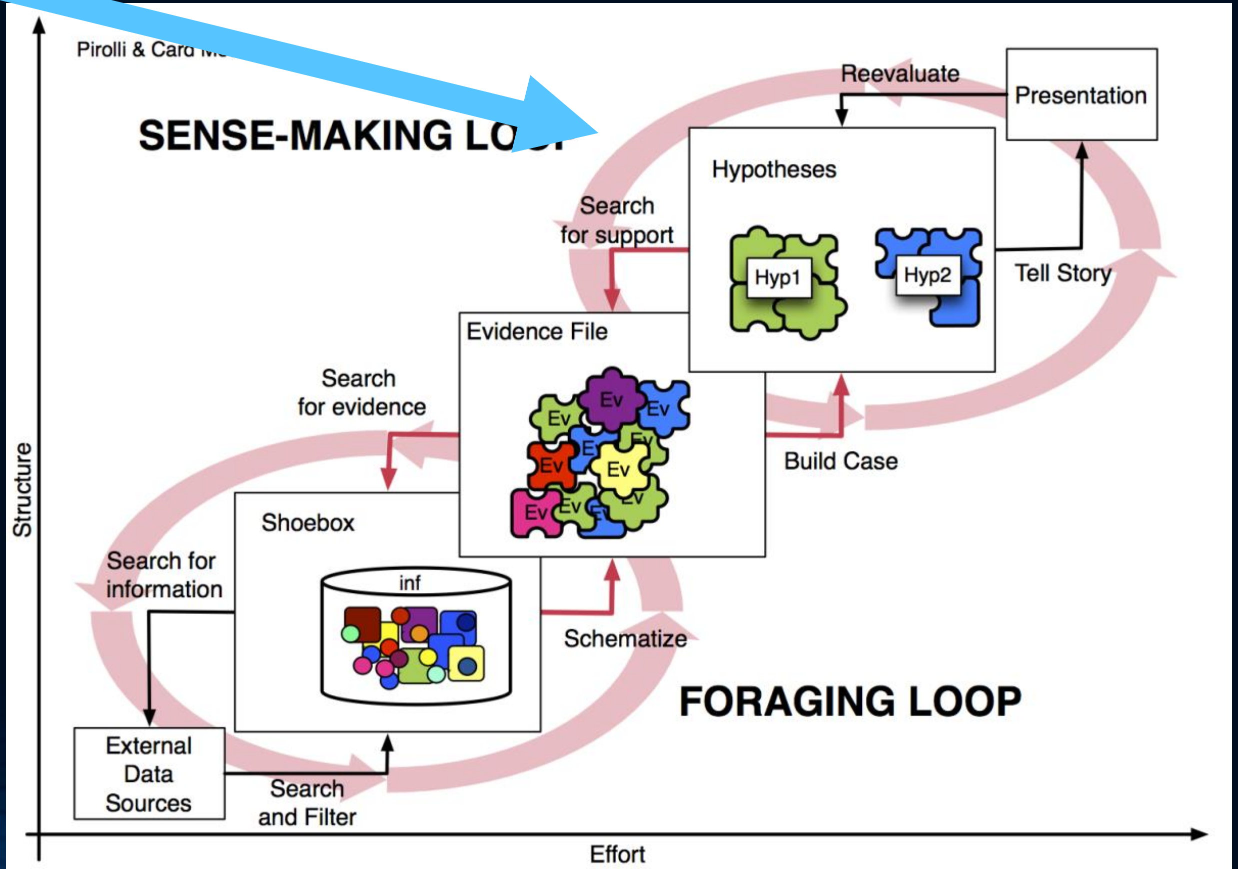


$$\Pr(H|E) = \frac{\Pr(E|H)}{\Pr(E)} \Pr(H)$$



Rational Level Analysis

- Information Foraging:
  - Humans optimize their information foraging to increase knowledge gained and reduce interaction costs
- Sensemaking:
  - Humans approximate rational (Bayesian) selection of evidence and hypothesis updating



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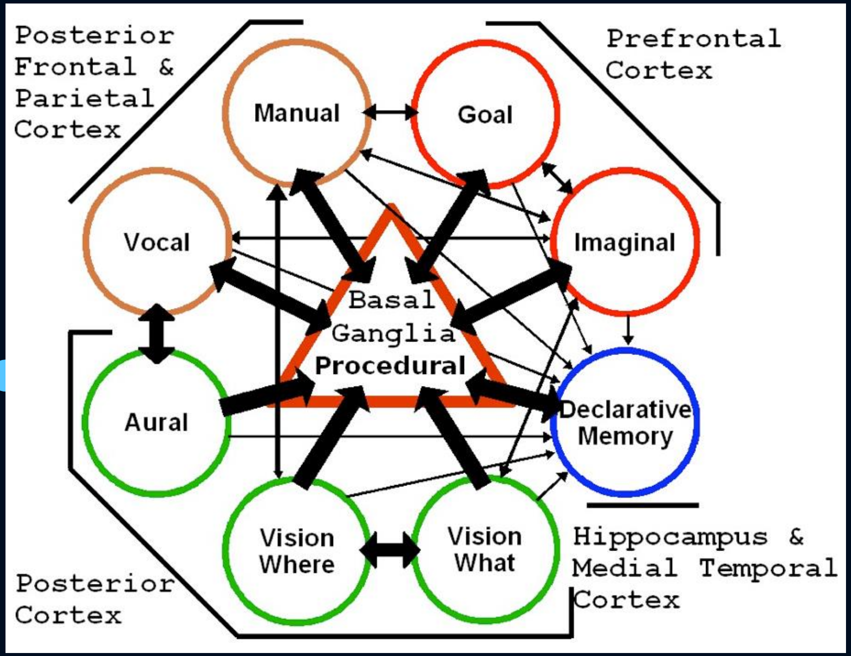
Functional Cognitive Model (ACT-R)



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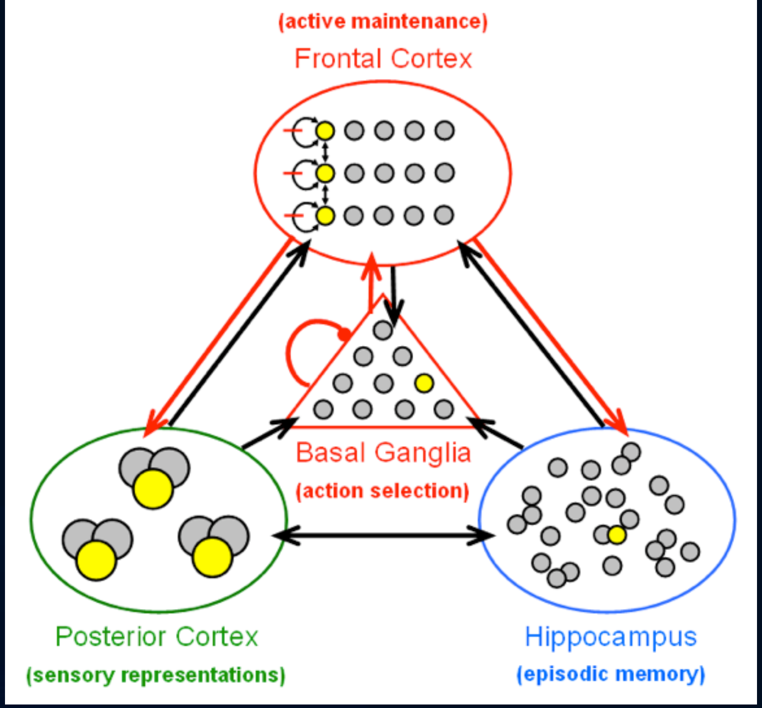
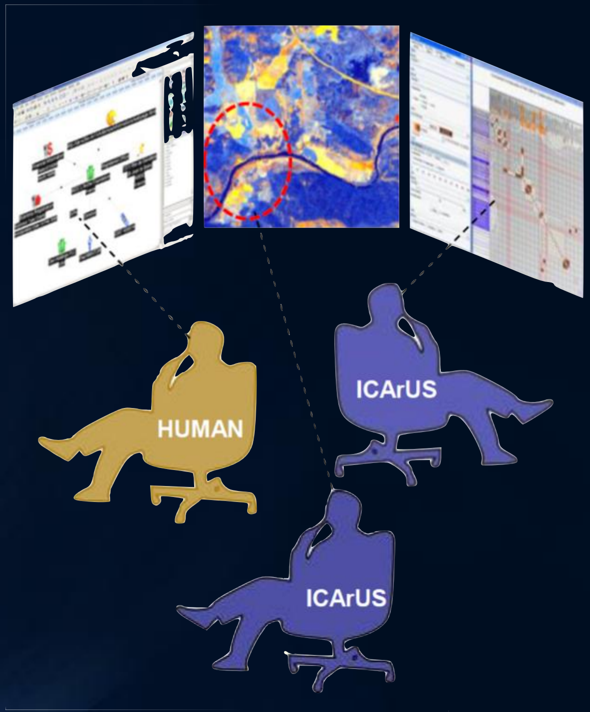
Neural Model (Leabra)



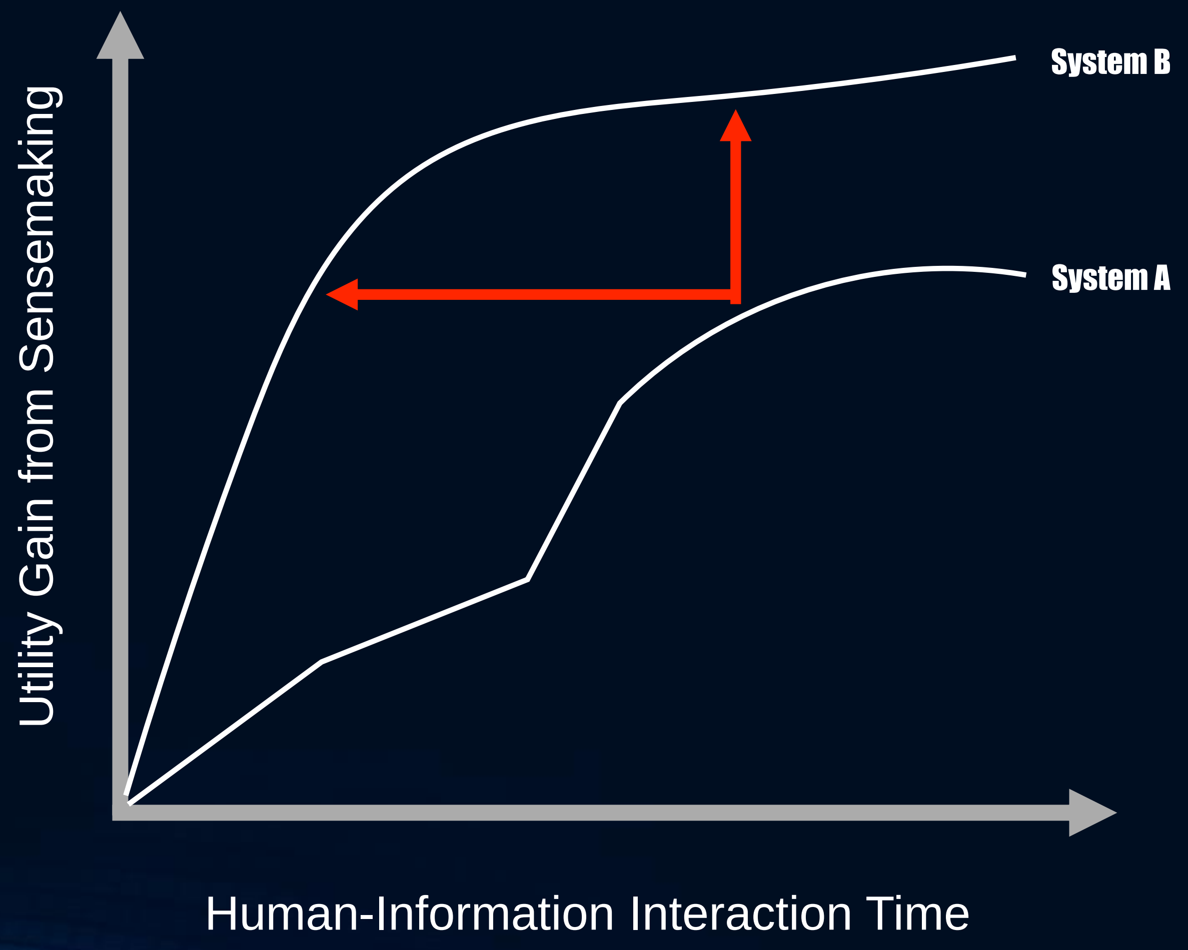
ICArUS-MINDS Multilevel Modeling: Fidelity to Observed Analyst Performance and Biases



- Confirmation bias
- Anchoring and adjustment
- Intentional blindness
- Change blindness
- Representativeness
- Availability
- Probability matching

Improving Sensemaking Systems

- System improvements that increase knowledge that improves the utility of an inference, decision, action, problem solution…
- Often may include system improvements that reduce cognitive bias, increase accuracy of assessments of system/source capabilities, trustworthiness, and credibility



Role of Predictive Cognitive Models

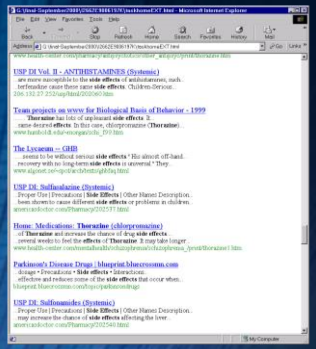
- Understanding and insight
- Predict performance biases and failure modes
- Develop new design principles
- Develop new tools and methods
- Predict impact of new technology, media, interaction techniques
- Develop intelligent systems & agents as, guides, collaborators, assistants

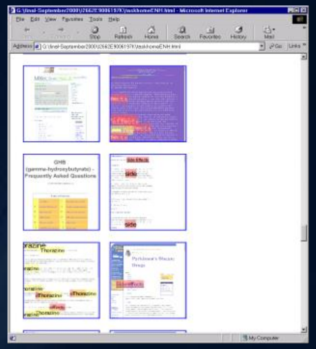
Questions Answered by Cognitive Models of Human-Computer Systems

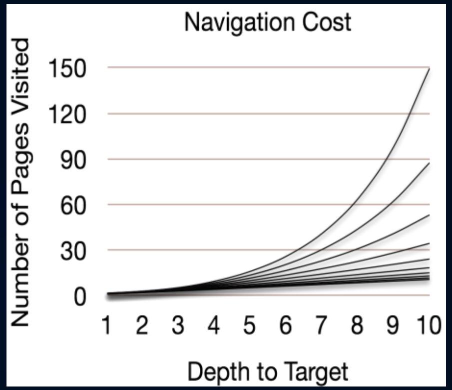
- What is the time it would take to perform elementary tasks?
- How long will it take to learn the skills to use the systems?

Questions Answered by Cognitive Models of Human-Computer Systems

If we change this display technique…



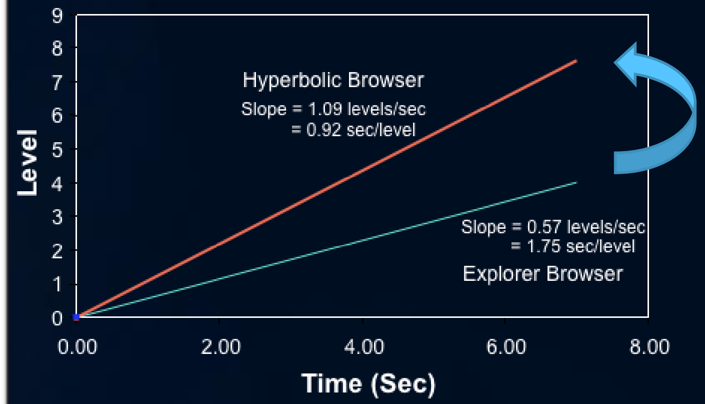




- What arrangement of information on a display yields more effective visual search?
- How difficult will it be for a user to find information?

…we change the cost structure of information foraging this way.

Questions Answered by Cognitive Models of Human-Computer Systems



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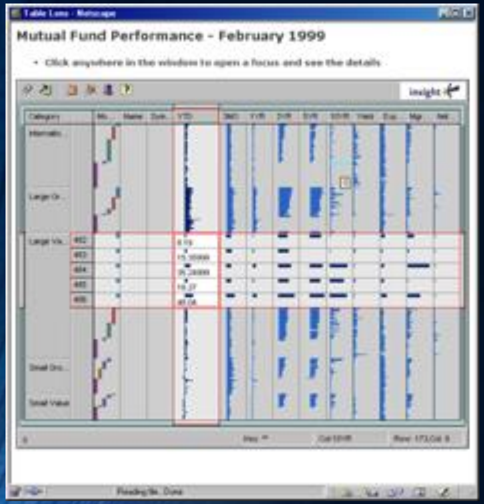

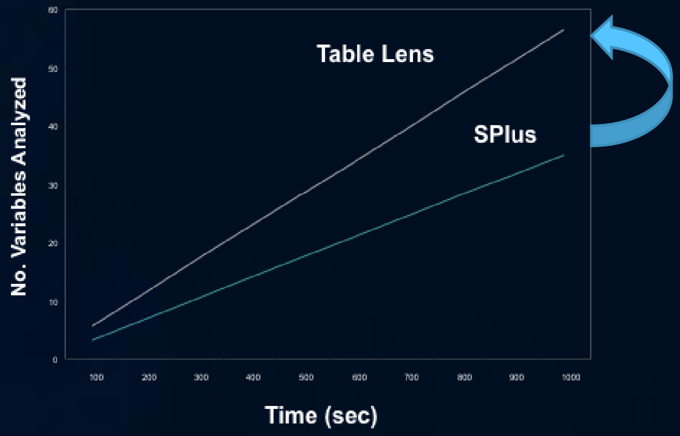

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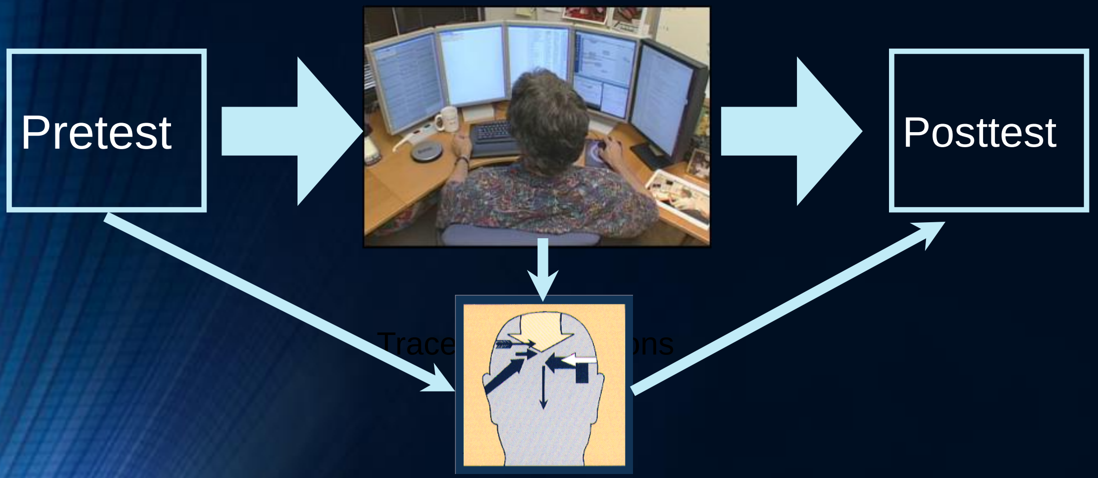
Questions Answered by Cognitive Models of Human-Computer Systems

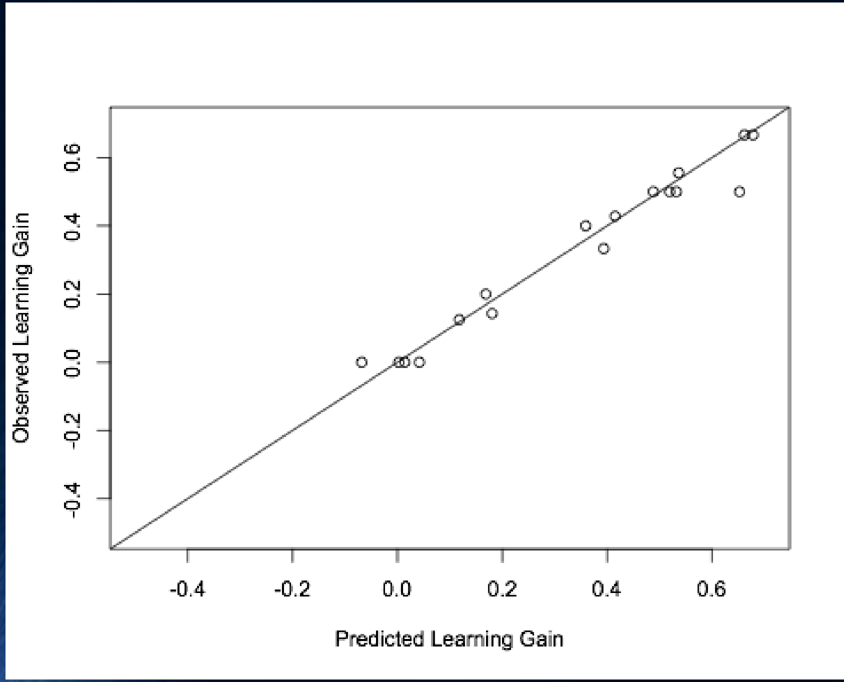
User performs sensemaking task



Knowledge-tracing model predicts topics learned from sensemaking

- What arrangement of information on a display yields more effective visual search?
- How difficult will it be for a user to find information?
- What will this person learn with this sensemaking tool?

Questions Answered by Cognitive Models of Human-Computer Systems



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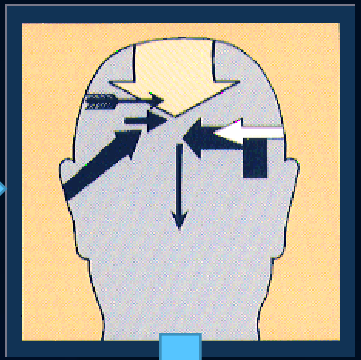
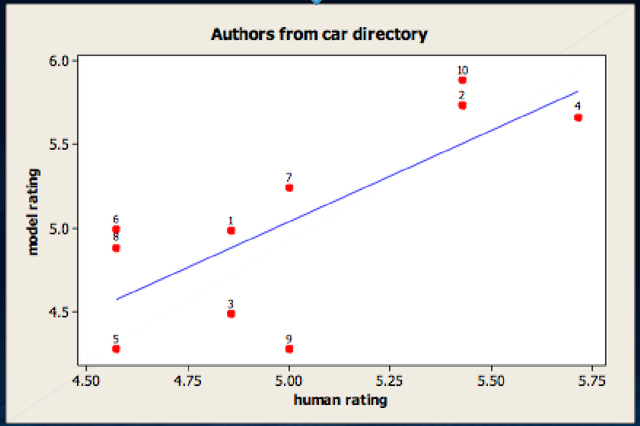
Questions Answered by Cognitive Models of Human-Computer Systems

Twitter Interface

Cognitive Model





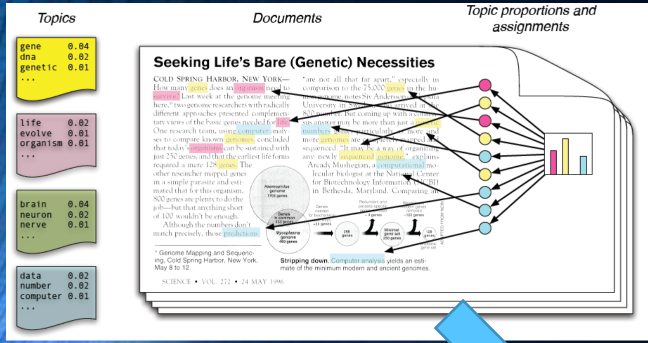
Predict User Credibility Judgments & Decisions

- What arrangement of information on a display yields more effective visual search?
- How difficult will it be for a user to find information?
- What will this person learn with this sensemaking tool?
- Will this person judge this Twitter user to be a credible source?

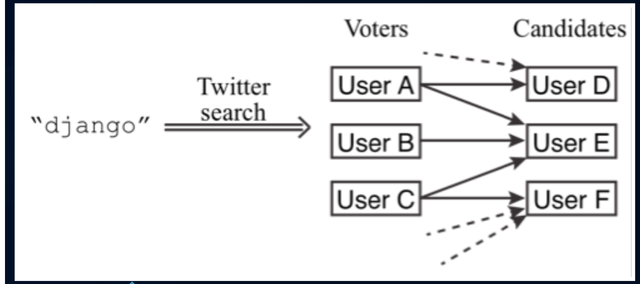
Questions Answered by Cognitive Models of Human-Computer Systems

Twitter Interface

Topic analysis



Social network analysis



User Credibility Ranking Algorithm

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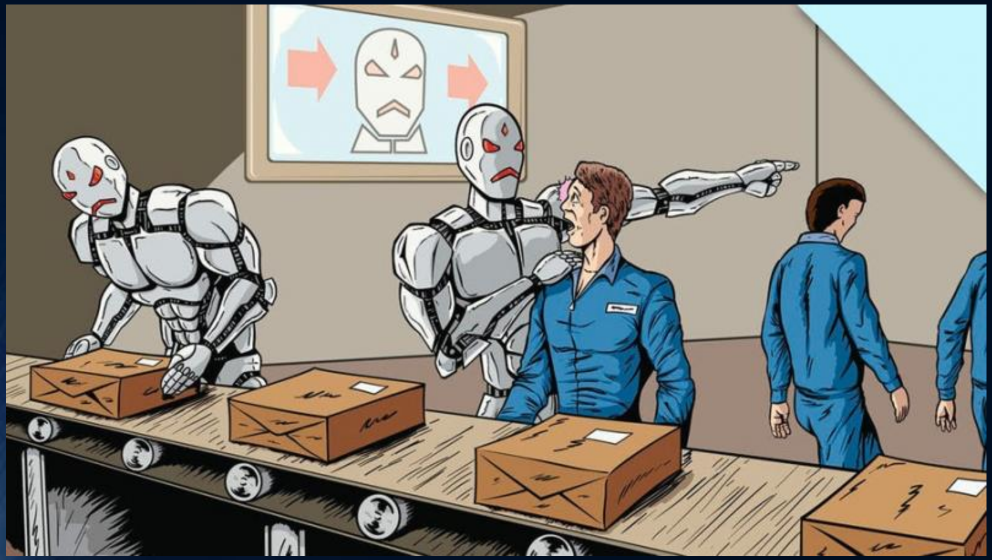
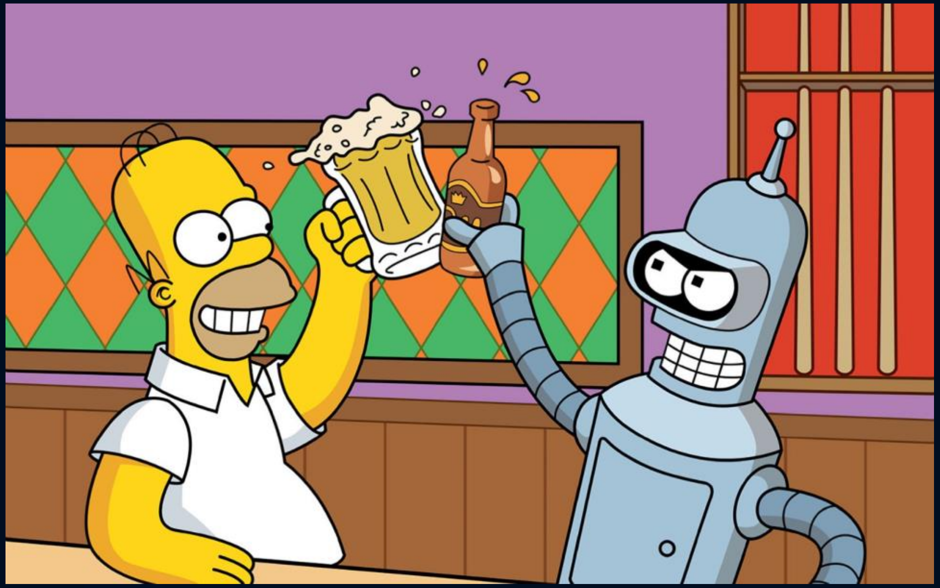
Some Challenges of Engineering Interdependent Human-AI Systems





Source: http://news.ifmo.ru/en/news/6361/
https://chatbotnewsdaily.com/how-humans-surrender-to-language-ai-880bf24796ce

Some Challenges of Engineering Interdependent Human-AI Systems

- **Suitable for Machine Learning** problem

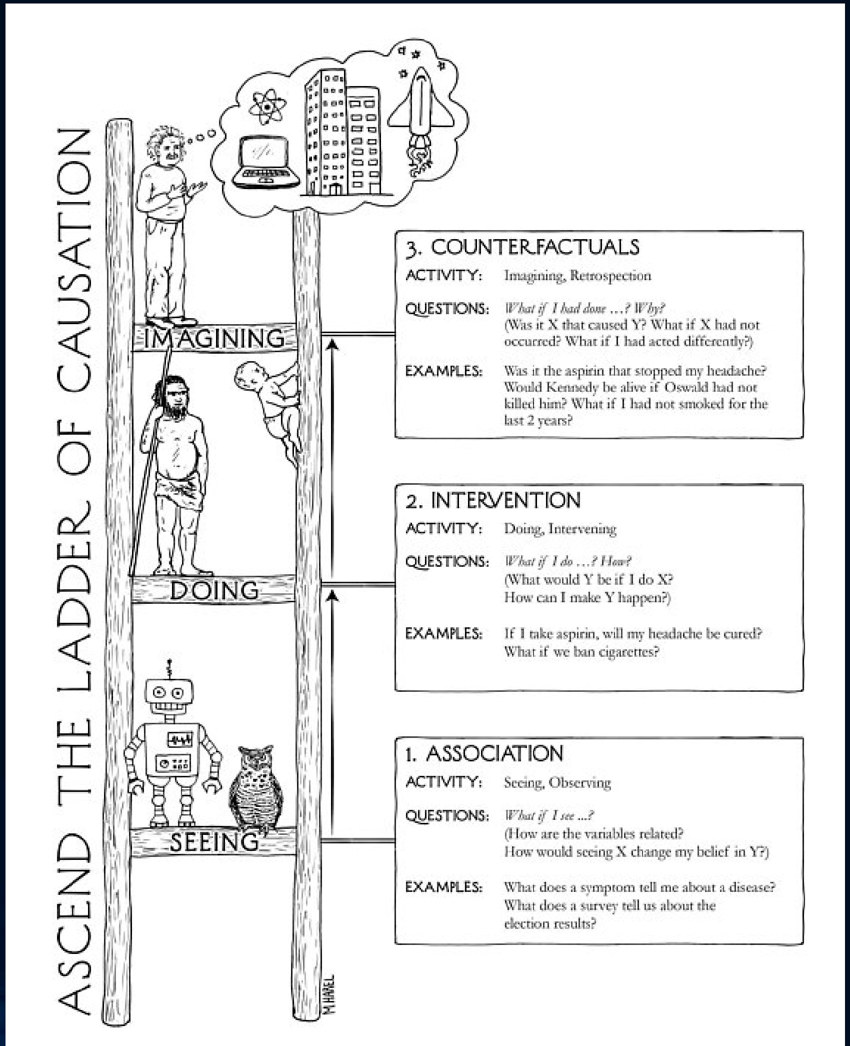
Bynjolfsson & Mitchell (2017). What can machine learning do? Workforce implications. *Science*.

- Well-defined task
- Well defined function with well-defined inputs and outcomes
- Large digital data sets available for input-output training
- Clear goals, feedback, and evaluation functions
- No long chains of reasoning or need for common sense/background knowledge
- No need to provide a clear explanation of what, how, and why
- Tolerance for error and suboptimal solutions
- Phenomena or to-be-learned function do not change with time

Some Challenges of Engineering Interdependent Human-AI Systems

- **Suitable for Machine Learning** problem
- **Ladder of Causal Understanding** (J. Pearl)
  - *Prediction/Associations*
  - Reasoning about *interventions*
  - *Counterfactual* reasoning about what would have happened if..

Pearl, J. (2018). *The book of why.* New York: Basic Books.



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- **Autonomy Paradox**
  - Often creates new tasks and training requirements

U.S. Navy Littoral Combat Ship

- Designed to support multiple unmanned systems
- Still require 60 sailors
- 3X typical training time
- Typically older (30 yr as opposed to 21) & more senior

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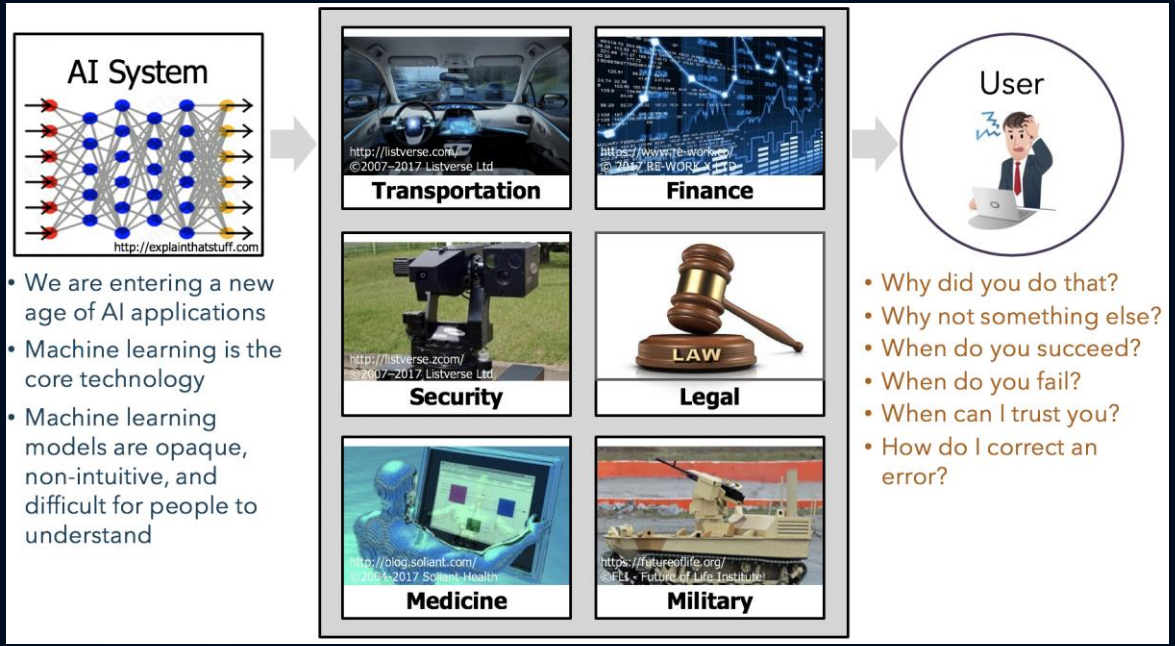
- **Explainable AI**



Source: Dave Gunning

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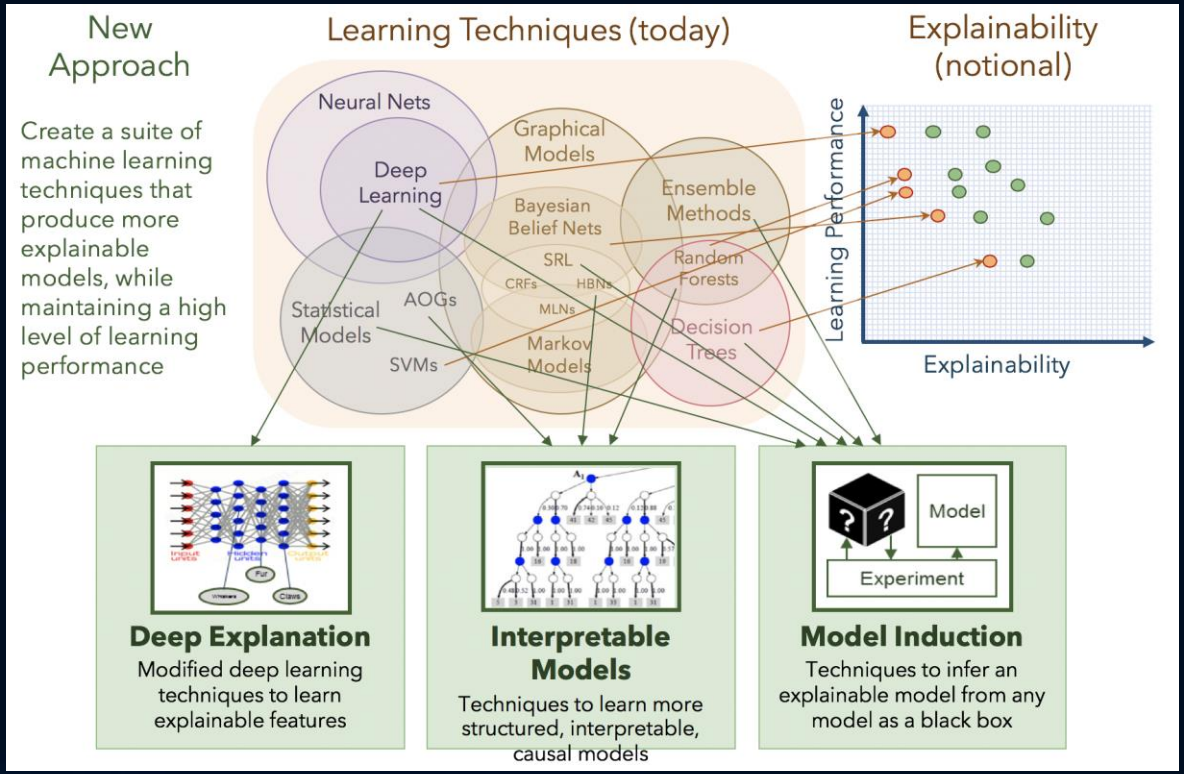

Source: Dave Gunning

Conclusion

- Models of human cognition in sensemaking have informed the design and engineering of higher-performance systems
- For the foreseeable future, AI components in complex sensemaking tasks will not be autonomous—they will work interdependently with human specialists
- Mixed human-AI systems “teams” pose new challenges and require new designs
- My bet is that those designs can be informed by new cognitive science research focused specifically on human-AI interaction in sensemaking tasks


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