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

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Peter Pirolli Institute for Human and Machine Cognition $f = cos \theta$ for $0 \le \theta \le 1/2$

Overview

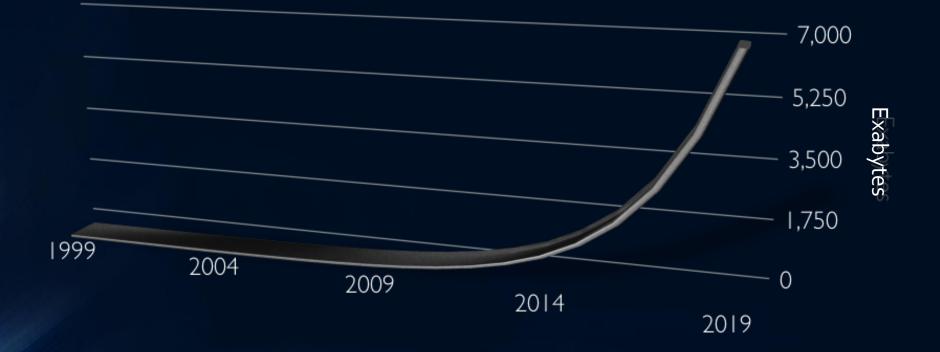
- Multi-level models of sensemaking
 - Computational models that predict the cognition and performance of users of sensemaking systems
- Augment the intelligence of humans engaged in sensemaking
 - By increasing the rate of gain of knowledge from information systems
- Challenges of artificial intelligence

Human-Computer Interaction + Cognitive science

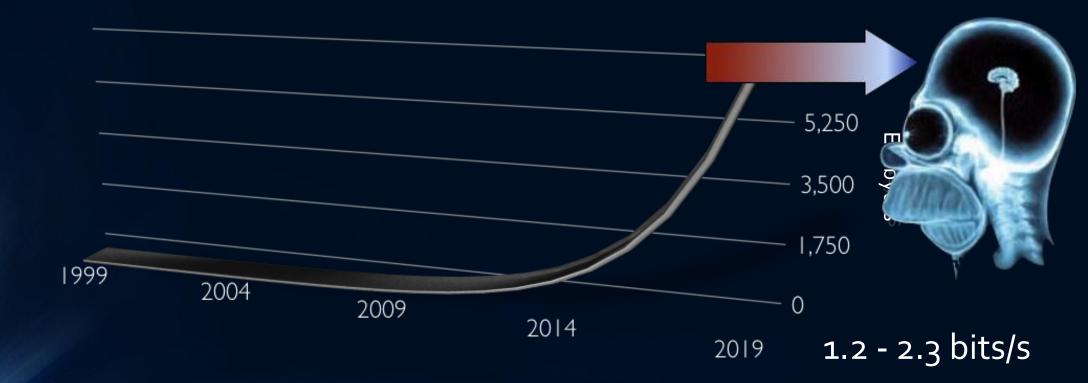
- New computer applications benefit from sound cognitive science.
- Interactive digital systems are a testbed for advanced theories of human cognition.



Challenge: Adaptation to the Volume of Information



Challenge: Adaptation to the Volume of Information

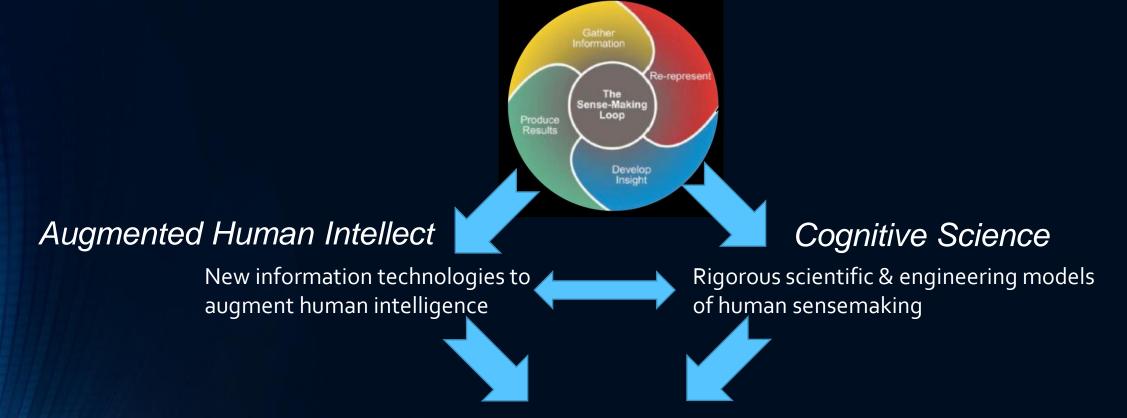


Sensemaking

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

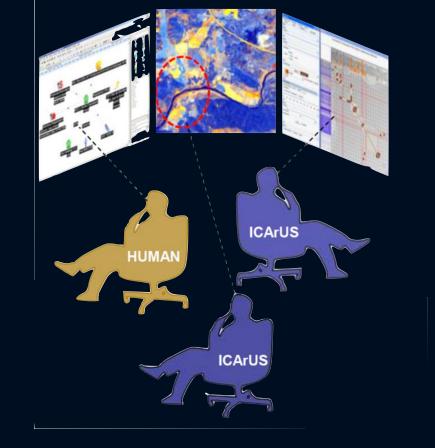




- Useful (valuable) knowledge improves the utility of an inference, decision, action, problem solution...
- We can improve human intelligence by *increasing the rate of useful knowledge gained* as a function of interaction time
- Not just "more information" or more data
- Often may include system improvements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

Example: Geospatial Intelligence Analysis













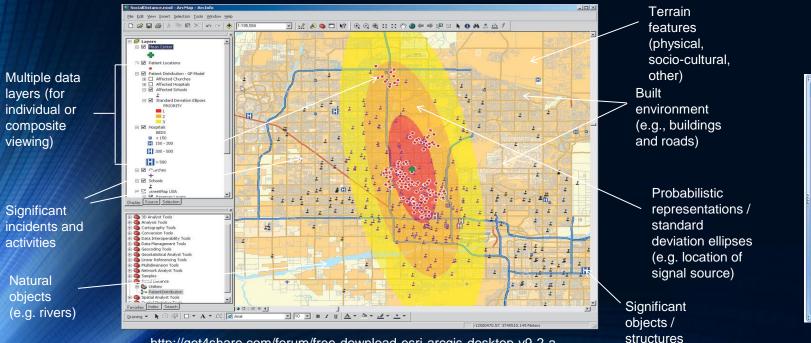




Example: Geospatial Intelligence Analysis

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

Typical GIS display for geospatial analysis



Use information to updaterrisk assessment of attack from Groups A,B,C, **ICArUS** INTs Description If A or B attack then the attack is four times as likely to occur on a IMINT Government vs. Military building If C or D attack then vice versa If A or C attack then the attack is four times as likely to occur on a Major vs. Minor road MOVINT If B or D attack then vice versa

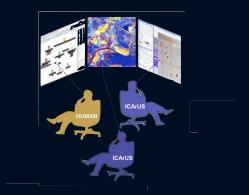
 SIGINT
 If SIGINT on a group reports chatter, then attack by that group is seven times as likely as attack by each other group

 If SIGINT on a group reports silent, then attack by that group is one-third as likely as attack by each other group

 If a group attacks then that group is twice as likely to attack in the group we have a stack by each other group

SOCINT If a group attacks then that group is twice as likely to attack in tis *own* vs. *other* region

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



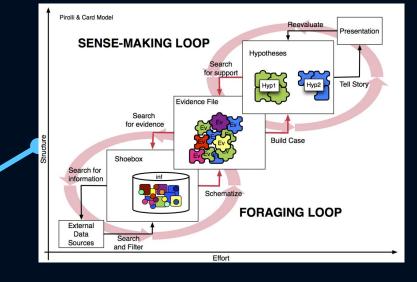
Levels of Information Interaction

| Scale | Time Unit | Band |
|--------------------|------------|-----------------------|
| 10 ⁷ s | Months | |
| 10 ⁶ s | Weeks | Social/Organizational |
| 10 ⁵ s | Days | |
| 10 ⁴ s | Hours | |
| 10 ³ s | 10 min | Rational |
| 10 ² s | Minutes | |
| 10 ¹ s | 10 seconds | |
| 10 ⁰ s | Seconds | Psychological |
| 10 ⁻¹ s | 100 msec | |
| 10 ⁻² s | 10 msec | Biological |

Levels of Information Interaction

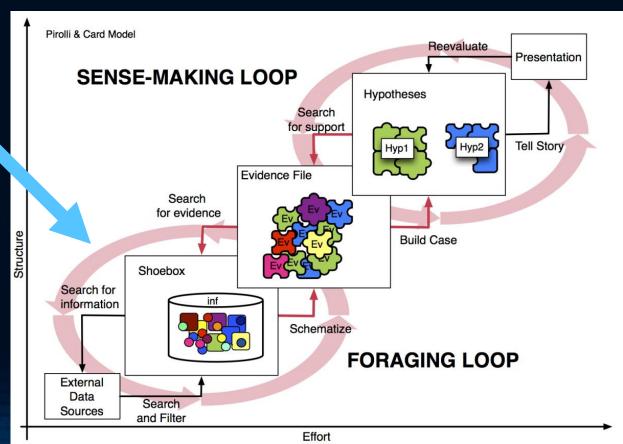
Macrocognitive Model Information Foraging Theory

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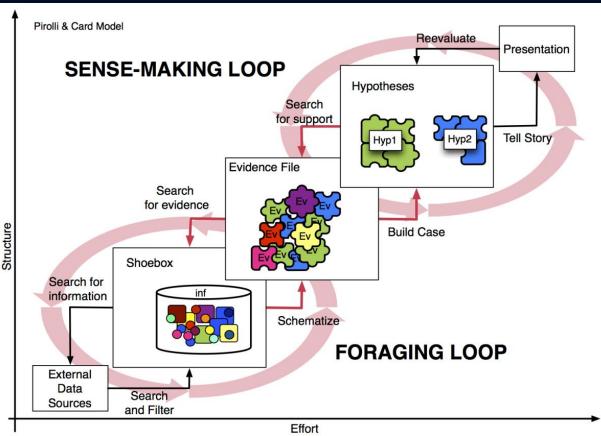


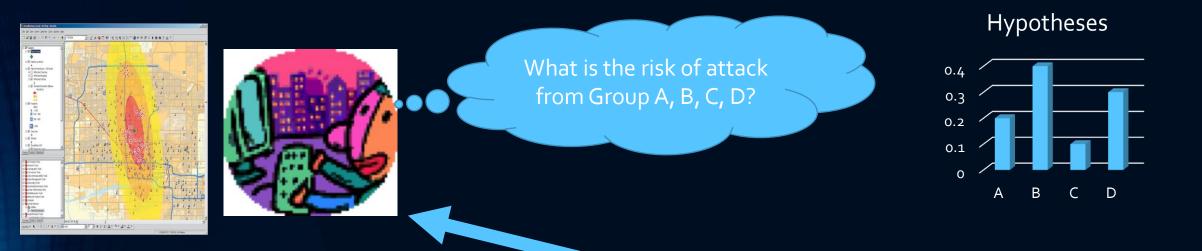
• Information Foraging:





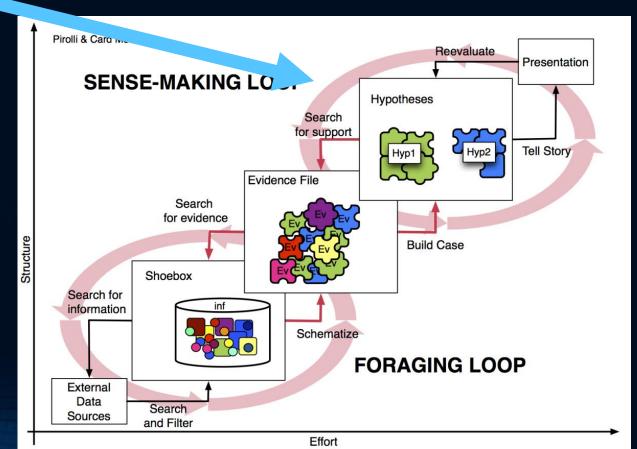
- Information Foraging:
 - Humans optimize their information foraging to increase knowledge gained and reduce interaction costs

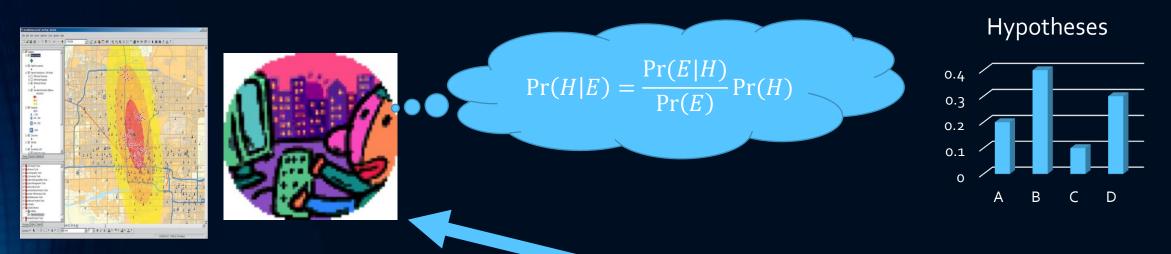




• Information Foraging:

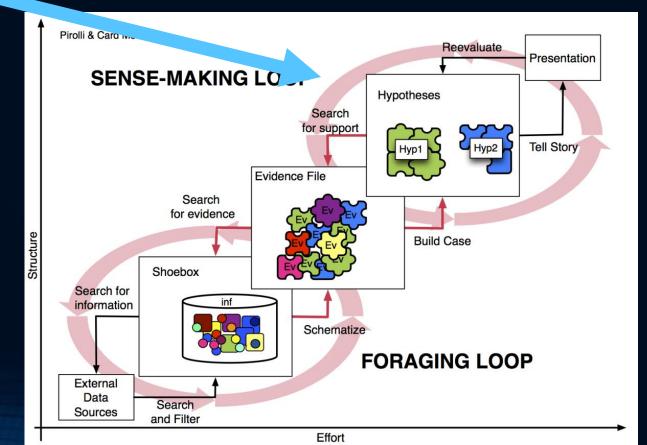
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- Sensemaking:





Information Foraging:

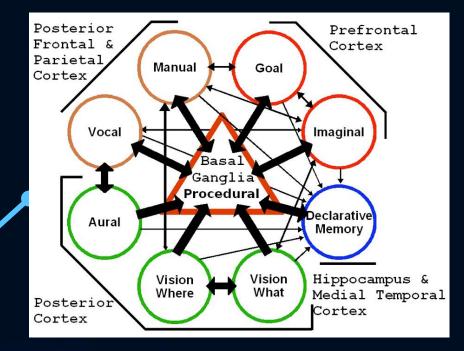
- Humans optimize their information foraging to increase knowledge gained and reduce interaction costs
- Sensemaking:
 - Humans approximate rational (Bayesian) selection of evidence and hypothesis updating



Levels of Information Interaction

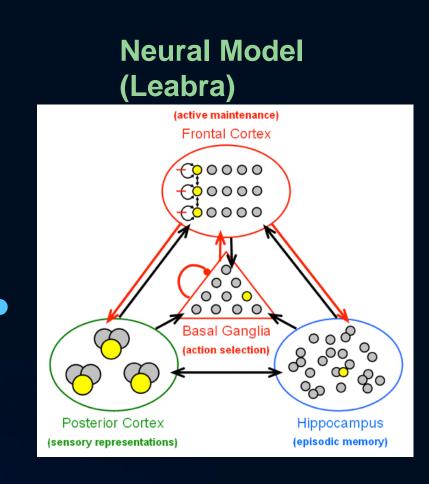
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Functional Cognitive Model (ACT-R)

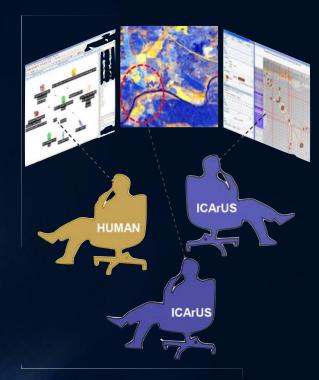


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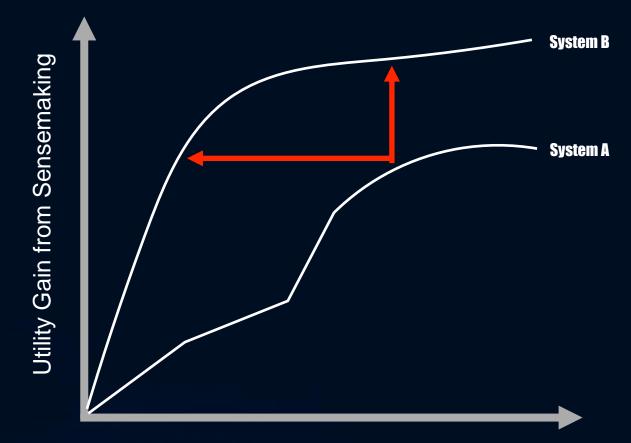
ICArUS-MINDS Multilevel Modeling: Fidelity to Observed Analyst Performance and Biases



- 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



Human-Information Interaction Time

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

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



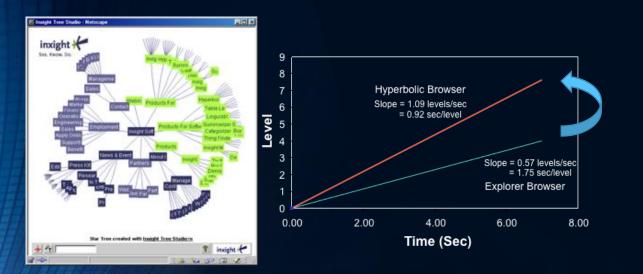
If we change this display technique...



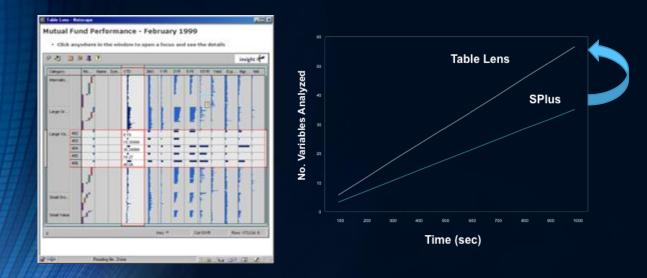
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- What arrangement of information on a display yields more effective visual search?
- How difficult will it be for a user to find information?

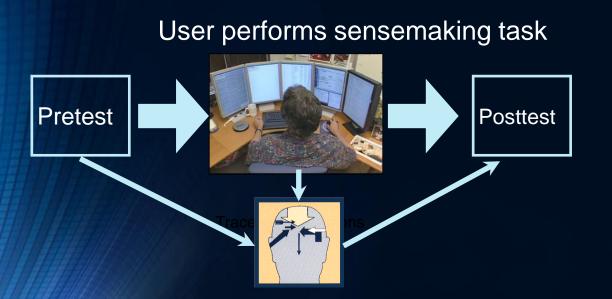
...we change the cost structure of information foraging this way.



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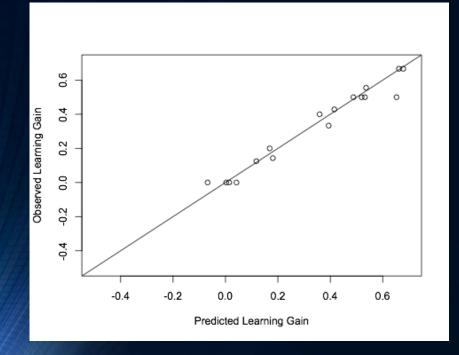


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Knowledge-tracing model predicts topics learned from sensemaking

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Twitter Interface

| User2602 | Following Followers Listed Tweets | 478 74,875 260 1,686 |
|---|--|--|
| #fantasyfootball #nt brady brandon browns chatter fantasy fave filbrarian foo great looking marshall marshawn n mock nfl pick players post qb rb rookie running season signed s theendzoneview time trade twitter up wr year | crabtree draf tball footba mcnabb michae reading rea tart team thank | t allguys I mike ceivers s |
| Blog post: WRs Continue Workhorse Strea in a row, wide receivers with 90+ reception | | r |

in a row, wide receivers with 90+ receptions outnumbe... http://bit.ly/9bqzOr Blog post: Mock Draft on your iPad: If you're one of the lucky

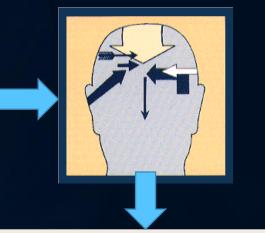
people out there who owns an iPad, you'll be happy ... http://bit.ly/cM9BFg

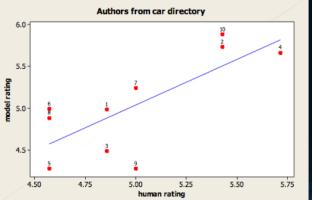
SI_JayClemons Here are today's NFL Fantasy Clicks, starting with the obligatory Favre comeback special ... http://tinyurl.com/279ohya

@Mikey8ubonik Flacco Seagulls. Not my original idea though. Saw it in this draft: http://fantasyfootballcalculator.com/draft /784543

Predict User Credibility Judgments & Decisions

Cognitive Model





- 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?

Candidates

► User E

Twitter Interface

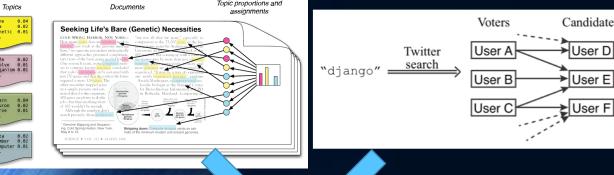
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nock off pick players post gb rb reading receive ng season signed start team than wr year ue Workhorse Streak: For the third rs with 90+ receptions outnumbe...

User2602

Following Followers Listed

Social network analysis



Topic analysis

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User Credibility Ranking Algorithm

Some Challenges of Engineering Interdependent Human-Al Systems



Source: http://news.ifmo.ru/en/news/6361/

https://chatbotnewsdaily.com/how-humans-surrender-to-language-ai-88obf24796ce

Some Challenges of Engineering Interdependent Human-AI Systems

• Suitable for Machine Learning problem



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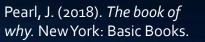
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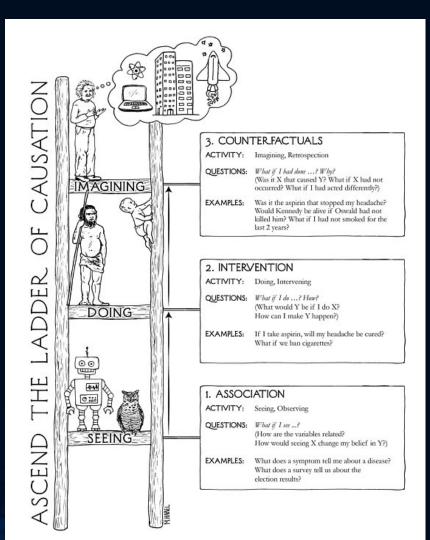
Bynjolfsson & Mitchell (2017). What can machine learning do? Workforce implications. *Science*.

- 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..





Some Challenges of Engineering Interdependent Human-AI Systems Horal Combat Ship

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



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

Some Challenges of Engineering Interdependent Human-Al Systems

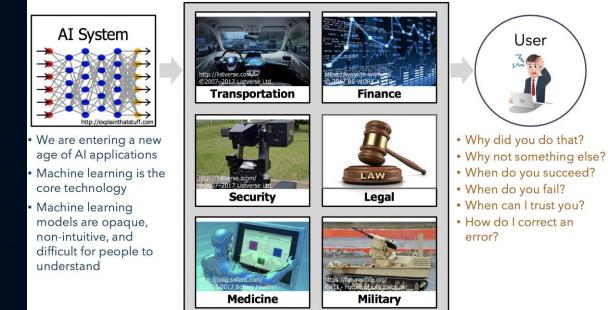




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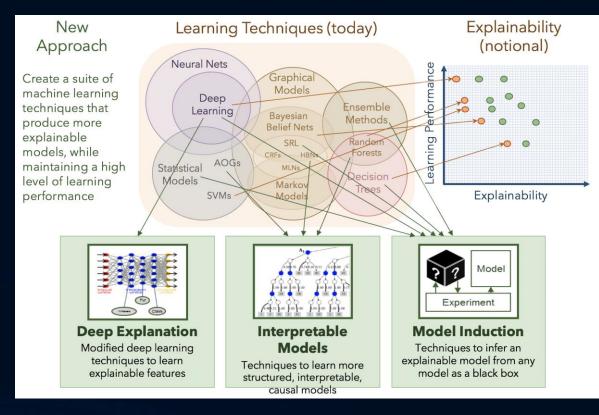




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- Often creates new tasks and training requirements **Explainable AI**



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

