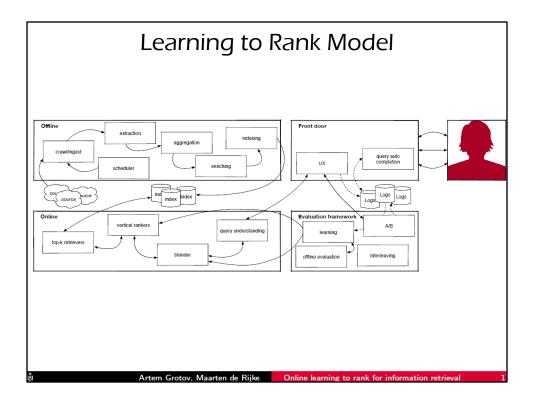
## How Human Factors Can Improve Neural IR

Formerly known as

IR Intelligence: Introduction to Neural IR & Learning to Rank

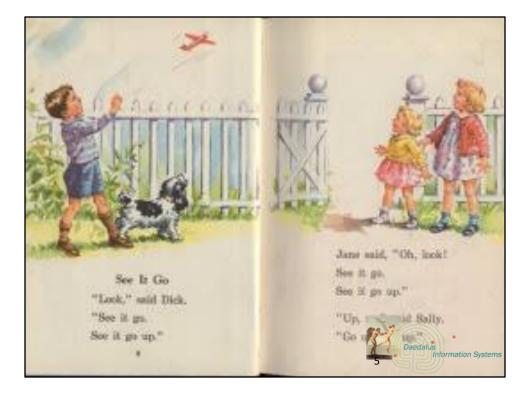
Search Solutions 2020

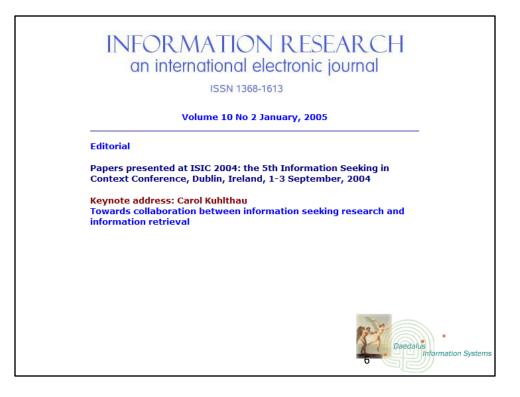




	Michael Bendersky Google Research Verified email at google.com - <u>Homepage</u> Information Retrieval Natural Language Processing	Web Search & Data Mining		Follo
TITLE		C	NTED BY	YEA
M Bendersky, WB Crot	ncepts in verbose queries ft t annual international ACM SIGIR conference on		304	200
Learning concept importance using a weighted dependence model M Bendersky, D Metzler, WB Croft Proceedings of the third ACM international conference on Web search and data			198	201
M Bendersky, WB Cro	king of web documents h, Y Diao th ACM international conference on Web search and		126	201
Analysis of long queries in a large scale search log 12   M Bendersky, WB Croft Proceedings of the 2009 workshop on Web Search Click Data, 8-14			123	200
M Bendersky, D Metzle	cept weighting in verbose queries ar, WB Croft h international ACM SIGIR conference on Research and	12-T	122	201
Learning to rank with selection bias in personal search X Wang, M Bendersky, D Metzler, M Najork Proceedings of the 39th International ACM SIGIR conference on Research and				







Information Seeking in Context 2004 – Dublin

Carol Kuhlthau calls out lack of collaboration between computer science and information science observing that they are isolated by practice and by distance (on college campuses)

	CHIISCODIICI Main	e e e e e e e e e e e e e e e e e e e	00125		
	Replying to @msweeny and @MDoornenbal The status and role of consciousness is a complex one—perhaps see frontiersin.org/articles/10.33—but more than I intended to address here; but I think we must certainly reject being able to execute some list of tasks as a sufficient criterion for intelligence				
	Ē,	Artificial Intelliger	ce: Does Conscious ce: Does Conscious ness plays an impor	sness	
	$\Diamond$	1	♥ 1	$\uparrow$	
9	Christopher Manning @chrmanning · Oct 29 Replying to @stanfordnlp @msweeny and @MDoornenbal As someone notes in a later comment, even though I wasn't thinking of it at the time I wrote my definitions, the position I adopt is ar to the one @fchollet argues for in much greater detail in his pap /pdf/1911.01547				-

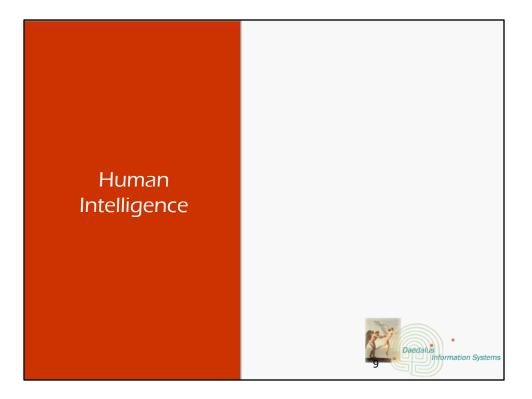
And then this happened...Christopher Manning who literally wrote the standard text for information retrieval, showed me the way.

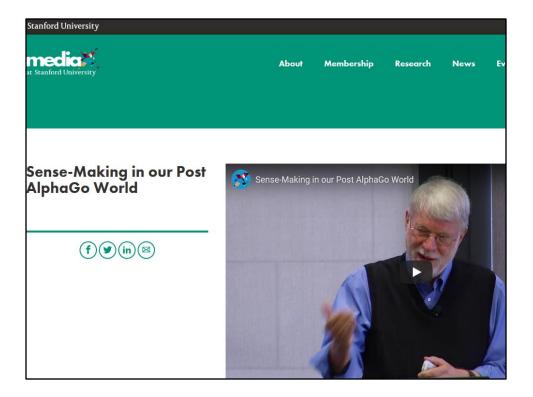
≡ Google Scholar			
François Chollet Google, Inc. Verified email at google.com	On the Measure of Intelligence		
ARTICLES CITED BY CO-AUTHORS	François Chollet * Google, Inc. fchollet@google.com		
keras F Chollet	November 5, 2019		
Control Contro Control Control Control Control Control Control Control Control Co	Abstract To make deliberate progress towards more intelligent and more human-like artificial systems, we need to be following an appropriate feedback signal: we need to be able to define and evaluate intelligence in a way that enables comparisons between two systems, as well as comparisons with humans. Over the past bundred years, there has been an abun- dance of attempts to define and measure intelligence, across both the fields of psychology and AI. We summarize and critically assess these definitions and evaluation approaches, while making apparent the two historial conceptions of intelligence that have implicitly		
Tensor2tensor for neural machine translation A Vaswani, S Bengio, E Brevdo, F Chollet, AN Gomez, S Gouws, L Jones, arXiv preprint arXiv:1803.07416	guided them. We note that in practice, the contemporary AI community still gravitates to- wards benchmarking intelligence by comparing the <i>skill</i> exhibited by AIs and humans at specific tasks, such as board games and video games. We argue that solely measuring skill at any given task falls short of measuring intelligence, because skill is heavily modulated by prior knowledge and experience: unlimited priors or unlimited training data allow ex-		
Deep Learning with R F Chollet, JJ Allaire Manning Publications	perimenters to "bay" arbitrary levels of skills for a system, in a way that masks the system's own generalization power. We then articulate a new formal definition of finelligence based on Algorithmic Information Theory, describing intelligence as skill acquisition efficiency and highlighting the concepts of scope, generalization difficulty, priors, and experience, as critical pieces to be accounted for in characterizing intelligence systems. Using this defi- nition, we propose a set of guidelines for what a general AI benchmark should look like. Finally, we present a new benchmark closely following these guidelines, the Abstraction and Reasoning Corpus (ARC), built upon an explicit set of priors designed to be as close as possible to innate human priors. We argue that GRC can be used to measure a human-like form of general fluid intelligence and that it canables fair general intelligence comparisons		
Deepmath-deep sequence models for premise selection G Inving, C Szegedy, AA Alemi, N Eén, F Chollet, J Urban Advances in Neural Information Processing Systems, 2235-2243			

No shared definition of what intelligence is No shared set of tests to find out

Intelligence is the rate at which a learner turns its experience and priors into new skills at valuable tasks that involve uncertainty and adaptation. Definition is based on assessment of intelligent system with definition of intelligence grounded in: priors, experience, generalization of difficulty.

The measure of intelligence may be interpreted as a conversion rate between current state of information and the ability to perform well under an uncertain future. On Measure of Intelligence by F Chollet – Robert Tjarko Lange



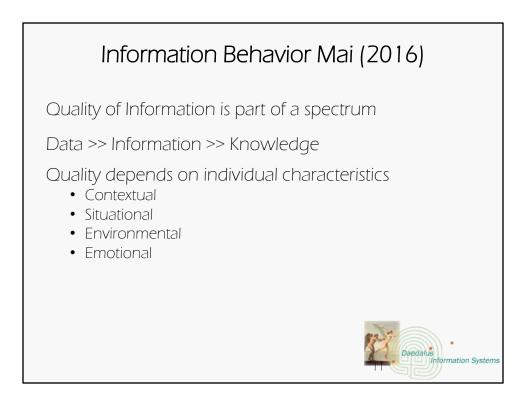


Current world is about shaping knowledge flows and reading context = reading context is different than reading signals (data), e.g. Brexit & USA 2016 presidential election – data is not information b/c it does not incorporate beliefs or values – sensemaking is a state that requires knowledge (an outcome of processed data)

Searle AI:

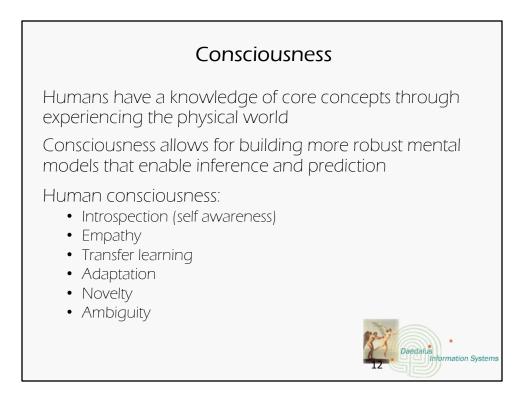
- Strong AI: system has a "mind" that can understand cognitive states (self aware)
- Weak AI: system can only simulate understanding (no mind)

https://mediax.stanford.edu/featured-events/john-seely-brown-mediax2017/ http://www.johnseelybrown.com/SensemakingStanford.pdf



Jens Erik Mai, 2011

Further illustrates the singularly human aspect of intelligence



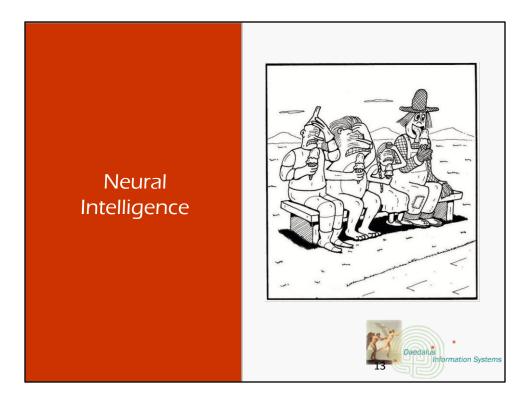
David Gelernter, Computer science Yale University, artist and writer (Tides of Mind: Uncovering the Spectrum of Consciousness)

The human mind is not just creation of thought and collection of data; also a product of feelings, composite of sensations, memories, ideas that are worked and reworked over a lifetime.

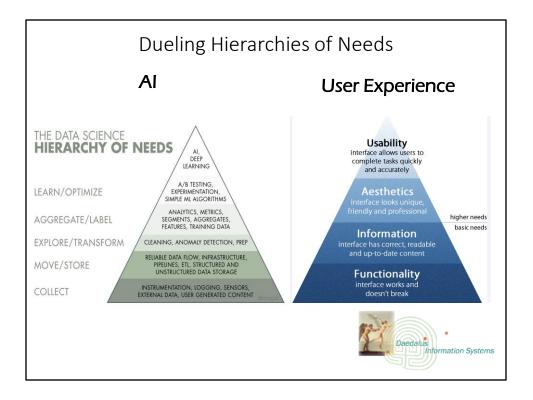
Human consciousness is a first-person experience, AI consciousness can only be known from a 3<sup>rd</sup> person perspective (that of the programmer).

Ned Block (Philosophy faculty NYU): 2 distinct dimensions:

- Access consciousness (introspection, self-referential, monitor own processing
- Phenomenal consciousness: what it is "like" to be consciousness



https://arnoldzwicky.org/2018/08/19/another-puzzle-in-cartoon-understanding/



Human needs are influenced by feelings, engagement, values and moral codes AI is influenced by data, data, data and programming

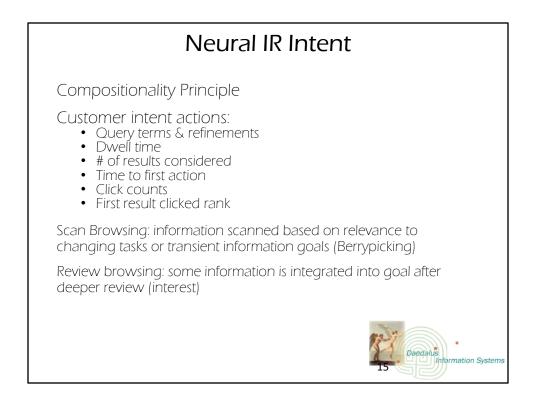
Machine Behavior

- Fundamentally different from human behavior (consciousness, empathy)
- Operates in a wider socio-technologic spectrum than human stakeholders
- Should not separate environment (the data used to train) from explicit behavior across diverse environments (variable use cases)

Influencing machine behavior to represent human needs requires a cross discipline effort, a human shaped hybrid-behavior

Start developing human-machine decision systems where human behavior shapes machine output through intricate involvement in training

- Understand the parameters of AI engineering to understand the outcomes and impact on human behavior
- Cooperation (traffic flow alterations), competition (gaming, chess, alpha go), coordination (robo trading financial markets): intersections of machine behavior



Compositionality Principle: meaning of word compounds is derived from the meaning of individual words + the way they are combined, e.g. the components of language can be broken down into sub-components

Query intent = individual words that are possible indicators of customer intent. Uses term cooccurrence (proximity) models to improve retrieval relevance

Content units: specify need,

Intent units: modify the need in one of many possible ways

LTR attempts to capture and interpret hidden customer goals through clicked URLs

- Submitted queries
- Clicked URLs

## Neural IR Intent Deconstruction

Query intent = individual words that are possible indicators of customer intent. Uses term cooccurrence (proximity) models to improve retrieval relevance

Intent words = articulated by customer to refine their information needs

Content words = core topic of query

Content unites further specify the need; intent units further modify the need in one of many possible ways

Queries are classified as either content or intent

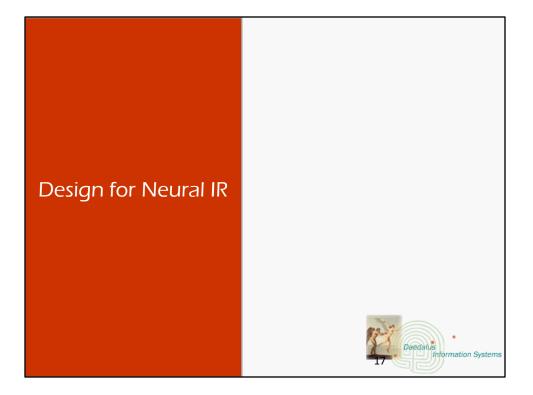
- Content words: nouns, verbs, adjectives
- Function words: pronouns, determiners, preposition, conjunctions

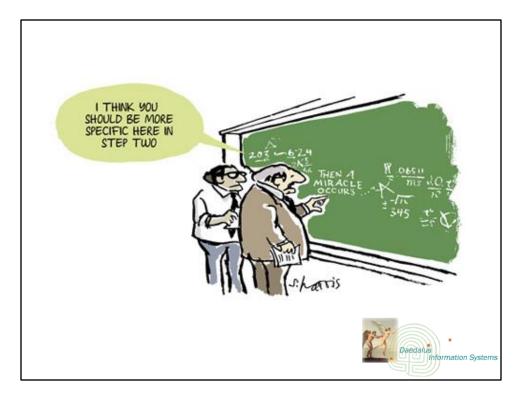
Tracked customer intent actions:

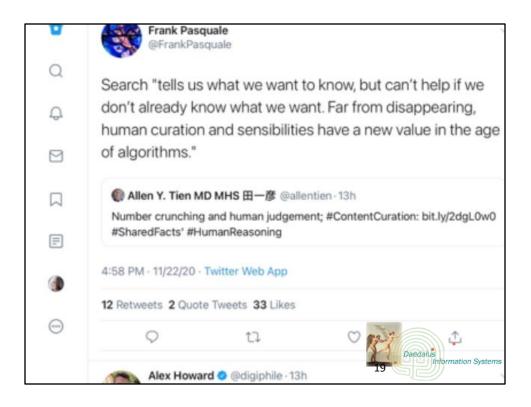
- Query terms & refinements
- Dwell time
- # of results considered
- Time to first action
- Click counts
- First result clicked rank

Scan Browsing: information scanned based on relevance to changing tasks or transient information goals (Berrypicking)

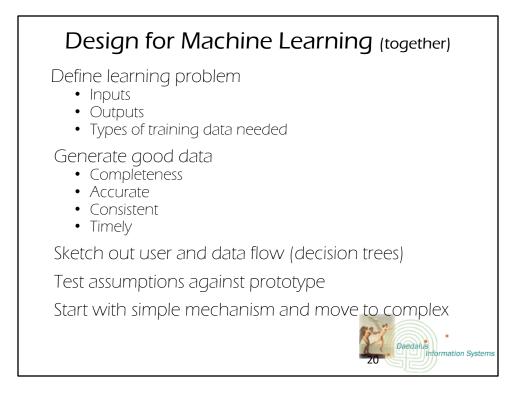
Review browsing: some information is integrated into goal after deeper review (interest)







This cannot be distilled from NLP or predictions on user behavior

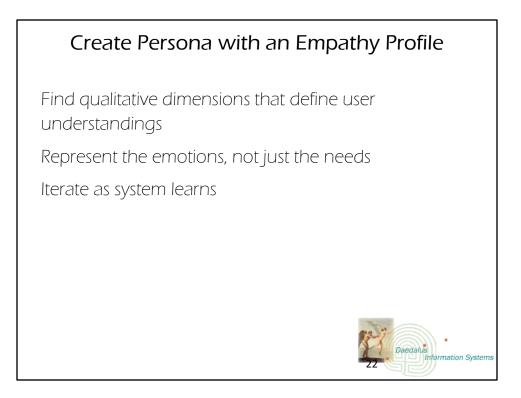


Behavior cannot be separated from environment (data used to train AI) – focus has to be on characterizing AI behavior across diverse environments (persona, use case)

Al can help with correlated behavior – can interpret actual user data to detect patterns that can inform design changes (IoT, digital assistants). We can contribute by:

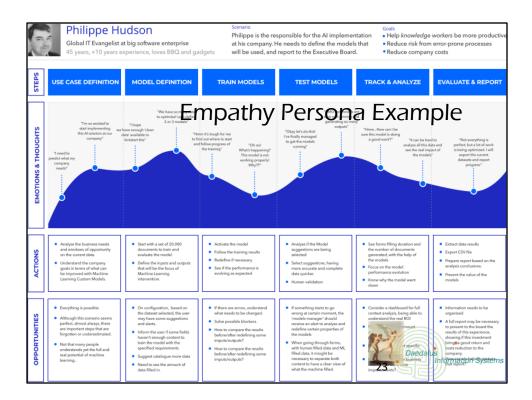
- Creation of interfaces that capture actual situation behavior, that maximize instructions to ML and AI to become a learning decision tree
- Classification for inputs, effective labels, etc.
- Enable design of interactions systems that can restate its understanding of tasks to be performed
- Provide user interfaces that allow user to bypass ML for implicit logic of user
- Create baseline to measure no go if system failure would cause serious consequences or irrevocable change (Postman's caution about new technology)
- Test the software across many environments



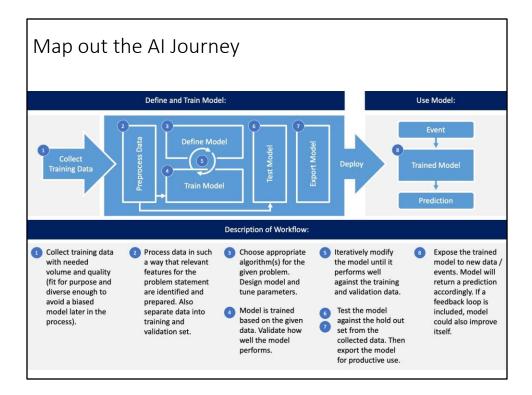


Grounded Theory – qualitative components that differentiate shared experiences – synthesize beliefs and values with tastes and preferences

- 1. Define the solution
- 2. Understand the problem-solving options
- 3. Define the characteristics of a good solution (heuristics)
- 4. Map the environment (customer journey)
- 5. Benchmark success (quantitative, qualitative)



https://dribbble.com/shots/7595433-AI-Journey-Map



Human journey map focuses on Instinctual actions

Here, phases are influenced by thinking, expressing and acting

Al journey maps must be programmatically explicit as Al lacks intuitive movement

Al uses decision trees for journey progress. Info professionals can be useful for mapping more explicit and expansive decision trees



## Bob Boiko: Faculty, UW information School 6-part series called Information Systems from the Info Out

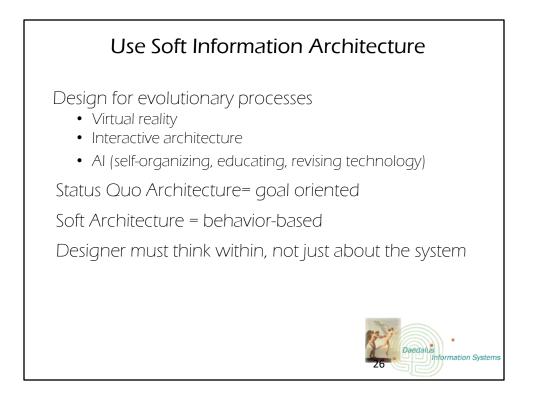
Much of the influence of IA practice stems from the power of naming objects in the system

Naming is a representative task that illustrates both the complexity and value of Information Architecture practice

Naming is a framing, an understanding of what everything is and how it fits into a system.

IA contributions to LTR

- Name object for cross system compatibility
- Problem definition and structure
- Connections
- Proto-typicality (mental models)
- Visual complexity (rely on text more than images)



Status Quo Architecture= goal-oriented, e.g. laser focus on task at hand or problem

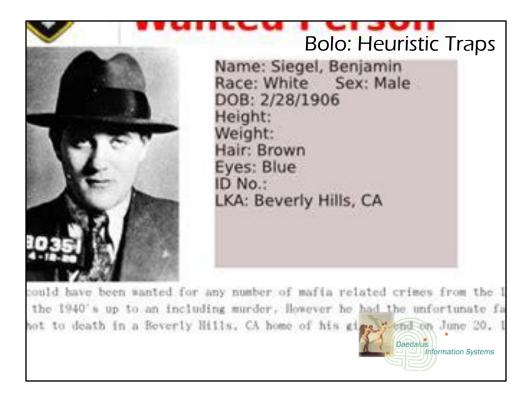
Soft Architecture = behavior-based, iterative, incorporates user input/output to iterate

Soft Architecture uses system to create various methods of presentation and structure to accommodate self-evolutionary/adaptive nature of system performance (no more "set it and forget it")

Structure uses feedback to influence behavior

- Inner structure = algorithms
- Physical structure = environment (digital, product, etc.)

Behavior based design can better incorporate changing nature of conditions and impact on system (self-driving car fatality)



Familiarity: False confidence by failing to vigilant when faced with the known

Social Facilitation: Everyone is doing it so it must be okay

**Expert Halo**: False confidence in experts that we assume know what they are doing. So, it must be okay to follow them without question.

Anchoring:

Scarcity: If I don't do it now, I never will. Powder fever – it might be gone later

Acceptance: The cool kids are doing it and I want to be like them.

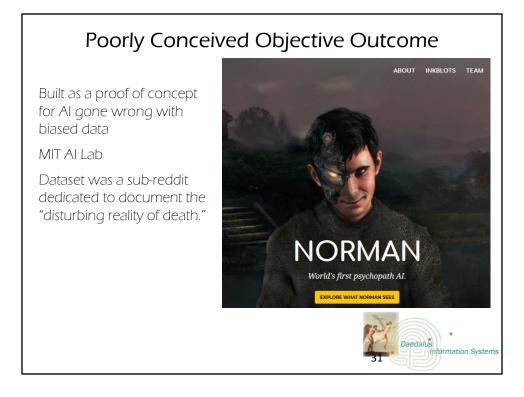




Technology inherits ideas and values of the group that develops it

Ben Schneiderman, winner ACM Turing Award, calls for a national algorithm safety board to monitor and assess safety of algorithms as they access social systems





http://norman-ai.mit.edu/ -

"Norman suffered from extended exposure to the darkest corners of Reddit and represents a case study on the dangers of Artificial Intelligence gone wrong when biased data is used in machine learning algorithms. "

Also produced Shelley (http://shelley.ai/), Al assisted horror stories, and Deep Empathy (https://deepempathy.mit.edu/) that produces images of what US cities would look like after conflict similar to that experienced in Syria





LTR reliance on SERP Abandonment

- Studies show 41% of abandonments were bad, 32% abandonments were good, with the remaining 27% associated with alternate reasons (e.g. choosing a better query before considering returned SERP)
- Segmented as either good or bad abandonment

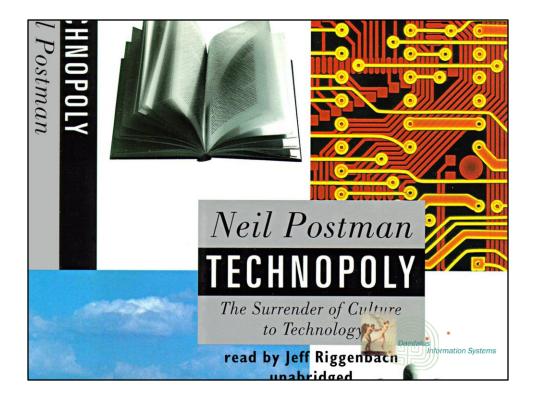
Search Abandonment Issues:

System ability to accurately categorizing abandoned queries into good and bad Noisy indicators in user preference (emotional state, object, environmental conditions) User bias

- User transformation of SERP into knowledge. SE cannot measure this so must calculate a sequence of interactions
- User biases
  - o Position
  - o Search engine
  - $\circ \ \ \text{Cultural}$

Explore/Exploit hurdles

- System goal is to exploit the best ones (highest probability of success) to find better ones
- System must present results that produce feedback (explore) Results cannot always be perfect, or system stops looking for a better results (exploit)



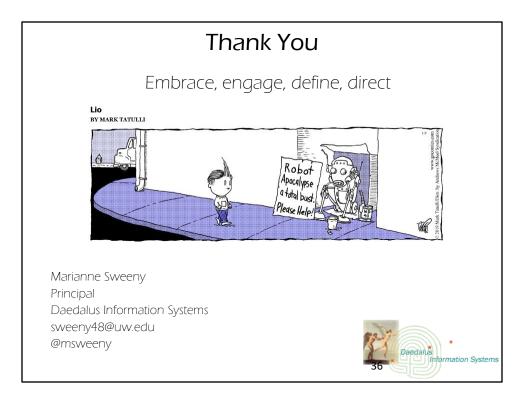
- 1. All technological change is a trade-off: The greater the wonders of technology, the greater will be its negative consequences. Culture always pays a price (algorithmic bias, social, psychological impacts)
- 2. The advantages and disadvantages of new technologies are never distributed evenly among the population: Some gain, some lose, few remain the same (predictive search, end of browsing, information induced blindness systemic problems need action informed by information, not just more information)
- **3.** Embedded in every technology there is a powerful idea, sometime two or three ideas: focus on all functions, not just the profitable ones.
- 4. Technological change is not additive; it is ecological: A new medium does not add something it changes everything (unintended consequences) often unpredictable and irreversible
- 5. Media tends to become mythic: Jaron Lanier (computationalism) enthusiasm for the technology becomes a form a idolatry (AI is the new hammer and everything is a nail.) Capacity for good or evil requires human awareness and participation (human factors professionals included in development and execution)

Five things We Need to Know About Technological Change: Neil Postman: March 1998

(gratitude to Christine Emba, Wa post columnist for highlighting in her article)



We are the representatives of the qualitative self that is truer than the quantitative self represented by AI



We can circumvent the AI apocalypse.