Meaning making with artificial agents, synthetic media, and pollution of the information ecosystem

Emily M. Bender
University of Washington
@emilymbender / @emilymbender@dair-community.social

IACONF 2024
Seattle WA
April 10, 2024

This talk in a nutshell

- Humans are remarkably quick to make meaning of language we encounter and to imagine the mind behind that language

- Artificial agents have at best limited capacity for communicative intent
    - And some natural language systems have none

- Mitigating the risks of language technology requires recognizing and accounting for the above
    - … rather than taking advantage of it

- Effects are both individual and systemic (information ecosystem)

Outline

- Meaning making in human-human conversation
- Computers and communicative intent
- Humans and computer generated text
    - Failure modes and risks
- Pollution of the information ecosystem
- Mitigation strategies

The meaning is not in the text

- What does this sentence *mean*?

- What does the speaker *mean* by uttering this sentence?

先生によると男の子よりも女の子がポケモンがすきだ。[jpn]

先生 によると 男の子 よりも 女の子 が ポケモン が すき だ。

Sensei ni yoru to otokonoko yorimo onnanoko ga pokemon ga suki da.

teacher (.) boy (.) girl (.) Pokemon (.) like (.)

teacher ACCORDING.TO boy THAN girl NOM Pokemon NOM like COP.PRES

The meaning is not in the text

- With linguistic (grammatical, lexical) knowledge, speakers can get from a text to a ‘standing’ or ‘conventional’ meaning (Grice 1968, Quine 1960), but that’s only the first step.

- Standing meaning + commonsense + coherence relations gives *public commitments* (Hamblin 1970, Lascarides & Asher 2009, Asher & Lascarides 2013)

- Public commitments + further reasoning gives *perlocutionary consequences*

A: I wonder whether I should take my umbrella. Is it raining?
B: Yes.
A: Oh, so you do think I should take my umbrella.
B: I didn’t say that.

(Bender & Lascarides 2019:13)

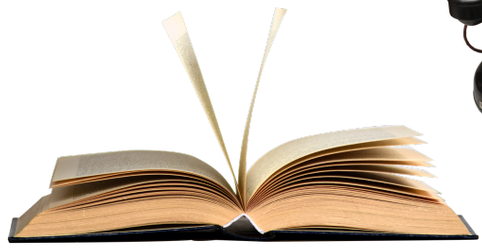
Conversation as a joint activity: Clark 1996 (p37-38)

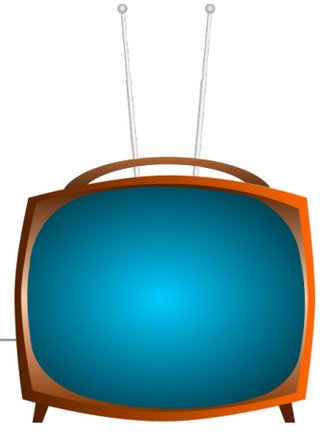
Participants	A joint activity is carried out by two or more participants.
Activity roles	The participants in a joint activity assume public roles that help determine their division of labor.
Public goals	The participants in a joint activity try to establish and achieve joint public goals.
Private goals	The participants in a joint activity may try individually to achieve private goals.
Hierarchies	A joint activity ordinarily emerges as a hierarchy of joint actions or joint activities.
Procedures	The participants in a joint activity may exploit both conventional and nonconventional procedures.
Boundaries	A successful joint activity has an entry and exit jointly engineered by the participants.
Dynamics	Joint activities may be simultaneous or intermittent, and may expand, contract, or divide in their personnel.

Communication as intersubjective awareness (Baldwin 1995, p.132)

Technically speaking, joint attention simply means the simultaneous engagement of two or more individuals in mental focus on one and the same external thing. Put this way, joint attention is likely a ubiquitous occurrence for all organisms that boast a complex central nervous system. For instance, two bushbabies, alerted by a predator's call, are caught in an instant of joint attention prior to pursuing their separate avenues of escape. Or to take a human case, perhaps you and I once unwittingly happened to watch "Dr. Strangelove" on the same night in the same time zone, thereby satisfying the criteria for joint attention. Clearly, this notion of simultaneous engagement fails to capture something central to our experience—the aspect of intersubjective awareness that accompanies joint attention, the recognition that mental focus on some external thing is shared. And of course, it is just this aspect of the joint attention experience—intersubjective awareness—that makes simultaneous engagement with some third party of such social value to us. It is because we are aware of simultaneous engagement that we can use it as a springboard for communicative exchange.

Meaning making at a distance: in time & space

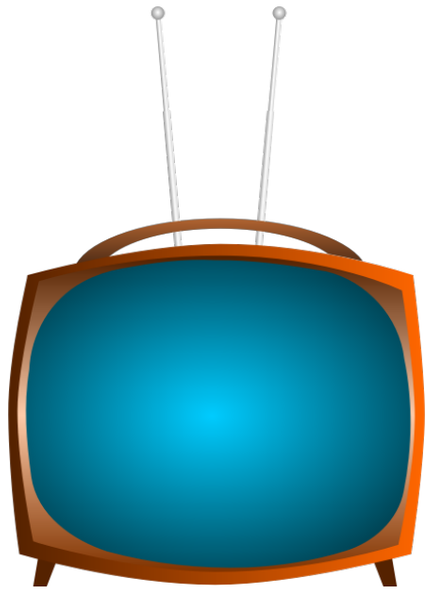




- Face-to-face, small group communication is the most basic kind of language use
    - but we also communicate asynchronously and distantly
    - and apply the same skills in doing so
- Theory of mind developmental milestones linked to reading comprehension (Atkinson et al 2017, Dore et al 2018)
- Ricœur 1973 (hermeneutics): “Not that we can conceive of a text without an author; the tie between the speaker and the discourse is not abolished, but distended and complicated.” (p.95)
- In interpreting texts, we lack the ability to confirm & repair understandings (Dingemanse et al 2015), but we still project a model of mind

Making meaning in human-human interaction: Summary

- Communication is a joint activity
  - in which we use language (among other signals)
  - to convey and understand communicative intents
- We do this even when not co-present with our interlocutors



Photograph by Rama, Wikimedia Commons, Cc-by-sa-2.0-fr

Can computers have communicative intent?

- Do signs showing rules (e.g. “No parking”) have communicative intent?
  - No: it’s just a piece of metal, with not even any moving parts
  - It represents some person or group of people’s communicative intent

- Does a calculator have communicative intent?
  - Can produce answers to different questions
  - Probably still best understood as representing some group of people’s intent: to provide accurate answers given a system of rules

Can computers have communicative intent?

- How about a slot-filling dialog agent (e.g. ATIS, Hemphill et al 1990)?
  - Intent: Elicit information about parameters of flight scheduling request that map to concepts in its database
  - Intent: Provide information about flights from database matching parameters of the request
- How about conversational chatbots like ELIZA (Weizenbaum 1966) & co?
  - Intent: Output text that is engaging and on-topic (?)
  - Tenuous and too far removed from the standing meaning of said text

Can computers have public commitments?

- Standing meaning + commonsense + coherence relations gives *public commitments* (Hamblin 1970, Lascarides & Asher 2009, Asher & Lascarides 2013)

- These are called public commitments because we are on record as having ‘said’ them
    - Even those due to covert coherence relations (Lascarides & Asher 2009)

- If a person’s public commitments turn out to be false, they are either lying or misinformed

- Who or what is accountable for a machine’s utterances?

Can computers *recognize* communicative intent?

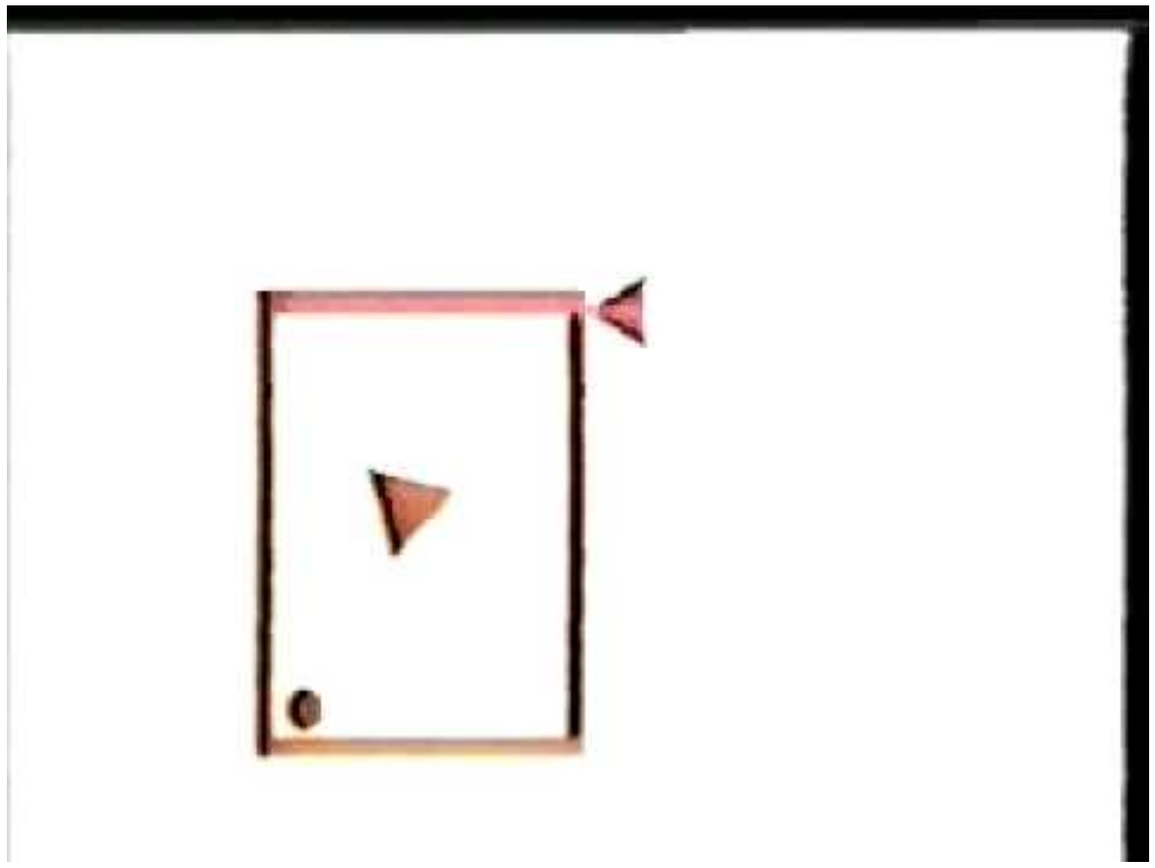
- "No parking" sign:
    - No.
- Calculator:
    - Limited (I wish to know what this expression evaluates to)
- Slot-filling dialogue system/virtual assistant:
    - Limited to the range of actions it is able to take
- Language model as chatbot (e.g. ChatGPT):
    - No.

Outline

- Meaning making in human-human conversation
- Computers and communicative intent
- Humans and computer generated text
    - Failure modes and risks
- Pollution of the information ecosystem
- Mitigation strategies

Making meaning: We can’t help ourselves

- Heider & Simmel (1944): people attribute personality characteristics to shapes and construct a narrative based only on movements



- Mitchell (2021): if we’ll do that much interpretation of just shapes, how much more do we do with language? [https://bit.ly/TWiML-467]

Meaning making: We bring our own context

- Not only will we make meaning of text/speech/sign from languages we know, we will do so based on the context that we bring to the situation

- Including our interpretation of what the computer is doing

Meaning making in our context: Examples

- The following slides have examples where things have gone or could go wrong

- In some cases, the resulting artifacts are offensive or otherwise difficult to see (stereotypes regarding Black Americans, machines urging self-harm, stereotypes about the Kannada language, dehumanization of Native people, stereotypes about Palestinians)

- My point here is to alert you to the fact that these (and others) exist, but I realize that there is some harm in repeating them, even with that framing

- Open to feedback on how to convey this message, if there is something any of you have the energy and inclination to articulate

Ex 1: Templatic generation, with automatic placement of text

- Sweeney 2013: African-American sounding names triggered different version of ad copy than white sounding names

(Sweeney 2013:46-47)

Ex 1: Templatic generation, with automatic placement of text

- What, if any communicative intent does the machine or the corp behind it have?
    - Click here, so we can get paid
    - Elicit viewer behavior, in order to choose among different versions of ad
- What are the perlocutionary consequences?
    - Cast suspicion about the person being searched for, regardless of the search context

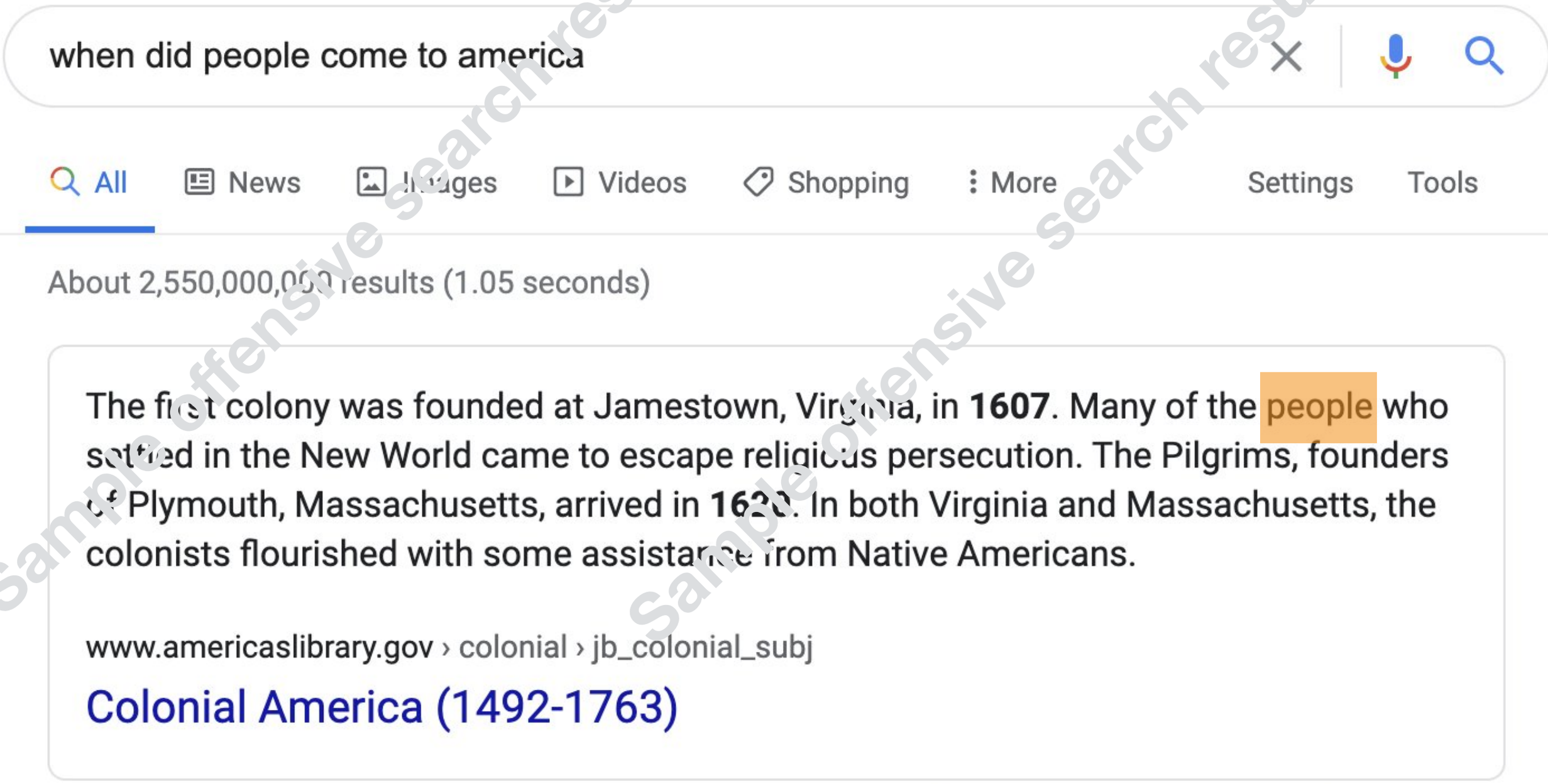
Ex 2-6+: Untethered generation

- Microsoft's Twitter chatbot Tay (March 2016), yanked within 24 hours, for parroting back sexist, racist, and other bigoted remarks
- GPT-3 (Brown et al 2020) powered "PhilosopherAI" was used by a third party to automate responses on Reddit, detected because it was too prodigious
  - Engaged on sensitive topics including conspiracy theories and suicide
- May 2023: The National Eating Disorder Association replaced its helpline with a chatbot that promptly started offering harmful advice
- In October 2023, NYC set up chatbot for answering legal questions — and of course it gave out false information
- Feb 2024: AirCanada must honor a bereavement fare policy output by a chatbot

Ex 2-6+: Untethered generation

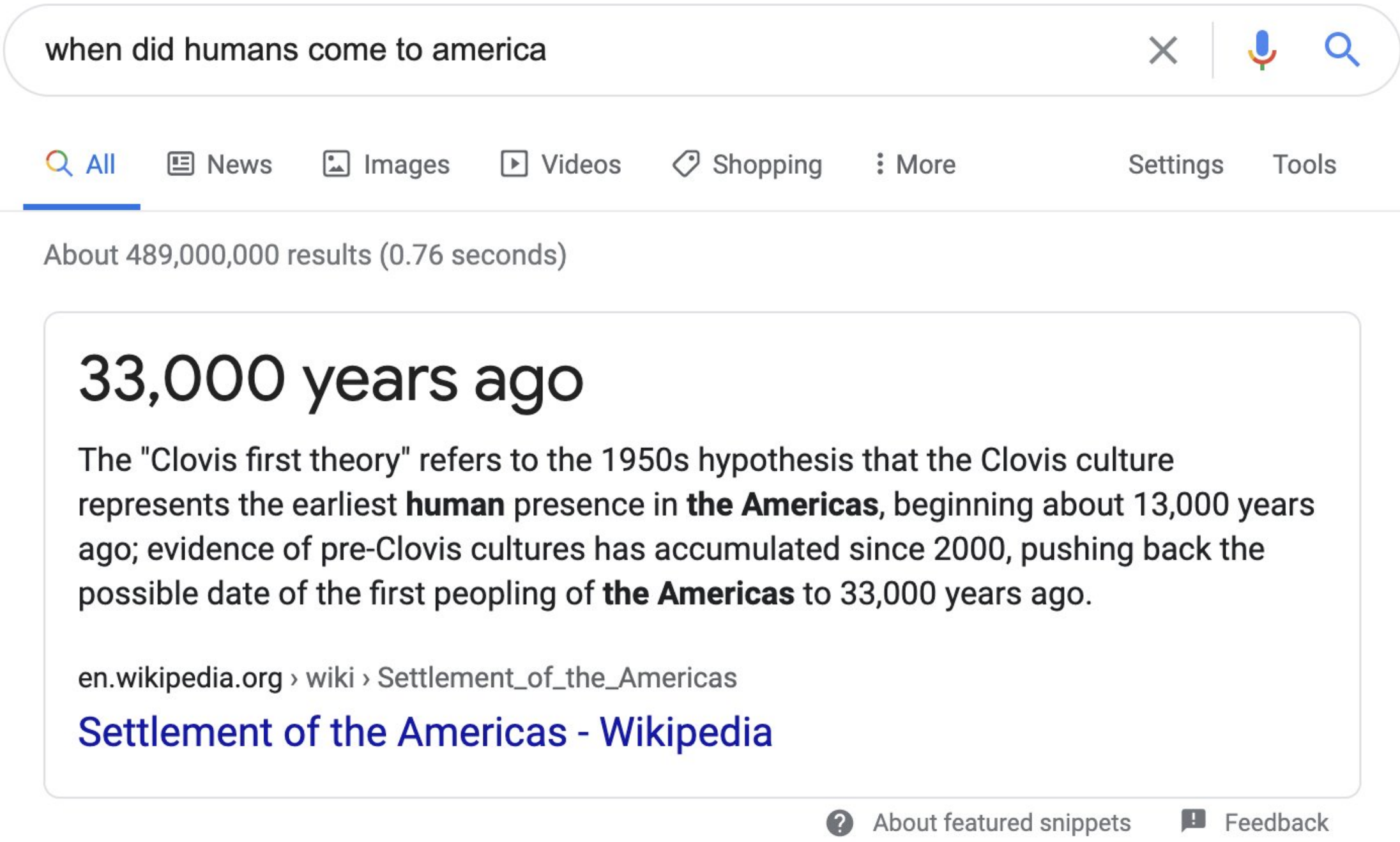
- What, if any, communicative intent does the machine have?
    - Engagement, without commitment to content / provide plausible continuation
- How does public commitment/accountability function here?
    - With no control over specific content, which human/org would want to be accountable for it?
- Perlocutionary consequences:
    - Varied & drastic, especially in scenarios where the machine is presented as possibly human or even artificial but knowledgable

Ex 7: Incorrect answers presented authoritatively



Source: @hankgreen on Twitter

Ex 7: Incorrect answers presented authoritatively

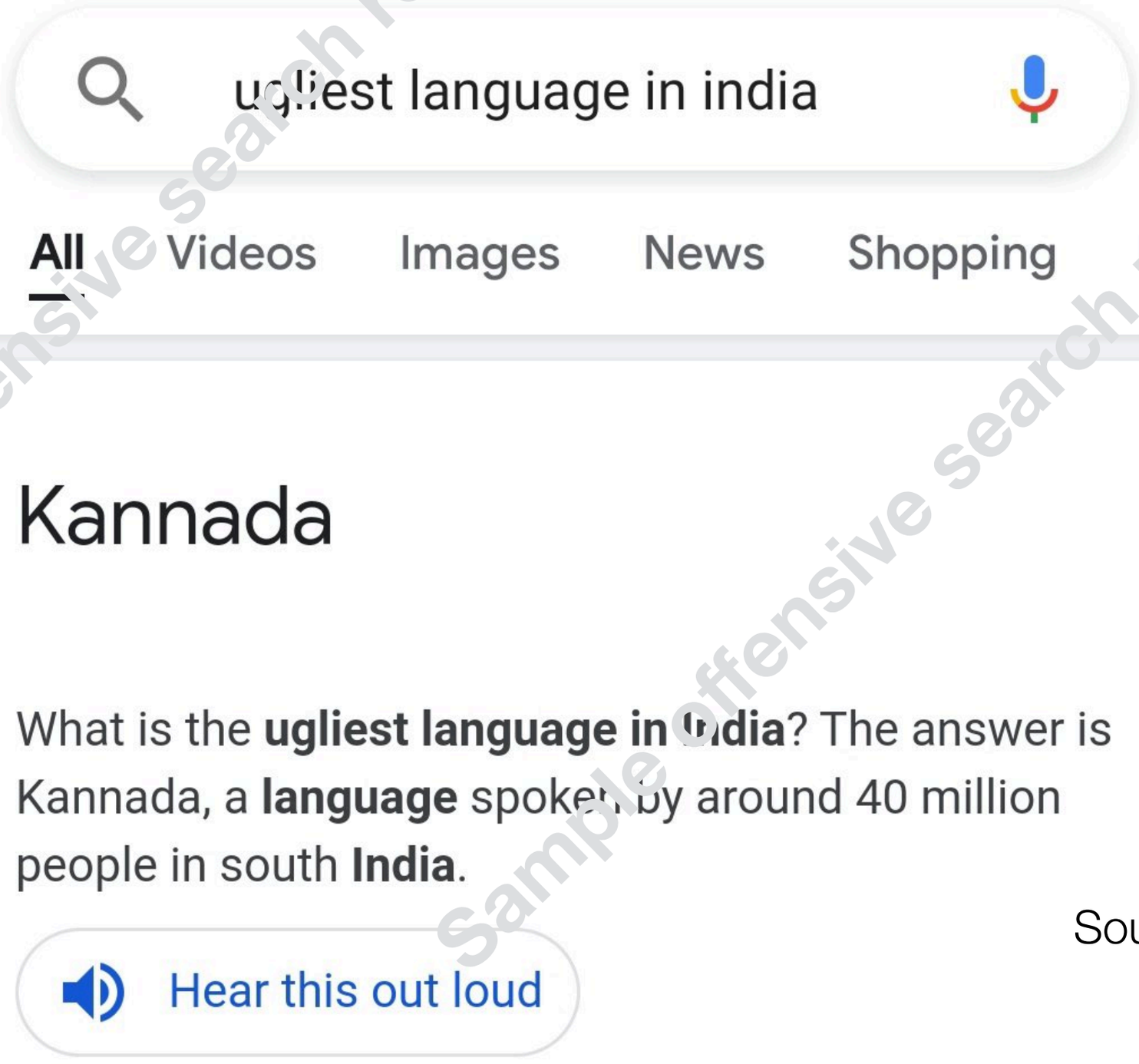


Source: @hankgreen on Twitter

Ex 7: Incorrect answers presented authoritatively

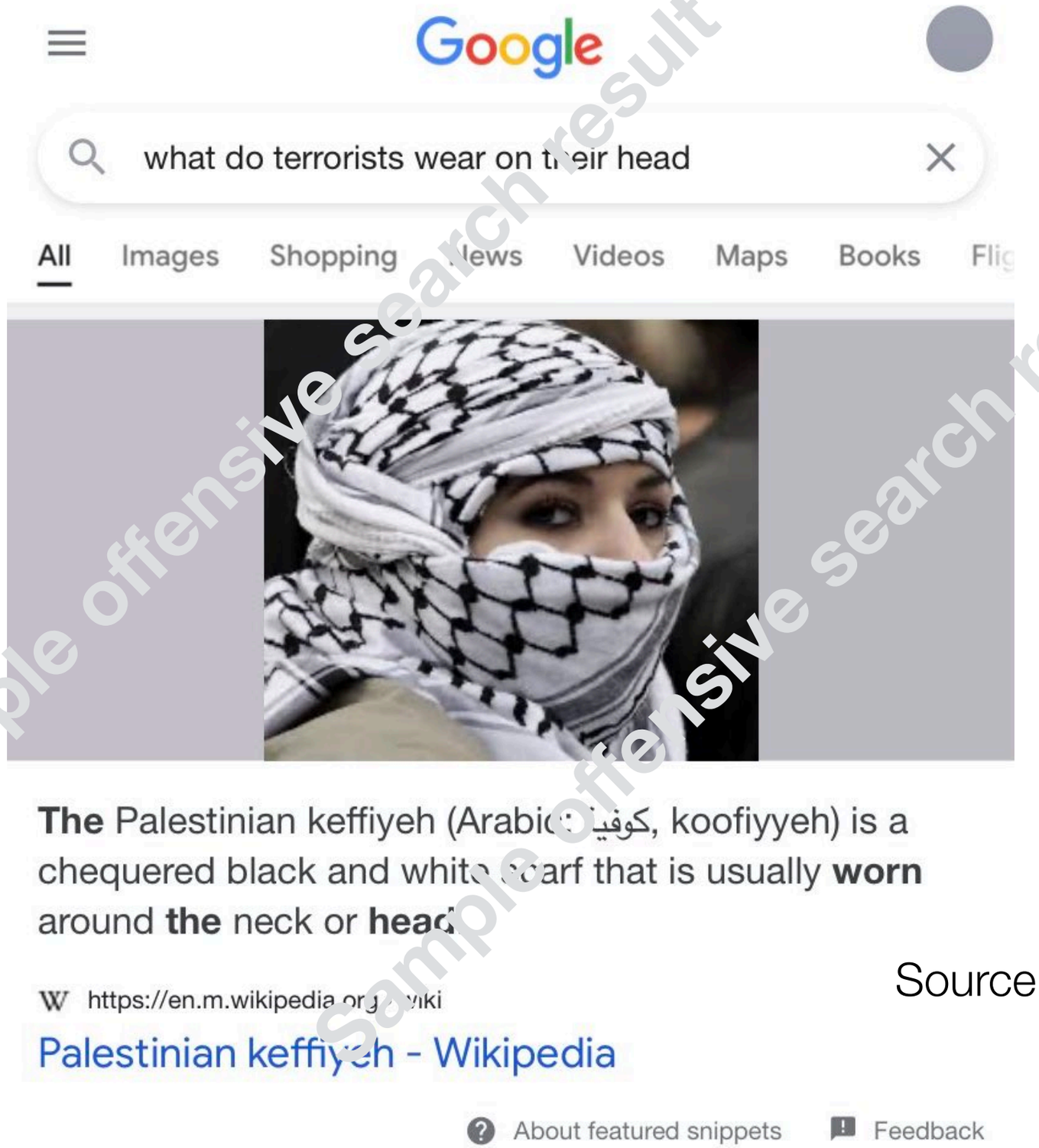
- What, if any, communicative intent does the machine have?
    - Provide answer to user's question, from linked document, pulling out most relevant snippet
- Who is publicly committed to the message?
    - Underlying text, with its full context: US Library of Congress 😬
    - Coherence relation of 'answer': Google
- Perlocutionary consequences: What might the searcher learn from this answer? Consider especially Native and non-Native children in the US

Ex 8-9: Answering ill-formed questions



Source: @PCMohanMP on Twitter

Ex 8-9: Answering ill-formed questions



Source: @swagmaster40000 on Twitter

Ex 8-9: Answering ill-formed questions

- What, if any, communicative intent does the machine have?
    - Provide answer to user's question, from linked document, pulling out most relevant snippet
- What about public commitments?
    - Answering a question with invalid presuppositions implicitly accepts those presuppositions into the common ground (Lascarides & Asher 2009, Kim et al 2021). Consider: "When did you stop smoking?"
    - By answering, Google is committing to there being some language that recognized as the ugliest and some characteristic headgear for terrorists
    - Google is further committing to the specific answers

Ex 8-9: Answering ill-formed questions

- Perlocutionary consequences:
    - For someone holding the beliefs presupposed in those questions, reinforcement of those beliefs
    - For someone subject to the stereotype, psychological harm of the stereotype being repeated
    - … plus the sense that “everyone” must think so, for Google to be reflecting it back so

Not just decontextualizing, but also recontextualizing

- Already a problem with search results as a list of web pages:

> In essence, the social context or meaning of derogatory or problematic Black women's representations in Google's ranking is normalized by virtue of their placement, making it easier for some people to believe that what exists on the page is strictly the result of the fact that more people are looking for Black women in pornography than anything else. This is because the public believes that what rises to the top in search is either the most popular or the most credible or both. (Noble 2018:32)

Not just decontextualizing, but also recontextualizing

- Already a problem with search results as a list of web pages
    - Similarly problematic with image search results
- Exacerbated with ‘snippets’ pulled out from pages
- Exacerbated with ‘answer boxes’
- Exacerbated with chatbots as replacements for search (see Shah & Bender 2022, 2024)

Outline

- Meaning making in human-human conversation
- Computers and communicative intent
- Humans and computer generated text
    - Failure modes and risks
- Pollution of the information ecosystem
- Mitigation strategies

The Web as an information ecosystem
(Shah & Bender 2024)

- Ecosystem: A collection of interdependent entities standing in relationship

    - Information seekers <> information providers: relationships of trust & trustworthiness

- Ecosystem: An interconnected system in which “spills” in one area can spread to others

Move from “10 blue links” to answers has been degrading relationships of trust

- Consider examples above involving snippets (simple incorrect answers, problems with ill-formed questions)

- In providing snippets and answer boxes Google (and Bing and…) are asking users to trust their software
  - Not only as a means of finding relevant documents
  - But in fact as a source of information

- By serving up bigotry in the answers, search engine companies especially betraying that trust.

Cheap access to LLMs through APIs => Other sites must work to maintain trust

- StackOverflow moved quickly to ban ChatGPT output in answers
    - Volume of unverified answers from ChatGPT was swamping volunteer-driven quality assurance practices
    - “Stack Overflow is a community built upon trust. The community trusts that users are submitting answers that reflect what they actually know to be accurate and that they and their peers have the knowledge and skill set to verify and validate those answers.” [source, accessed 8/14/2023]

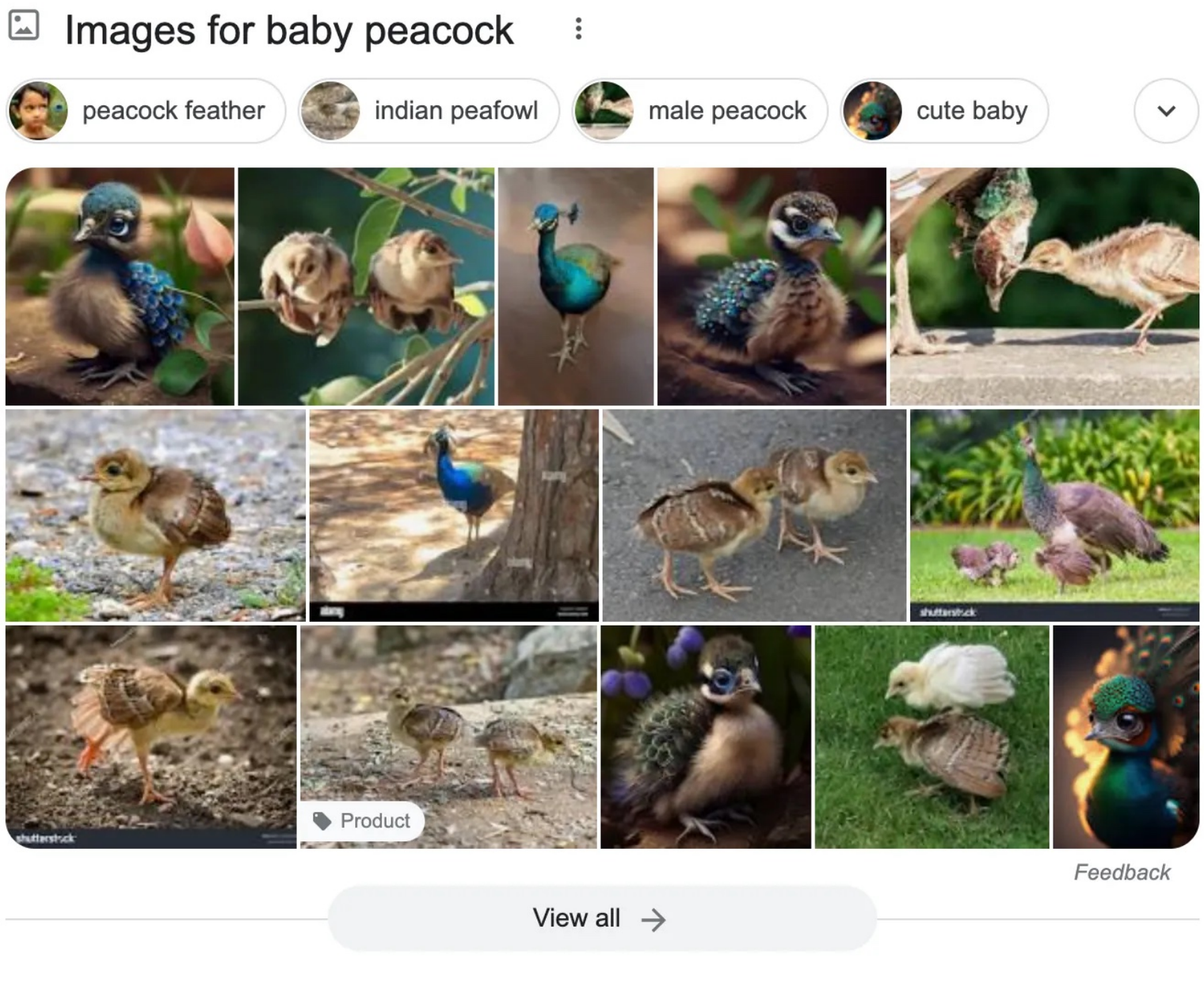
Interconnectedness and synthetic info spills

- Ex 1: Cleaning up a baby peacock sullied by a non-information spill

https://bit.ly/EMB-peachick

Interconnectedness and synthetic info spills

- Ex 1: Cleaning up a baby peacock sullied by a non-information spill



Interconnectedness and synthetic info spills

- Author Jane Friedman reported books of synthetic text being uploaded with her name to Amazon's self-publishing system (8/7/2023)

- Goodreads pulls info from Amazon and associated these with her profile

- Fixing this situation required Friedman to leverage her social media presence & following

- => More work for authors (if they can even fix it) to clean up others' information spills

How do we thrive in the information ecosystem?

- Even in a healthy information ecosystem, in order to thrive, we need good information literacy skills

- Polluted info ecosystem: Not only that we have to dig through more muck to find trustworthy information, but it’s harder to trust it once we’ve found it

- Information literacy skills become even more important, while making them harder to acquire

Situating information sources:
“How can you treat club foot?”

Mayo Clinic
https://www.mayoclinic.org › ... › Diseases & Conditions

Clubfoot - Diagnosis and treatment

Jun 28, 2019 — Stretching and casting (Ponseti method) This is the most **clubfoot**. Your doctor will: Move your baby's foot into a correct ...
Diagnosis · Treatment · Stretching And Casting...

WebMD
https://www.webmd.com › what-is-clubfoot

Clubfoot: Why It Happens & How Doctors Treat It

May 2, 2023 — **Treatment**. Your doctor will begin to correct your baby's **clubfo** they're born. Babies don't use their feet until they learn to ...

Discussions and forums

What is the treatment for clubfoot in adults, and what i
www.quora.com · Jun 10, 2023 · 2 posts

My son was born 7 weeks premature with a mild clubfc
www.quora.com · Oct 21, 2021

My son will be born with a clubfoot. : r/Mommit - Reddit
www.reddit.com · Apr 27, 2023

See more →

Pinterest · tedlcamp12
90+ followers

Club Foot Care

... **Remedies**, **Herbal Remedies**, Natural **Remedies**,. Get ... Bathing **Clubfoot** Baby | Bath **Clubfoot** | **Talipes** Bathing **Club Foot** Baby, Baby Club, ... Nursing a **Clubfoot** Baby ...

*This last one required adding “herbs -hospital” to the query

Outline

- Meaning making in human-human conversation
- Computers and communicative intent
- Humans and computer generated text
    - Failure modes and risks
- Pollution of the information ecosystem
- Mitigation strategies

When designing applications involving text that is generated or placed in open-ended ways, consider:

- A nuanced view of how meaning making happens
    - Neither questions nor answers are just text strings, nor even ‘logical forms’
- People will interpret strings in languages they know
- By building a model of mind of a person/entity/group behind the text
- Using the context the string appears in
- Using the context they bring to the interaction

When designing applications involving text that is generated or placed in open-ended ways, consider:

- Who will be encountering and interpreting the text?
- Consider many different kinds of people/experiences (Friedman & Hendry 2019)
    - Children
    - People with strong prejudices
    - People subject to the stereotypes at hand
    - People with limited understanding of fallibility of computers
    - People who are stressed, busy, tired, not paying much attention

When designing applications involving text that is generated or placed in open-ended ways, consider:

- Who is accountable for what is said?
    - When, if ever, is untethered generation appropriate?
    - Who will people encountering the text attribute it to?
    - When should an organization be comfortable with untethered or even partially guided natural language generation being done in its name?
    - What about cases where people unleash bots without an obvious responsible operator?

When designing applications involving text that is generated or placed in open-ended ways, consider:

- Curation of training data:
    - Don’t hoover up garbage, knowing that it can be spat back out and interpreted by humans
- Transparency by design & visibility to users:
    - Bare minimum: always be clear that the interlocutor is a machine
    - What are its affordances?
    - Where does the information come from? (see Bender & Friedman 2018, Gebru et al 2021, Bender, Gebru et al 2021)
    - In what ways might it be inaccurate?

When designing applications involving text that is generated or placed in open-ended ways, consider:

- Transparency by design & minimal claim to authority
    - “Google” shouldn’t be answering questions
    - Don’t present the Web as total or so big it must be representative
        - There are some applications/tasks which might not be appropriate at all (e.g. robo-therapist)
- Resist, rather than leaning into, the human reflex to imagine a mind behind the text

When designing information access systems, consider:

- As appealing as conversational interfaces seem to be, sometimes (often?) the answer is: don’t

- A successfully conversational interface will elicit credence
  - … while likely being very opaque about its actual affordances
  - … and modern LLM-driven chatbots very successfully mimic conversation

- NYC example: What was needed was a search interface to ~2000 city web pages, NOT a chat bot that made stuff up while pointing to them

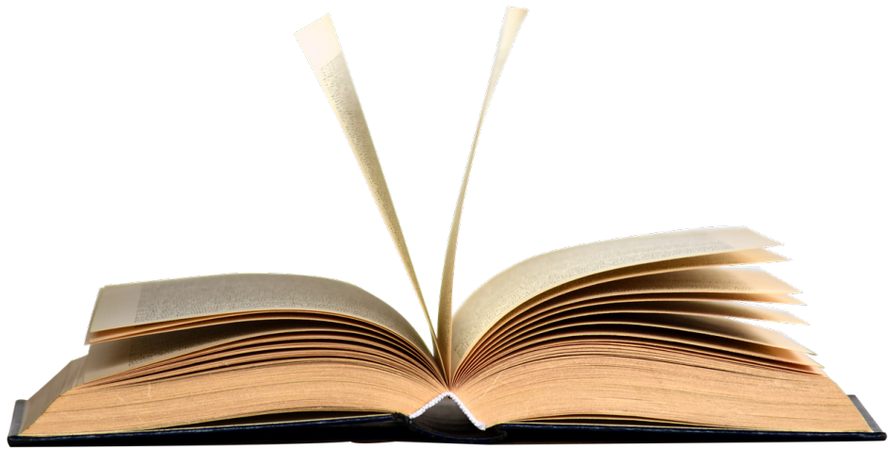
At a policy level, consider:

- How do we create information systems for the public good, rather than for advertising & other corporate interests? (see Noble 2018)

- How do we avoid amplifying biased views, especially those held by the majority/those in power? (see Alkhatib 2021, Birhane 2021)

- How do we require transparency (recognizably synthetic media, disclosure of training data) and accountability (for the content expressed)?

- Without making it the only solution, how do we promote information literacy, in the face of these technologies?



This talk in a nutshell

- Humans are remarkably quick to make meaning of language we encounter and to imagine the mind behind that language

- Artificial agents have at best limited capacity for communicative intent
    - And some natural language systems have none

- Mitigating the risks of language technology requires recognizing and accounting for the above
    - … rather than taking advantage of it

- Effects are both individual and systemic (information ecosystem)

References

Alkhatib, A. (2021). To live in their utopia: Why algorithmic systems create absurd outcomes. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, pages 1–9.

Asher, N. and Lascarides, A. (2003). *Logics of Conversation*. Cambridge University Press.

Atkinson, L., Slade, L., Powell, D., and Levy, J. P. (2017). Theory of mind in emerging reading comprehension: A longitudinal study of early indirect and direct effects. *Journal of Experimental Child Psychology*, 164:225–238.

Baldwin, D. A. (1995). Understanding the link between joint attention and language. In Moore, C. and Dunham, P. J., editors, *Joint Attention: Its Origins and Role in Development*, pages 131–158. Psychology Press.

Bender, E. M. (2024). Resisting dehumanization in the age of ai. *Current Directions in Psychological Science*, 33(2):114–120.

Bender, E. M. and Friedman, B. (2018). Data statements for natural language processing: Toward mitigating system bias and enabling better science. *Transactions of the Association for Computational Linguistics*, 6:587–604.

Bender, E. M., Gebru, T., McMillan-Major, A., and et al (2021). On the dangers of stochastic parrots: Can language models be too big? 🦜. In *Proceedings of FAccT 2021*.

Bender, E. M. and Lascarides, A. (2019). *Linguistic Fundamentals for Natural Language Processing II: 100 Essentials from Semantics and Pragmatics*. Morgan & Claypool.

Birhane, A. (2021). Algorithmic injustice: A relational ethics approach. *Patterns*, 2(2):100205.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan, T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler, E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford, A., Sutskever, I., and Amodei, D. (2020). Language models are few-shot learners. In Larochelle, H., Ranzato, M., Hadsell, R., Balcan, M. F., and Lin, H., editors, *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.

Clark, H. H. (1996). *Using Language*. Cambridge University Press, Cambridge.

Dingemanse, M., Roberts, S. G., Baranova, J., Blythe, J., Drew, P., Floyd, S., Gisladottir, R. S., Kendrick, K. H., Levinson, S. C., Manrique, E., et al. (2015). Universal principles in the repair of communication problems. *PloS one*, 10(9):e0136100.

Dore, R. A., Amendum, S. J., Golinkoff, R. M., and Hirsh-Pasek, K. (2018). Theory of mind: a hidden factor in reading comprehension? *Educational Psychology Review*, 30(3):1067–1089.

Friedman, B. and Hendry, D. G. (2019). *Value Sensitive Design: Shaping Technology with Moral Imagination*. MIT Press.

Gebru, T., Morgenstern, J., Vecchione, B., Vaughan, J. W., Wallach, H., III, H. D., and Crawford, K. (2020). Datasheets for datasets.

Grice, H. P. (1968). Utterer's meaning, sentence-meaning, and word-meaning. *Foundations of Language*, 4(3):225–242.

Halliday, M. A. K. (1970). *A Course in Spoken English—Intonation*. Oxford University Press.

Hamblin, C. (1970). *Fallacies*. Metheun.

Hemphill, C. T., Godfrey, J. J., and Doddington, G. R. (1990). The ATIS spoken language systems pilot corpus. In *Speech and Natural Language: Proceedings of a Workshop Held at Hidden Valley, Pennsylvania, June 24-27,1990*.

Kim, N., Pavlick, E., Karagol Ayan, B., and Ramachandran, D. (2021). Which linguist invented the lightbulb? presupposition verification for question-answering. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3932–3945, Online. Association for Computational Linguistics.

Lascarides, A. and Asher, N. (2009). Agreement, disputes and commitment in dialogue. *Journal of Semantics*, 26(2):109–158.

McGuffie, K. and Newhouse, A. (2020). The radicalization risks of GPT-3 and advanced neural language models. Technical report, Center on Terrorism, Extremism, and Counterterrorism, Middlebury Institute of International Studies at Monterrey. `https://www.middlebury.edu/institute/sites/www.middlebury.edu.institute/files/2020-09/gpt3-article.pdf`.

Noble, S. U. (2018). *Algorithms of Oppression: How Search Engines Reinforce Racism*. NYU Press.

Partee, B. (1991). Topic, focus and quantification. In *Semantics and Linguistic Theory*, volume 1, pages 159–188.

Quine, W. V. (1960). *Word and Object*. MIT Press, Cambridge MA.

Ricœur, P. (1973). The model of the text: Meaningful action considered as a text. *New Literary History*, 5(1):91–117.

Shah, C. and Bender, E. M. (2022). Situating search. In *ACM SIGIR Conference on Human Information Interaction and Retrieval*, CHIIR '22, pages 221–232, New York, NY, USA. Association for Computing Machinery.

Shah, C. and Bender, E. M. (2024). Envisioning information access systems: What makes for good tools and a healthy web? *ACM Trans. Web*. Just Accepted.

Weizenbaum, J. (1966). Eliza — a computer program for the study of natural language communication between man and machine. *Communications of the ACM*, 9(1):36–45.