(Generative) Al in Online Social Spaces

Ruotong Wang 2024.03.05

The rest of the quarter...

Wrap up prototype implementation

Thursday

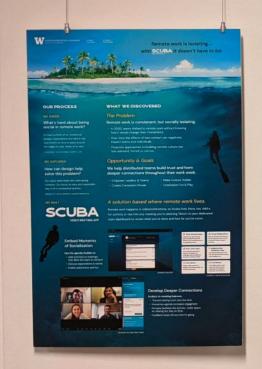
- Prepare poster
- Prepare pitch
- Prepare demo video

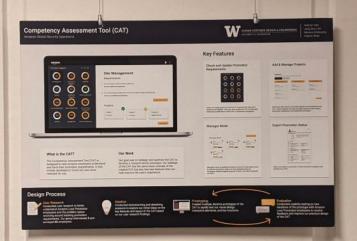
Poster Printing!

 Use Figma, Google Slides, PowerPoint, Keynote, Adobe Illustrator or some other design software

- MAKE SURE: Set your page size to 32in x 40in (portrait) or 40in x 32in (landscape)
 - For Google Slides go to File > Page Setup > Custom to set the page size to 32" x 40" or 40" x 32".
 - If you're making your poster in Figma, the dimensions for your frame should be 2800 x 2304
 - If you're making your poster in Keynote, the dimensions should be 2595pt x 3456pt

If you email a PDF to <u>ruotongw@cs.washington.edu</u> by Mar 11 MONDAY 2 PM, I will print it for you for free.









What to include in a poster

- Title, group members, contact info
- Problem statement
- Brief description of your system
- Key features + screenshots
- Overview of your process

Tips

- Use high-quality images
- Minimize text, use visual cues instead

Competency Assessment Tool (CAT)

Amazon Global Security Operations



Nathan Han Jang Soo Lim Monica Posluszny Helene Shea



What is the CAT?

The Competency Assessment Tool (CAT) is designed to help Amazon employees understand and track their promotion requirements. It was initially developed in Excel, but was never released for use.

Our Work

Our goal was to redesign and optimize the CAT to develop a research-driven prototype. Our redesign of the CAT has the same basic concept of the original CAT, but also has new features that can help improve the user's experience.

Key Features

Check and Update Promotion Requirements



and have not fulfilled. They can also update the CAT as they gain additional qualifications within the 12 promotion categories.

Manager Mode



Managers have an additional feature in the CAT that allows them managing, assign/suggest projects to them, and leave feedback for them.

Add & Manage Projects



Users can add, remove, and edit projects to be archived in the CAT. These projects can also be organized by project status, promotion categories, and leadership principles.

Export Promotion Status



Users can export a summary of their promotion progress and

Design Process



User Research Conducted user research to better understand Amazon Loss Prevention employees and the problem space revolving around tracking promotion requirements. Our group interviewed 5 and surveyed 65 employees.



Conducted brainstorming and sketching sessions to explore our initial ideas on the key features and layout of the CAT based on our user research findings.



Prototyping
Created multiple, iterative prototypes of the
CAT to rapidly test our visual design,
interactive elements, and key functions.



Conducted usability testing on new iterations of the prototype with Amazon Loss Prevention employees to receive feedback and improve our previous design of the CAT.



Today's plan

 Guest Speaker: Deepti, Co-Director of <u>New Public</u>, community organizer, former Director at Meta

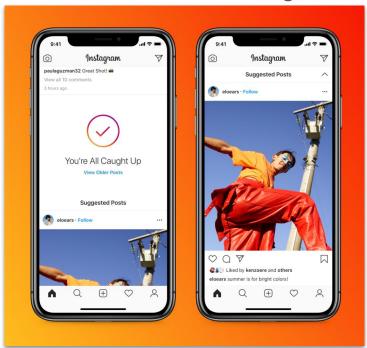


Today's plan

- Lecture on generative AI in social environments
 - Al bots
 - Al generated content
 - Trust
- Poster & pitch work time

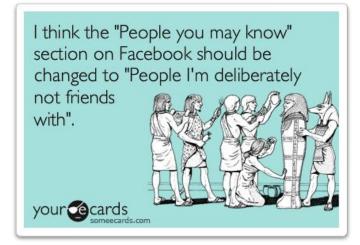
Al in social computing systems

Social media feed ranking



"People you may know"

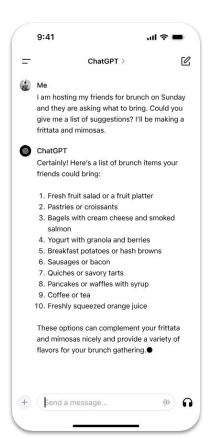


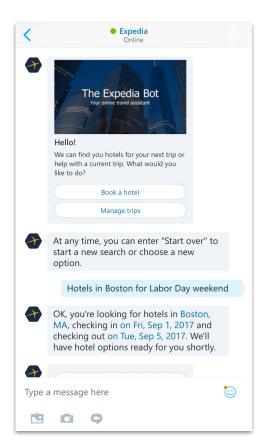


Al bots in online spaces

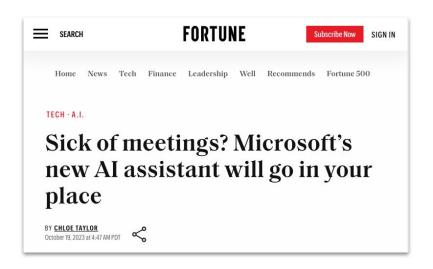
All not only sort and organize social data, but could also act as **an agent that directly interacts with users**.

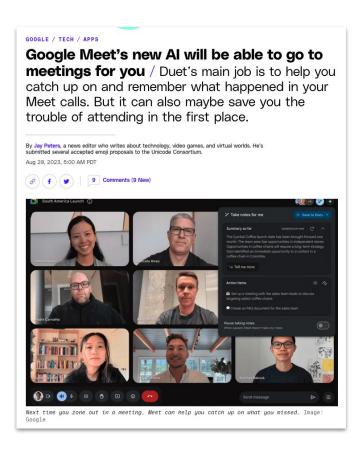
Al chat assistants





Al bots to attend meetings





Al bots to go on virtual first dates and become therapist

HOME \ NEWS \ NATIONAL

Skip the first date: New matchmaker app sends AI avatars to meet each other



Dating app in smartphone. File photo ... more >

PREMIUM

By Sean Salai The Washington Times Tuesday, January 23, 2024 TECHNOLOGY | ARTIFICIAL INTELLIGENCE

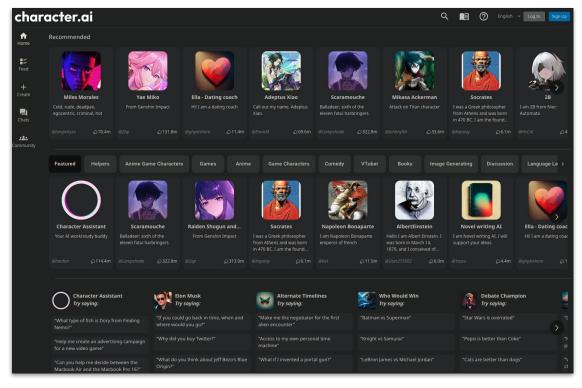
Employers Are Offering a New Worker Benefit: Wellness Chatbots

The apps use artificial intelligence to hold therapist-like conversations or make diagnoses

By Stephanie Armour Follow and Ryan Tracy Follow

Dec. 27, 2023 8:00 am ET

Al bots are becoming important actors in online social spaces, and increasingly more in critical contexts



Should we interact with AI bot the same as human actors?

Al or Stochastic Parrots?

Large Language Models are just stochastic parrots - they simply replicate patterns found in the text they are trained on and therefore can't be or become generally intelligent like a human.



On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?

Emily M. Bender* ebender@uw.edu University of Washington Seattle, WA, USA

Angelina McMillan-Major aymm@uw.edu University of Washington Seattle, WA, USA

ABSTRACT

The past 3 years of work in NLP have been characterized by the development and deployment of ever larger language models, especially for English. BERT, its variants, GPT-2/3, and others, most recently Switch-C, have pushed the boundaries of the possible both through architectural innovations and through sheer size. Using these pretrained models and the methodology of fine-tuning them for specific tasks, researchers have extended the state of the art on a wide array of tasks as measured by leaderboards on specific benchmarks for English. In this paper, we take a step back and ask: How big is too big? What are the possible risks associated with this technology and what paths are available for mitigating those risks? We provide recommendations including weighing the environmental and financial costs first, investing resources into curating and carefully documenting datasets rather than ingesting everything on the web, carrying out pre-development exercises evaluating how the planned approach fits into research and development goals and supports stakeholder values, and encouraging research directions beyond ever larger language models.

CCS CONCEPTS

Computing methodologies → Natural language processing.
 ACM Reference Format:

Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big 7. In. Conference on Fatirens. Accountability, and Transpurency (FAccT '21), March 3–10, 2021, Virtual Event, Canada. ACM, New York, NY, USA. J. Hagges, https://doi.org/10.1145/34218.83445922

1 INTRODUCTION

Timnit Gebru* timnit@blackinai.org Black in AI Palo Alto, CA, USA

Shmargaret Shmitchell shmargaret.shmitchell@gmail.com The Aether

alone, we have seen the emergence of BERT and its variants [39, 70, 74, 113, 146], GPT-2 [106], T-NLG [112], GPT-3 [25], and most recently Switch-C [43], with institutions seemingly competing to produce ever larger LMs. While investigating properties of LMs and how they change with size holds scientific interest, and large LMs have shown improvements on various tasks (§2), we ask whether enough thought has been put into the potential risks associated with developing them and strategies to mitigate these risks.

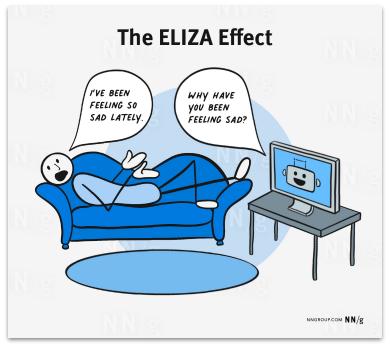
We first consider environmental risks. Echoing a line of recent work outlining the environmental and financial costs of deep learning systems [129], we encourage the research community to prioritize these impacts. One way this can be done is by reporting costs and evaluating works based on the amount of resources they consume [57]. As we outline in §3, increasing the environmental and financial costs of these models doubly punishes marginalized communities that are least likely to benefit from the progress achieved by large LMs and most likely to be harmed by negative environmental consequences of its resource consumption. At the seal we are discussing (outlined in §2), the first consideration should be the environmental cost.

Just as environmental impact scales with model size, so does the difficulty of understanding what is in the training data. In §4, we discuss how large datasets based on texts from the Internet overrepresent hegemonic viewpoints and encode biases potentially damaging to marginalized populations. In collecting ever larger datasets we risk incurring documentation debt. We recommend mitgating these risks by budgeting for curation and documentation at the start of a project and only creating datasets as large as can be sufficiently documented.

As argued by Bender and Koller [14], it is important to under-

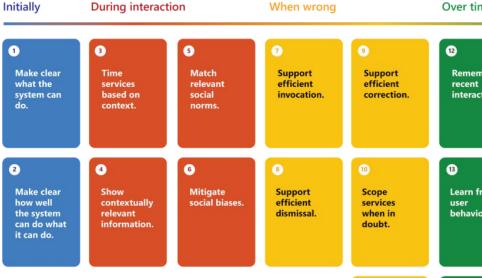
We tend to overtrust AI bots

```
Welcome to
                   EEEEEE LL
                                   IIII ZZZZZZZ
                                                  AAAAA
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                                                 АДДДДДД
                                                 AA
                                                     AA
                   EEEEEE LLLLLL IIII ZZZZZZZ AA AA
 Eliza is a mock Rogerian psychotherapist.
 The original program was described by Joseph Weizenbaum in 1966.
 This implementation by Norbert Landsteiner 2005.
ELIZA: Is something troubling you ?
YOU: Men are all alike.
ELIZA: What is the connection, do you suppose ?
YOU: They're always bugging us about something or other.
ELIZA: Can you think of a specific example ?
YOU: Well, my boyfriend made me come here.
ELIZA: Is it important to you that your boyfriend made you come here ?
YOU: He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
YOU: It's true. I am unhappy.
ELIZA: Can you explain what made you unhappy ?
```



How to help users better calibrate their trust with Al?

- Make clear what the system can do
 - Disclose Al's identity
- Make clear how well the system can do what it can do
 - Help users understand Al's capabilities



14

Update

adapt

cautiou

Make clear

system did

what it did.

why the

Carefully choose the terminology and metaphor

Tina Feldkamp

"Look! It's a Computer Program! It's an Algorithm! It's Al!": Does Terminology Affect Human Perceptions and Evaluations of Algorithmic Decision-Making Systems?

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Cornelius J. König Universität des Saarlandes

Germany ckoenig@mx.uni-saarland.de Nina Grgić-Hlača Max Planck Institute for Software Systems, Max Planck Institute for Research on Collective Goods Germany

nghlaca@mpi-sws.org

ABSTRACT

In the media, in policy-making, but also in research articles, algorithmic decision-making (ADM) systems are referred to as algorithms, artificial intelligence, and computer programs, amongst other terms. We hypothesize that such terminological differences can affect people's perceptions of properties of ADM systems, people's evaluations of systems in application contexts, and the replicability of research as findings may be influenced by terminological differences. In two studies (N = 397, N = 622), we show that terminology does indeed affect laypeople's perceptions of system properties (e.g., perceived complexity) and evaluations of systems (e.g., trust). Our findings highlight the need to be mindful when choosing terms to describe ADM systems, because terminology can have unintended consequences, and may impact the robustness and replicability of HCI research. Additionally, our findings indicate that terminology can be used strategically (e.g., in communication about ADM systems) to influence people's perceptions and evaluations of these systems.

CCS CONCEPTS

KEYWORDS

Human-centered computing → Empirical studies in HCI;
 User studies;

Algorithmic Decision-Making Systems?. In CHI Conference on Human Factors in Computing Systems (CHI '22), April 29-May 5, 2022, New Orleans, LA, USA. ACM, New York, NY, USA, 28 pages. https://doi.org/10.1145/3491102.3517527

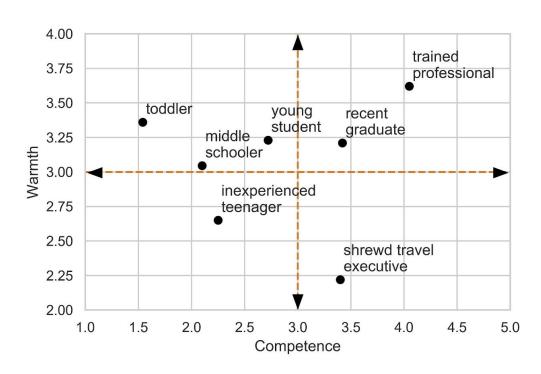
1 INTRODUCTION

When the public discusses algorithmic decision-making systems (ADM systems) – systems that either automate decision-making or support human decision-making – when journalists report about such systems, and when policy-makers develop regulations about such systems, there is a variety of terms used to refer to them. For instance, newspaper articles refer to such systems as intelligent systems [42], as algorithms [13], or robotic systems [22]. Likewise, there is large variety in terminology used to refer to ADM systems in policy-making documents. For instance, within the European Commission's "Ethics Guidelines for Trustworthy Al" [50], the authors refer to ADM systems as algorithms, artificial intelligence, AI technologies, AI systems, and robots whereas the General Data Protection Regulation (GDPR) refers to ADM systems as automated means.

Similar variation in the terminology used to refer to ADM systems also occurs in research investigating interactions between humans and ADM systems. In such research, researchers develop materials where they describe the respective system to their partieterminological differences (e.g., Al, automation, algorithm) affect

- Human perceptions of properties of assistive decision-making systems (e.g., perceived complexity)
- Human evaluations of systems (e.g., trust)

Carefully choose the terminology and metaphor



Effects of chatbot naming

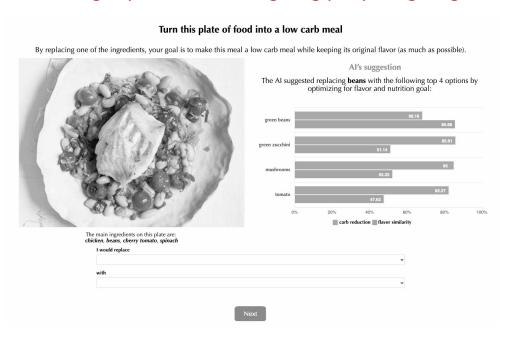
Referring to AI with a specific name / metaphor has an effect on how it is perceived, and even how it is used.

Projecting **competence** may help attract new users, but those users may discard the agent unless it can quickly correct with a **lower competence metaphor**.

Khadpe, Pranav, et al. "Conceptual metaphors impact perceptions of human-Al collaboration." Proceedings of the ACM on Human-Computer Interaction 4.CSCW2 (2020): 1-26.

Encourage critical engagement with Al

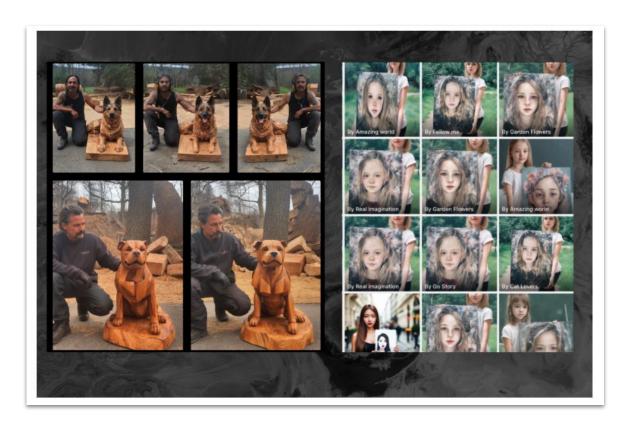
> Showing Explanations and giving people agency





Buçinca, Zana, Maja Barbara Malaya, and Krzysztof Z. Gajos. "To trust or to think: cognitive forcing functions can reduce overreliance on AI in AI-assisted decision-making." Proceedings of the ACM on Human-Computer Interaction 5.CSCW1 (2021): 1-21.

Al-generated content as Al tools become more accessible



We are bad at identifying AI-generated content



EPORT

Al-synthesized faces are indistinguishable from real faces and more trustworthy

Sophie J. Nightingale^{a,1} and Hany Farid^b

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Edited by William Press, Computer Sciences and Integrative Biology, University of Texas at Austin, Austin, TX; received November 11, 2021; accepted December 20, 2021

Artificial intelligence (AI)–synthesized text, audio, image, and video are being weaponized for the purposes of nonconsensual intimate imagery, financial fraud, and disinformation campaigns. Our evaluation of the photorealism of AI-synthesized faces indicates that synthesis engines have passed through the uncanny valley and are capable of creating faces that are indistinguishable—and more trustworthy—than real faces.

deep fakes | face perception

A rtificial intelligence (AI)–powered audio, image, and video synthesis—so-called deep fakes—has democratized access to previously exclusive Hollywood-grade, special effects technology. From synthesizing speech in anyone's voice (1) to synthesizing an image of a fictional person (2) and swapping one person's identity with another or altering what they are saying in a video (3), AI-synthesized content holds the power to entertain but also deceive.

Generative adversarial networks (GANs) are popular mechanisms for synthesizing content. A GAN pits two neural networks—a generator and discriminator—against each other. To synthesize an image of a fictional person, the generator starts with a random array of pixels and iteratively learns to synthesize a realistic face. On each iteration, the discriminator learns to distinguish the synthesized face from a corpus of real faces; if the synthesized face is distinguishable from the real faces, then the discriminator penalizes the generator. Over multiple iterations, the generator learns to synthesize increasingly more realistic faces until the discriminator is unable to distinguish it from real faces (see Fig. 1 for example real and synthetic faces).

Mark to the second state of the second secon

regression analyses were conducted—one for real and one for synthetic faces—to examine the effect of stimuli gender and race on accuracy. For real faces, there was a significant gender \times race interaction, $\chi^2(3,N=315)=95.03,P<0.001$. Post hoc Bonferroni-corrected comparisons revealed that mean accuracy was higher for male East Asian faces than female East Asian faces and higher for male White faces than female Boundary was least Asian faces and higher for male white faces than female Boundary race interaction, $\chi^2(3,N=315)=68.41,P<0.001$. For both male and female synthetic faces, White faces were the least accurately classified, and male White faces were less accurately classified than female White faces. We hypothesize that White faces are more difficult to classify because they are overrepresented in the StyleGAN2 training dataset and are therefore more realistic.

Experiment 2. In this study, 219 new participants, with training and trial-by-trial feedback, classified 128 faces taken from the same 800 set of faces as in experiment 1. Shown in Fig. 24 is the distribution of participant accuracy (orange bars). The average accuracy improved slightly to 59.0% (95% CI [57.7%, 60.4%]), with no response bias: d'=0.46; $\beta=0.99$. Despite providing trial-by-trial feedback, there was no improvement in accuracy over time, with an average accuracy of 59.3% (95% CI [57.8%, 60.7%]) for the first set of 64 faces and 58.8% (95% CI [57.8%, 60.3%]) for the second set of 64 faces. Further analyses to examine the effect of gender and race on accuracy replicated the primary findings of experiment 1. This analysis again revealed that, for both male and female synthetic faces, White faces were the most difficult to classify.

When made aware of rendering artifacts and given feedback, there was a reliable improvement in accuracy; however, overall 92% (R) 89% (R) 86% (R) 84% (R) 89% (S) 87% (S) 88% (S) 86% (S) 9% (R) 8% (R) 8% (R) 4% (R) 13% (S) 13% (S) 10% (S) 10% (S)

Fig. 1. The most (Top and Upper Middle) and least (Bottom and Lower Middle) accurately classified real (R) and synthetic (S) faces.

OLOGICAL AND TIVE SCIENCES

We are bad at identifying AI-generated content



RESEARCH ARTICLE

PSYCHOLOGICAL AND COGNITIVE SCIENCES



Human heuristics for Al-generated language are flawed

Maurice Jakesch^{a,b,1}, Jeffrey T. Hancock^c, and Mor Naaman^{a,b}

Edited by Timothy Wilson, University of Virginia, Charlottesville, VA; received June 29, 2022; accepted December 27, 2022

Human communication is increasingly intermixed with language generated by AI. Across chat, email, and social media, AI systems suggest words, complete sentences, or produce entire conversations. AI-generated language is often not identified as such but presented as language written by humans, raising concerns about novel forms of deception and manipulation. Here, we study how humans discern whether verbal self-presentations, one of the most personal and consequential forms of language, were generated by AI. In six experiments, participants (N = 4,600) were unable to detect self-presentations generated by state-of-the-art AI language models in professional, hospitality, and dating contexts. A computational analysis of language features shows that human judgments of AI-generated language are hindered by intuitive but flawed heuristics such as associating first-person pronouns, use of contractions, or family topics with human-written language. We experimentally demonstrate that these heuristics make human judgment of AI-generated language predictable and manipulable, allowing AI systems to produce text perceived as "more human than human." We discuss solutions, such as AI accents, to reduce the deceptive potential of language generated by AI, limiting the subversion of human intuition.

human-Al interaction | language generation | cognitive heuristics | risks of Al

Large generative language models (1, 2) produce semantic artifacts closely resembling language created by humans. Through applications like smart replies, writing autocompletion, grammatical assistance, and machine translation, AI-enabled systems infuse human communication with generated language at a massive scale. Large language models like OpenAI's GPT-3 and AI language applications like ChatGPT (1, 2) produce coherent writing pieces and generate entire conversations. AI-generated language enables novel interactions that reduce human effort but can facilitate novel forms of plagiarism, manipulation, and deception (1, 3–8) when people mistake AI-generated language for language created by humans.

In a series of experiments, we analyzed how humans detect ĀI-generated language in one of the most personal and consequential forms of speech—verbal self-presentation. Self-presentation refers to behaviors designed to control impressions of the self by others (9), while verbal self-presentation focuses on the words used to accomplish impression management. In this work, we operationalize self-presentation as self-descriptions of the type prevalent in online profiles (10), e.g., on professional or dating platforms. Researchers have extensively studied the importance of online self-presentation (11–13), showing that

Significance

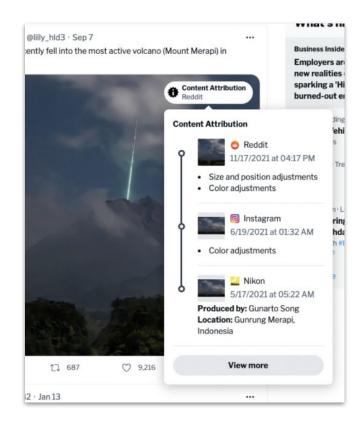
Human communication is now rife with language generated by Al. Every day, across the web, chat, email, and social media, Al systems produce billions of messages that could be perceived as created by humans. In this work, we analyze human judgments of self-presentations written by humans and generated by Al systems. We find that people cannot detect Al-generated self-presentations as their judgment is misguided by intuitive but flawed heuristics for Al-generated language. We demonstrate that AI systems can exploit these heuristics to produce text perceived as "more human than human." Our results raise the question of how humanity will adapt to Al-generated text, illustrating the need to reorient the development of Al language systems to ensure that they support rather than undermine human cognition.

Across AirBnB listings, online dating profiles, and LinkedIn profiles, people cannot distinguish text written by LLMs (e.g., GPT) from those written by people.

Al systems can exploit these heuristics on what we think is human to produce text perceived as "more human than human."

How to help people calibrate their trust?

Provenance can indeed help people better calibrate trust and accuracy perceptions of media.



Poster & pitch work time