Link to slides, citations and further reading

OR
(QR code and Bit.ly point to same link)

https://bit.ly/40RYp5E

Who gets to "do" responsible AI?

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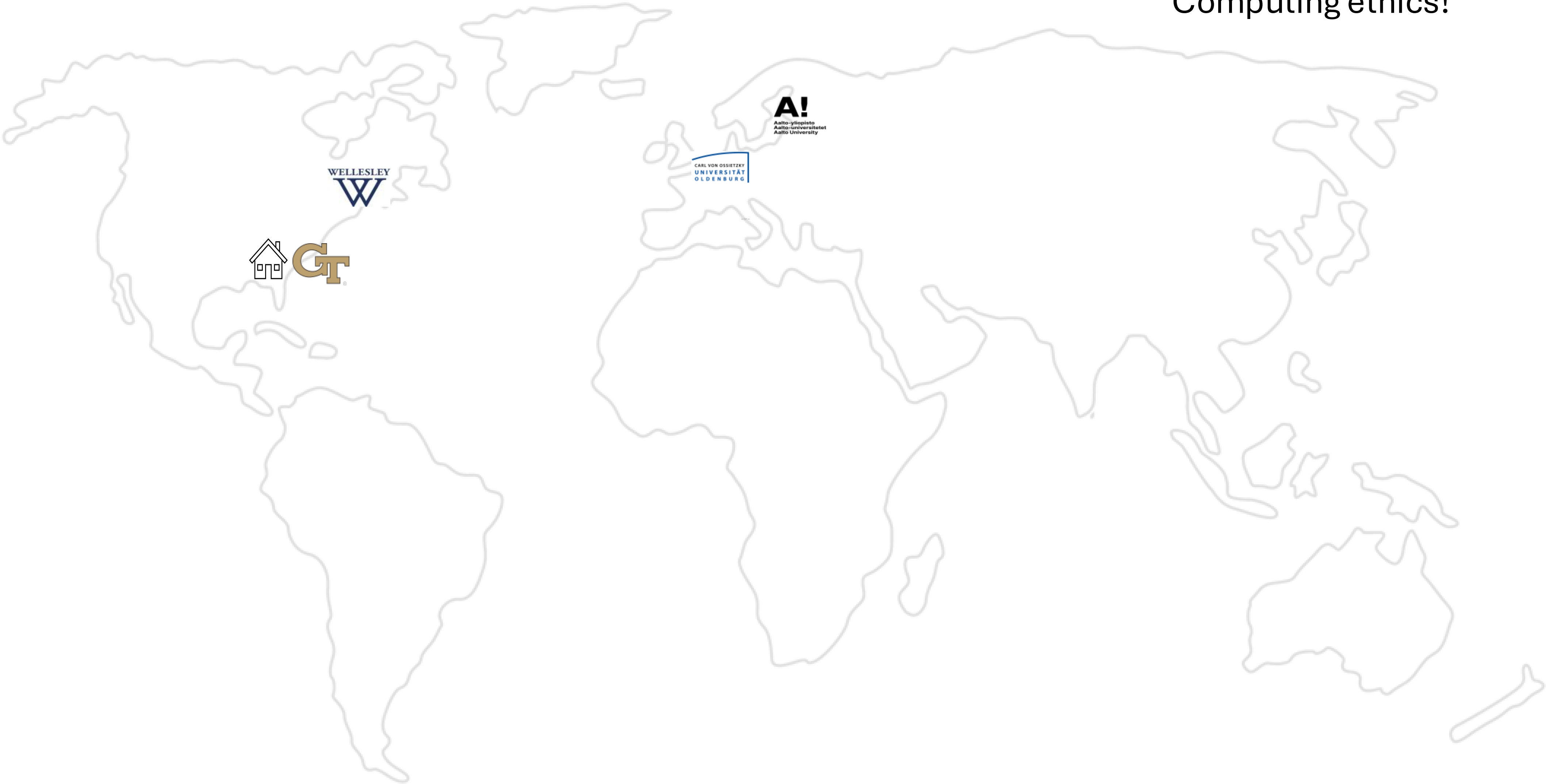
How'd I get here?

Liberal arts!

Computing ethics!



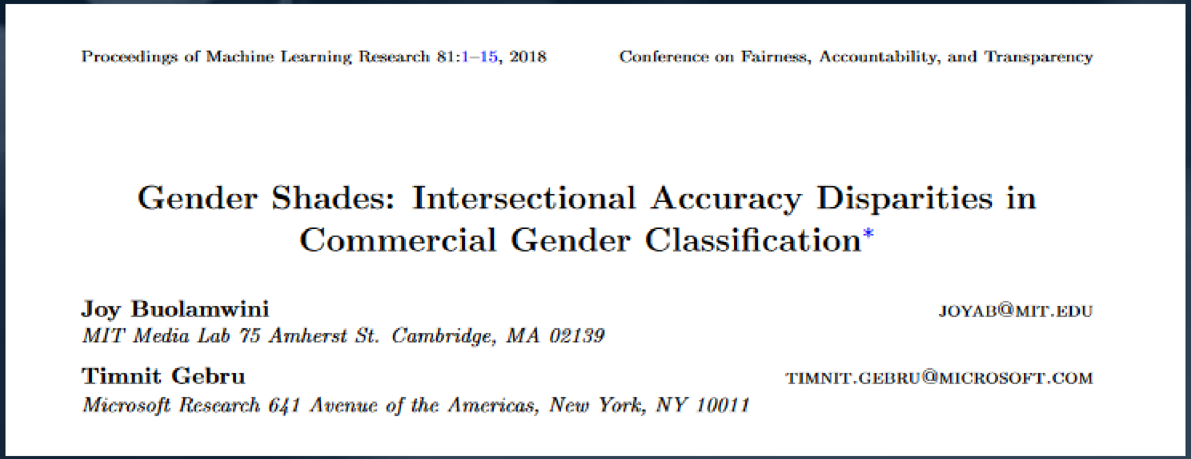
System accuracy: numerical or social?

Equality and equity in AI system performance.

(Borenstein & Howard, 2021; Hagendorff, 2020; Jobin et al., 2019)

Status Quo for Development of "unsafe" (or, unethical) AI systems

- Obtain training dataset(s) and use them to develop an AI system
- Check generative or predictive performance
- It works great! Go to market
- And then, an auditing body or individual notices something…
- Academic and/or media attention follows
- Product developer(s) try to fix the fault



Proceedings of Machine Learning Research 81:1–15, 2018 Conference on Fairness, Accountability, and Transparency

Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification*

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The Harms of AI Systems are not Abstract

Wrongfully accused by an algorithm

June 24, 2020 at 12:47 pm | *Updated June 24, 2020 at 6:46 pm*

1 of 4 | Robert Julian-Borchak Williams, who was arrested based on a faulty facial recognition match, at home with his wife, Melissa, and their daughters in Farmington Hills, Mich., June 20. (Sylvia Jarrus / The New York Times) **Less**

Two sides of this problem:

1. Our AI systems are faulty along cultural or social axes, because "the dataset wasn't good enough" or "the dataset didn't have enough diversity" .
2. We accept the decisions or predictions of these systems as incontestable truth.

We had an *unsafe* dataset.

We need *safe* datasets.

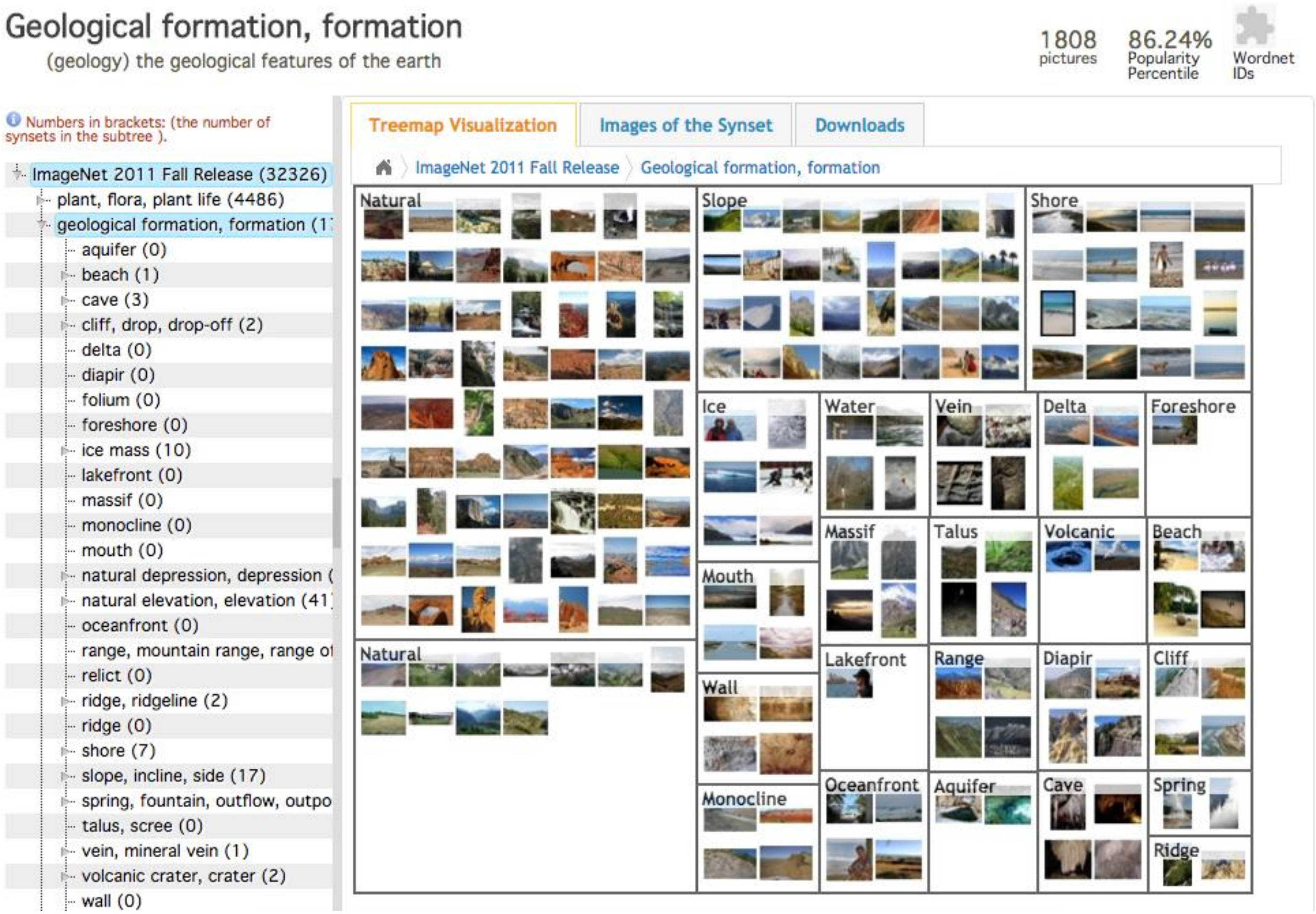
Outline for this Talk

1. ~~Who I am, and why I work in computing ethics~~
2. How AI training datasets get developed—ImageNet example
3. Demonstrating the potential of data annotators' insights and experiences
4. *Documenting the Status Quo: Understanding how AI dataset requesters understand and engage with data workers*
5. *Datum Fieldnotes: documenting data workers' insights to support safe dataset use*
6. Future work: the costs of data annotation

How datasets to train or refine AI systems get developed

J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li and L. Fei-Fei, ImageNet: A Large-Scale Hierarchical Image Database. IEEE Computer Vision and Pattern Recognition (CVPR), 2009.

What is ImageNet?



- Started in 2006; periodic updates
- 14 million photos of objects with labels—utility for object-recognition (CV) systems
- Labels sourced from Princeton's *WordNet*
- Scrape Goolge Images SERP for term, have Turkers verify

Why talk about ImageNet?

TITLE	CITED BY	YEAR
Imagenet: A large-scale hierarchical image database J Deng, W Dong, R Socher, LJ Li, K Li, L Fei-Fei Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on ...	76727	2009

Extremely impactful for the development of the field of computer vision (CV); key benchmarking dataset
(Raji et al. 2021.)

Pervasive Label Errors in Test Sets Destabilize Machine Learning Benchmarks

Curtis G. Northcutt*
ChipBrain, MIT, Cleanlab

Anish Athalye
MIT, Cleanlab

Jonas Mueller
AWS

Expensive to build; sticks around
(Northcutt et al., 2021)

One of the first major AI (CV) datasets to be assembled with crowdworkers (Amazon Mechanical Turkers)
(Tsipras et al., 2020)

The problem(s) with ImageNet

ImageNet given label:
tailed frog

Cleanlab guessed: **European green lizard**

MTurk consensus: **European green lizard**

ID: 00032415

ImageNet given label:
alligator lizard

Cleanlab guessed: **European green lizard**

MTurk consensus: **European green lizard**

ID: 00033036

ImageNet given label:
alligator lizard

Cleanlab guessed: **desert grassland whiptail lizard**

MTurk consensus: **desert grassland whiptail lizard**

ID: 00018979

ImageNet given label:
alligator lizard

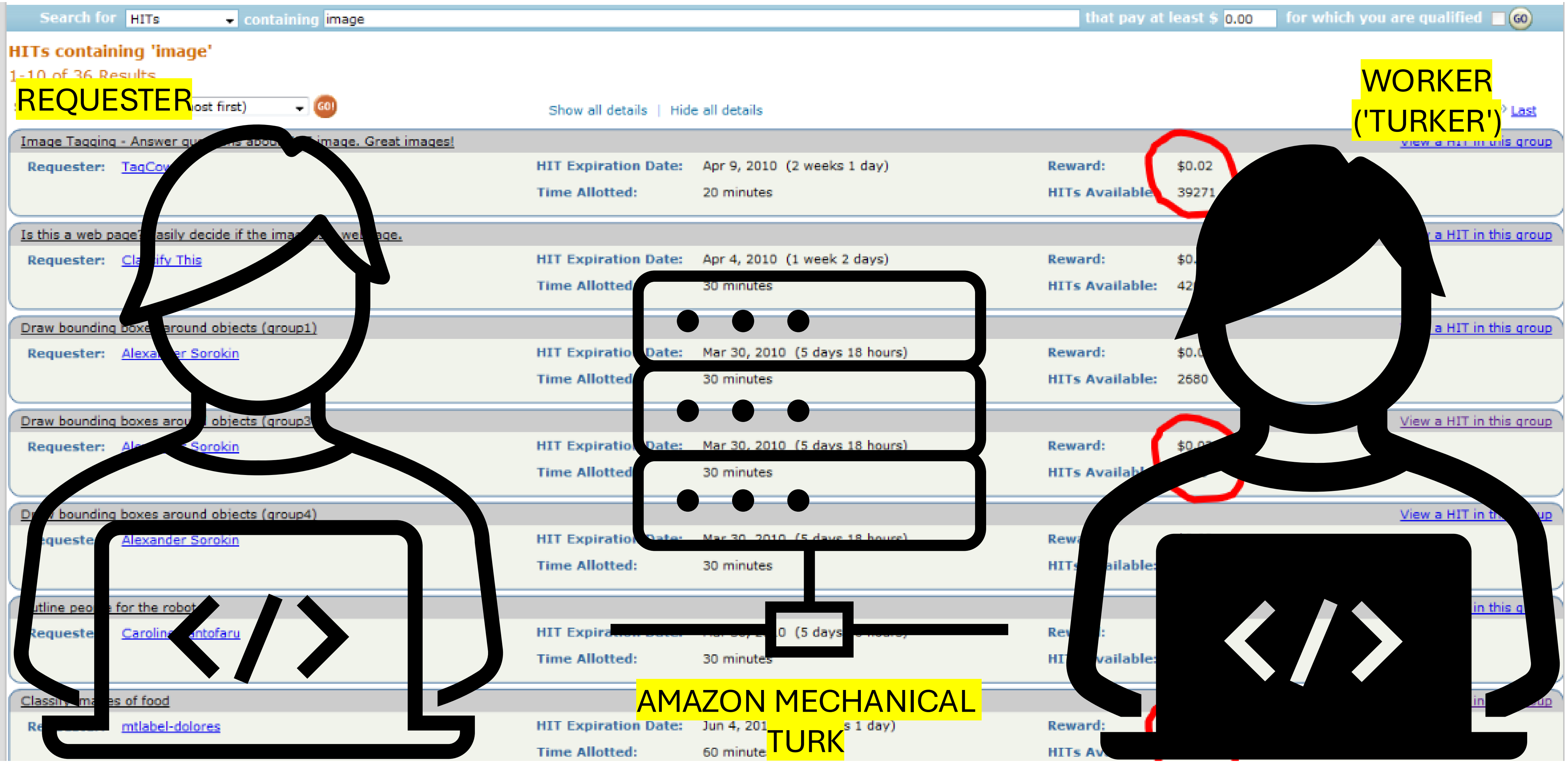
Cleanlab guessed: **desert grassland whiptail lizard**

MTurk consensus: **desert grassland whiptail lizard**

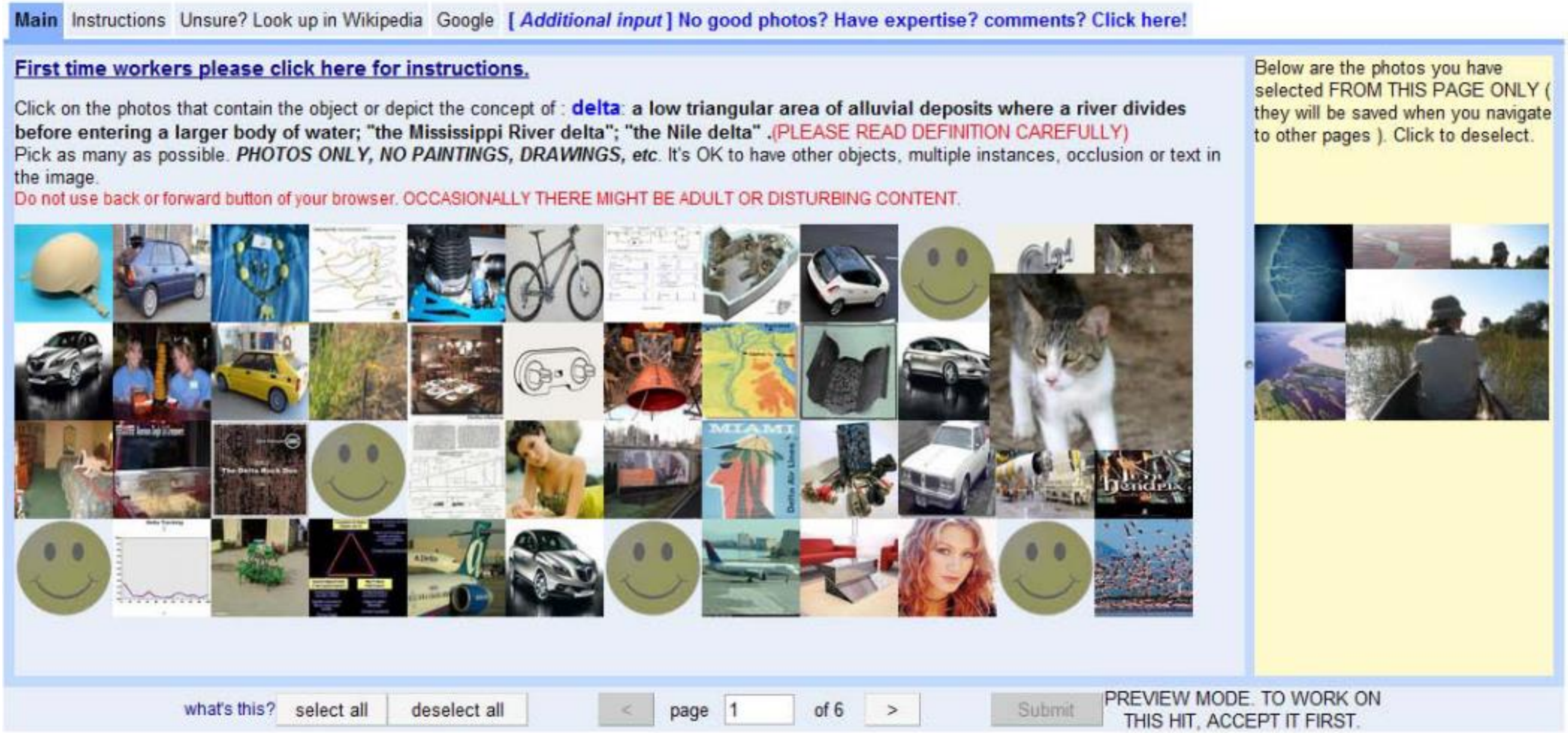
ID: 00028626

(Vasudevan et al., 2022); See for yourself: https://labelerrors.com/

What is the role of crowdsourcing?



What workers see when completing an *ImageNet* AMT task ('HIT')...



Returning to the harmful, discriminatory, and incorrect labels of *ImageNet*

1. Why weren't data workers asked for their impressions, concerns, and reflections?
2. Going forward, once we have impressions, concerns, and reflections from data workers, how do we record and archive this paradata?

This is where my work fits in!

My work in the context of R-AI more generally

Deb Raji
Mozilla

Margaret Mitchell
Ex-Google, Chief Ethicist at Hugging Face

Collecting, cleaning, organizing, and standardizing data needed to train AI system

Predictions generated by AI system are modified

Pre-processing

In-Processing

Post-processing

Arvind Narayanan & Sayash Kapoor
Princeton

Alondra Nelson
White House OSTP

Learning algorithm that comprises AI system is modified

Kate Crawford
Microsoft

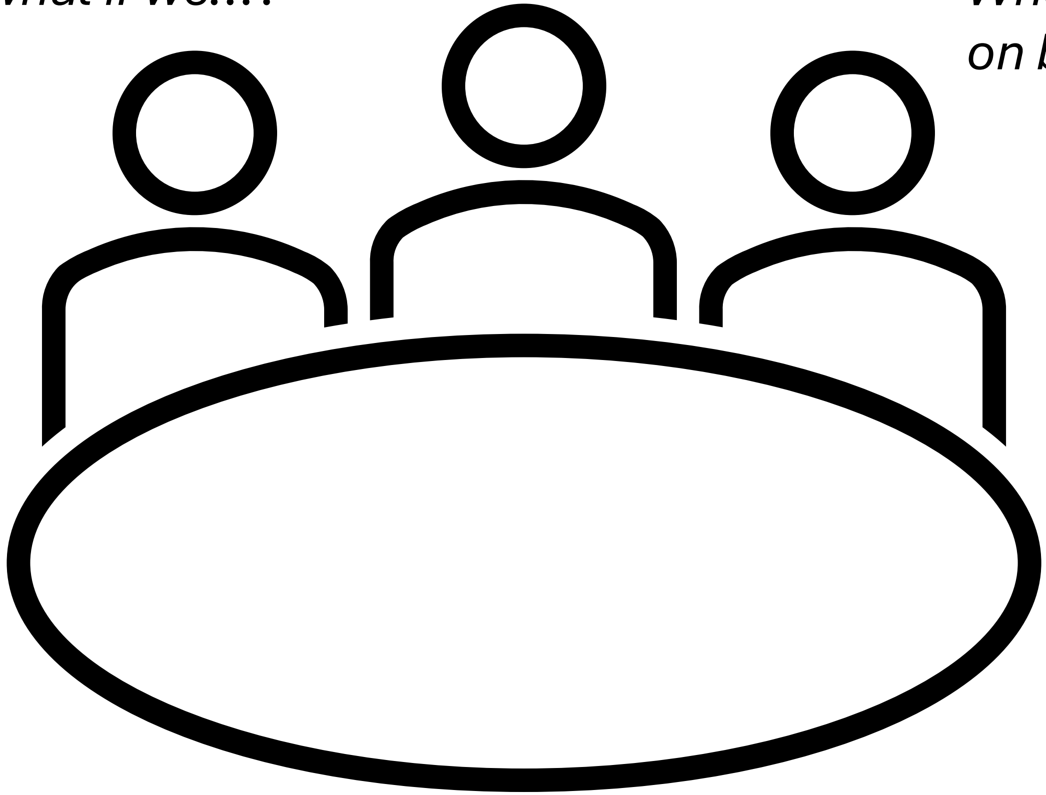
(D'Alessandro et al., 2017)

DataWorks: *the conference table model*

An ode to the conference table

Wait, what if we...?

What is the data we work on being used for?



What did you mean with this direction?

This is close but not quite there—can you readjust...?

Critical data literacy: developing dataset auditing skills

- **10 week** Critical Data Literacy curriculum at DataWorks
- **2 modules**: non-computational introducing to AI, data preparation skills
- **90 minute sessions:** mix of short lectures, hands on activities, worksheets, and creative activities

A medical company thinks they can diagnose different kinds of bug bites without patients having to see a doctor in person. Instead, patients will send photos of their bug bites to an algorithm that will tell them what bit them.

Lara Schenck, Dana Priest, Gabe Dubose, Zajerria Godfrey, Annabel Rothschild, Ben Rydal Shapiro, and Betsy DiSalvo. 2025. "A Window into Data Apprenticeship: Developing an Integrated Work-Training Curriculum for Novice Adults". In SIGCSE TS 2025 (ACM Special Interest Group on Computer Science Education).

Numerous problems quickly arose:

- There is no singular AAVE — locations matter and express differences
- The data was sexually suggestive and racist

The fundamental premise is suspect:

- “Who really wants to be able to identify Black speakers?”
- “It seems like this could be misused in a way that will hurt my community.”

* Nicholas Deas, Jessi Grieser, Shana Kleiner, Desmond Patton, Elsbeth Turcan, and Kathleen McKeown. 2023. Evaluation of African American Language Bias in Natural Language Generation. https://doi.org/10.48550/arXiv.2305.14291

Carl DiSalvo, Annabel Rothschild, Lara L. Schenck, Ben Shapiro, and Betsy DiSalvo. 2024. “When Workers Want to Say No: A View into Critical Consciousness and Workplace Democracy in Data Work”. Proc. ACM Hum.-Comput. Interact. 8, CSCW1, Article 156 (April 2024)

Data Use Agreement

Please copy the following agreement below: "I will not use the VALUE dataset for malicious purposes including (but not limited to): deception, impersonation, mockery, discrimination, hate speech, targeted harassment and cultural appropriation. In my use of this resource, I will respect the dignity and privacy of all people." *

Your answer

A reminder that this is human subject research. By clicking "Yes" below, you understand that this dataset is based on a small sample of individuals, and it does not represent all individuals in a culture. *

- YES
- NO

This resource contains synthetic data from transformations based on features of English dialects. This synthetic data was designed to stress-test current NLP systems. It may not fully or accurately represent the natural usage patterns of native speakers. *

- I understand
- I do not understand

This resource is available for non-commercial research purpose only. *

- I understand
- I do not understand

Data workers **are highly capable** of serving as dataset auditors, when requesters and workers are collaborators.

We also know from citizen science model that this is possible in platform based work.*

Now, how do we make collaboration happen at scale?

*Ashley Boone, Annabel Rothschild, Xander Koo, Grace Pfohl, Alyssa Sheehan, Betsy DiSalvo, Christopher Le Dantec, and Carl DiSalvo. 2024. "Reimagining Meaningful Data Work through Citizen Science". Proc. ACM Hum.-Comput. Interact. January 2024.

How do we build collaborative relationships between data work requesters and workers?

Pulling chairs up to the conference table

The Problem with Proxies: understanding the status quo in platform-mediated data work for AI systems

Research questions:

- (RQ1) how do requesters perceive the identity of platform workers?
- (RQ2) what are their views on the workers' motivations and work methods?

Annabel Rothschild, Ding Wang, Niveditha Jayakumar, Lauren Wilcox, Carl DiSalvo and Betsy DiSalvo. 2024. "The Problems with Proxies: Making Data Work Visible through Requester Practices". AIES (Conference on Artificial Intelligence, Ethics, and Society).

Final project for Qualitative Methods for HCI (GT MS-HCI course)

- Students want "real world" projects for their portfolios
- Accrue authentic experience of human factors work (e.g., recruiting)

Two years to conduct this work: starting from course project design in August 22, to publishing work in October 24.

Annabel Rothschild, Ding Wang, Niveditha Jayakumar, Lauren Wilcox, Carl DiSalvo and Betsy DiSalvo. 2024. “The Problems with Proxies: Making Data Work Visible through Requester Practices”. AIES (Conference on Artificial Intelligence, Ethics, and Society).

Design Interview Protocol <--> Figure Out Who to Talk to

Semi-structured Interview Protocol

Introduction

1. Introduce the study, the IRB protocol, and yourself.
2. Ask if participant has questions.
3. Ask them to verbally consent.

Ask participants to introduce themselves.

In general terms, without naming organizations, what do you do? Do you consider that research or product development?

Have participant tell us about their background as a requestor on digital pieceworking platforms (e.g., Amazon Mechanical Turk, Clickworker, Microworker).

How did you find out about these platforms?
If from an advisor (if interviewee was a PhD or MS student), how do you think your advisor learned about it?
Do you ever look at new platforms? If so, how do you think about those new platforms (review them for your purposes)?
What impact does crowdsourcing, crowd work, or human intelligence have on your career?
How does it contribute to your productivity or research agenda? (E.g., are there things you are uniquely able to do because of crowdsourcing?)
Do you anticipate publishing findings from the work you do with pieceworkers?

How did you start requesting on those platforms? E.g., for academic or professional role / duties, for personal project, etc.

How did you learn to be a requestor? (e.g., Googled it, knew from PhD work, watched YouTube videos, word of mouth, ...)
What kinds of tasks do you post as a requestor?
How would you describe the genre(s) of work you post? (E.g., image labeling, 'chat with a robot', quick NLP translation)

Can you walk me through a recent HIT that you posted (or had your students post)?

What made you choose this platform for this task?
How did you conceptualize the nature of this task? Why did you need (or choose) to have human annotators / labelers / conversation partners, etc.?
How did you decide to structure your HIT? What design choices -- e.g., having workers leave AMT proper and move to a Qualtrics survey setup -- did you make and why?

How do you design tasks?

Do you trial your HITs? Does your lab, workplace (or other professional setting) have any procedures for doing so? (E.g., creator checks for all required questions being answered, or has friends check that wording makes sense, etc.)
How do you select for workers? Do you have any common defaults (e.g., only accepting 'Master' Turkers)?
Who do you think works on your task? How do you estimate the time on tasks?
How do you determine payment? Do you have a mental model for what's an appropriate pay scale, or do you alter it task-by-task?
How do you use the data that is used to select workers (e.g., criteria info -- like a test to make sure if people are 'qualified')?

Industry and academic professionals who have:

(1) Used a crowdsourcing platform (e.g., Amazon MTurk) to source data work, AND:

(2) that data work was used to train or refine an AI system.

Potential participants were identified by the students through:

- Relevant online forums
- Own professional networks
- Course staff's professional networks

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Memoing --> Thematic Analysis --> Codebook and Final Analysis

Associate interaction

- Contradiction: they want the average American, but they filter works by perceived quality tags (G15P3)
  - Platform tries to qualify workers (eg Master Turker) but rise of requester-imposed qualifications suggests system does not work
- Based in US
  - Getting around GDPR
  - Can circumvent with VPN
- Technical fluency
  - Want to interact with / engage the average American, but posting on a site that requires a fair level of digital fluency and also access
- Associate feedback
  - None of them talk about worker as an equal counterpart; research-participant or requester-worker, where the requester self-describes as being in position of power – demonstrated by lack of feedback requester or solicited
  - No respect for worker – feedback / comment box would indicate respect, at least equal work or fellow worker
- G14P1 – usertesting.com
  - Good result because of modality that platform offers (facilitates think aloud sessions)
- G11P4 – fair payment
  - If people miss the gold standard, they will still pay but they will throw out their data
- Assumptions made, and use them to justify their behaviors, such as picking demographic profiles that are convenient for them (representative of entire United States)
  - Developer developing things – use high end computer, ppl using their systems are using low end devices and things don't render (ICT4D).
    - No one things about how their tasks are being experienced and in what technical setting
  - Requesters think associates are doing it just for pocket money, however people are using this as a primary income source
  - That a native English speaker indicates some kind of standard English (example of a proxy used for a certain level of English) – what does it mean to be a native speaker?
- How do they qualify / justify qualification criteria

Code in Dedoose	Description of Code	Examples	No
Requestor Background	Quotes that reference who the requestor is and how they approach being a requestor		
> RequestProfessionalContext	Participant describes where they worked AT TIME of requesting	Broken down into two child codes:	
>> Research Setting	Work(ed/s) in a research setting	1 - "I work at a research institute" 2 - "I am a research scientist"	
>> Commercial Setting	Work(ed/s) in a commercial setting	1 - "I work on the {FizzBuzz} Model, which we sell to customers looking for a {FizzBuzz} tool" 2 - "I was a Senior Engineer at {Large Tech Company}"	
> CurrentEmploymentSetting	Participant describes where they NOW work	1 - "Presently I am an associate professor" 2 - "I am currently a software engineer"	
> LearningPlatform	When participant mentions how they learned to use the digital pieceworking platform and/or familiarize themselves with the platform	1 - "I googled 'how do you post tasks on MTurk'" 2 - "My adviser sent me a document our lab compiled on how to post tasks" 3 - "Appen onboards you, so I worked with my contact there" 4 - "My friend {redacted} who had requested before on AMT showed me how to navigate the interface"	
> CareerContributions	When the the participant describes how use of (a/the) digital pieceworking platform(s) contributed to their career	1 - "If I didn't use MTurk, there's no way I could be the reach I need to make an NLP model based on common English variants — I wouldn't be able to do this work otherwise" 2 - "I use the datasets I get from MTurk for publications that I need to continue my career" 3 - "I actually got my current job because they needed someone who knew how to request on AMT" 4 - "Yeah so to train our {FizzBuzz} model [main product participant works on] we needed 1,000 annotated images of cars" 5 - "Right, to reach a pool of 20 young adults who had raised a younger sibling, to deploy our survey, we could only do that through AMT"	
> Funding	Participant describes where the funding for the tasks they post on the platform(s) comes from	1 - "Our lab is mostly funded by the NSF" 2 - "It's part of our organizational research budget" 3 - "Actually our University banned working on AMT in Spring 2020 so we couldn't get reimbursed for work we deployed on the platform"	No
PlatformChoiceRationale	Participant mentions using a specific digital pieceworking platform		
> AssociateAccess	Being able to reach outside of the requestor's own network to access a more general or "average" associates	1 - "I don't know that many people who want to draw bounding boxes" 2 - "I wanted members of the 'general public'"	
> NumberAssociates	Size of the associate population available to complete their tasks	1 - "To get the model right, we needed to get at least a million variations" 2 - "I needed lots of examples to get a robust response"	
> SpecificPopulation	Being able to access a specific population or demographic	1 - "I don't know where else to find video game players" 2 - "I needed to find Swedish speakers" 3 - "I didn't know where else to reach Arabic speakers"	
> AssociatesReputation	Reputation of associate labor and quality of work as a platform attribute	1 - "Prolific workers just have a better reputation generally since they have to share their demographics beforehand" 2 - "I think AMT workers are mostly bots so I don't really trust them"	
> Turnaround	How quickly their work (in the form of the tasks posted) are completed	1 - "I had a really quick turn around" 2 – "We needed just-in-time submissions"	
> Cost	Financial specifics of a given platform	1 - "It's the cheapest platform" 2 - "There's no minimum task number to post" 3 - "Prolific is generally not the cheapest, but we find the survey data is much more reliable from Prolific participants so the price is worth it"	
> CommonPractice	Choosing to use a specific platform because it is a common or accepted practice within their professional or academic field	1 - "Everyone in psychology now uses MTurk" 2 - "Lots of other papers use it, so we don't have to explain it in methodology" 3 - "I mean everyone in my lab uses AMT so I just used it too"	

Task design -- ALL .XLSX Saved to Drive

File Edit View Insert Format Data Tools Help

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H5 fx False

	A	B	C
1	Media Title	Excerpt Copy	Codes Applied Combined
2	G6P4.docx	And I am guessing if two years back you found resources good enough to help you navigate it, pretty sure in two years they must have more helpful resources out there. That's nice. Yeah. So, what kind of tasks did you post as a requester? Can you describe it a little?Myeonghan: Oh. So, I deployed an application using Microsoft's Azure Cloud platform, and so the task was basically go open the link and follow the instructions of the app, there were I guess around three visualization tasks. Yeah.	Progress_process, Task_design
3	G6P4.docx	No, I first tried the task. And also, I asked some people around me to do the task. So, I was thinking it would take around 30 minutes to do the task and then it really took about an hour for others. So, I, I even changed my experiment design from within subject to between subjects.	Task_timing, Testing, Task_design
4	G6P4.docx	So, do you have like, maybe like you or someone you work with, have any specific procedure on how they specifically design the trials to make it more efficient and user friendly?Myeonghan: Well, I think I thoroughly followed some basic principles of user centered design. So even though it was like not really designing an interface but looking at how people, how people interact and interpret with that, the color of the graphs and all. Mm hmm. And then based on that, I made some changes in the graph for better experience.Upasana: So, when you design these trials, do you have a specific crowd in mind, or you design it so that any layman can understand it and do it? Myeonghan: Oh, yeah. Upasana: So, for anyone? Myeonghan: Yeah. Oh. So. But while design the trial I included a few tests which didn't actually count towards the experiment result which were pretty straightforward. Also, I made it in such a way that they could attempt the activity several times.	Testing, Progress_process, Task_design
5	G6P4.docx	Okay, so what do you the think about the payment on these platforms? Do you think there is an appropriate pay scale?Myeonghan: I consider the minimum wage in the US. So, I, I was at Purdue University, Indiana for my Master's.Upasana: Oh, really!Myeonghan: Yeah, so, I'm not sure if minimum wage varies by, like, different states or not, but I am not sure about that. But, you know, in a paper I, I read while preparing for this study, they said they consider minimum wage in the US and they pay the amount relative to the time spent. Where, suppose if the minimum wage was $10 for an hour and you spent like 30 minutes, so they paid them $5 instead.	Payment_calibration, Task_design
6	G6P4.docx	Oh, no, no. Number of participants was in the plan. Okay. Yeah, because I ran an apriori power analysis which helped me decide the proper number of participants. Okay. It was around 200. And then I planned to recruit 200 crowd-workers. Okay. Yeah. Maybe because of some bugs in the system, I couldn't get data from some of them. Then I needed to recruit some additional crowd-workers. But yeah, everything was in the plan.	Progress_process, Task_design
7	G6P4.docx	Well. So, to make sure participants finish all the tasks, I requested them to show me some quote that they can see on the last page of the task. Oh, okay. Yeah. So, if they make it to the end, then they can see it. And if they tell me the correct quote, then I approved their submission.	Associate_validation, Task_design
8		o. I think the Prolific provided a feature to filter participants. So basically, many people just sort of come and go, like, they just come in and just leave. Leave without finishing the task, but only, only the participants who provided the quote for me, were considered valid workers. And also, I added a few attention checking test, which were very straightforward and easy, but to see if they just like mindlessly click anything, anything, and then they might, they might they are likely to give the wrong answers to those	

Annabel Rothschild, Ding Wang, Niveditha Jayakumar, Lauren Wilcox, Carl DiSalvo and Betsy DiSalvo. 2024. "The Problems with Proxies: Making Data Work Visible through Requester Practices". AIES (Conference on Artificial Intelligence, Ethics, and Society).

What We Found: Who is requesting these tasks?

- Mix of *commercial* (14) and *research* (38) participants
- Learning habits from *co-workers and collaborators*, *search engine links*, *platform documentation*, and *YouTube*
- Tasks include *data annotation & classification*, *data collection*, *tool or system feedback*
- Platforms ranging from *Amazon MTurk* to *Tokola* and *iMerit*

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What We Found: Proxies to Establish Worker Identity and Abilities

- Workers as "the general public," but simultaneously highly curated by requesters
- Good data vs bad actors
- Testing proxies, rather than actual attributes; quantification of lived experience and skills
  - Worker identity: *English fluency*, *age*, *location*
  - Aptitude: pre hoc (*approval rating, prior task completion*), post hoc (*keyboard interaction, answer pattern, attention check, gut reaction, coherence as trust*)

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What We Found: Proxies vs. Reality

- FA(C)T(E) notions of reliability and validity (Jacobs & Wallach, 2023)
- *Construct reliability* (reliable, replicable measurement; e.g., 10 vs 10,000 prior tasks)
- *Construct validity* (measurements grounded in construct, encompass all relevant aspects; e.g., worker actually skilled at the task)

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Why Do We Care About Proxies?

- Proxies demonstrate lack genuine trust and collaboration, which characterize the "conference table" model of data work.
- Without trust and collaboration, data workers as auditors is impossible…
- But there's hope! Requesters want to learn how to do this better, and we can build the tools, systems, and processes to help them do it!
- Short term future work (students take note!): pro-social task design for requesters.

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Archiving and Documenting Data Workers' Auditing Work

Making a record of conference table conversations

Motivation: Paradata is Critical to Algorithmic Accountability

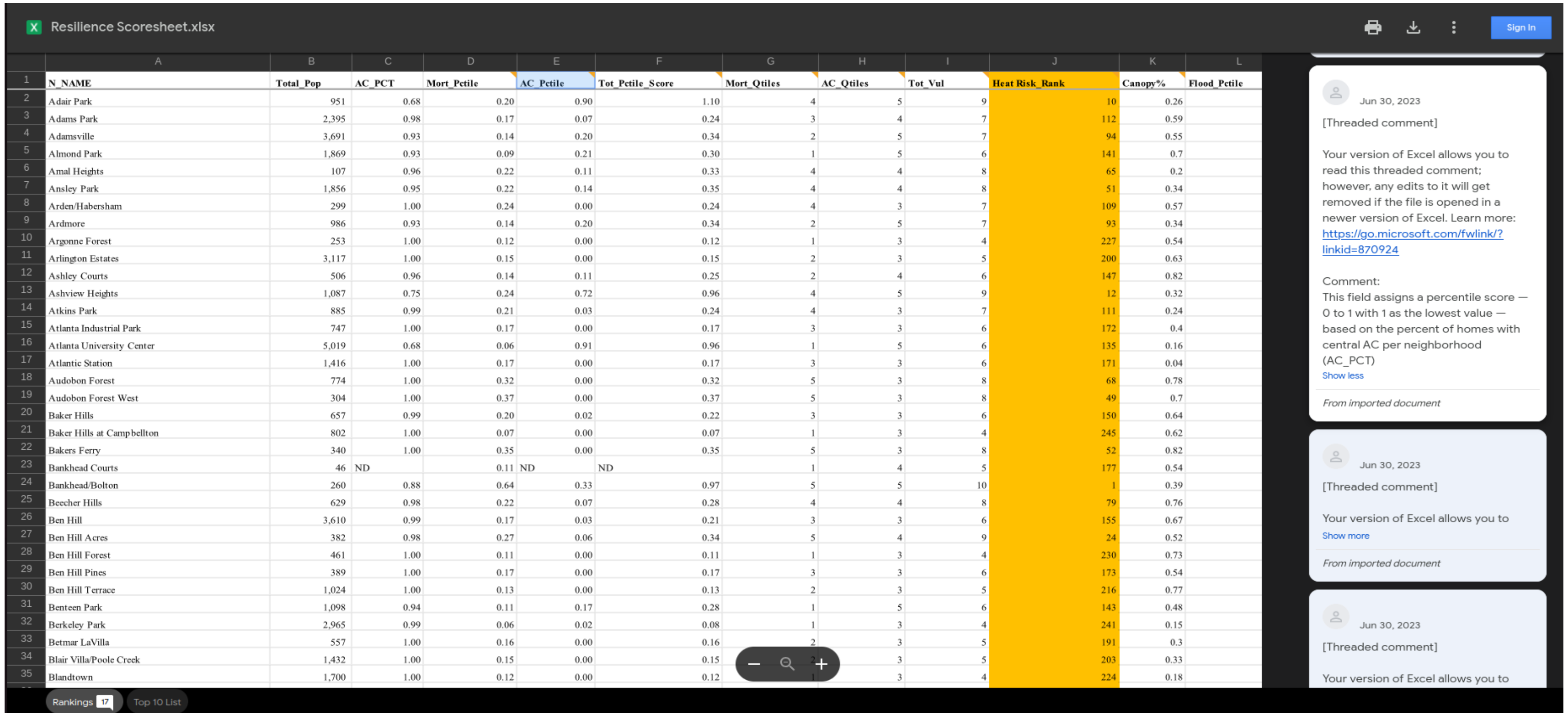
That the AI community should "**use paradata to create unified reporting models** that enhance the explainability of algorithms and algorithmic systems" and that" packaged data in the form of descriptions and documentation are contextualized understandings of work practices and processes."[1]

In the electronics industry, every component, no matter how simple or complex, is accompanied with a datasheet describing its operating characteristics, test results, recommended usage, and other information. By analogy, **we propose that every dataset be accompanied with a datasheet that documents its motivation, composition, collection process, recommended uses, and so on**.[2]

1. Ciaran B. Trace and James A. Hodges. 2024. The Role of Paradata in Algorithmic Accountability. In Perspectives on Paradata: Research and Practice of Documenting Process Knowledge, Isto Huvila, Lisa Andersson and Olle Sköld (eds.). Springer International Publishing, Cham, 197–213. https://doi.org/10.1007/978-3-031-53946-6_11
2. Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. 2021. Datasheets for datasets. Communications of the ACM 64, 12: 86–92. https://doi.org/10.1145/3458723

Datum Fieldnotes Inspiration

Civic and non-profit (as non tech industry) data workers have novel ways of documenting and contextualizing the datasets they work with.*

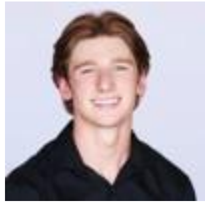


N_NAME	Total_Pop	AC_PCT	Mort_Pctile	AC_Pctile	Tot_Pctile_Score	Mort_Qtiles	AC_Qtiles	Tot_Vul	Heat Risk_Rank	Canopy%	Flood_Pctile
Adair Park	951	0.68	0.20	0.90	1.10	4	5	9	10	0.26	
Adams Park	2,395	0.98	0.17	0.07	0.24	3	4	7	112	0.59	
Adamsville	3,691	0.93	0.14	0.20	0.34	2	5	7	94	0.55	
Almond Park	1,869	0.93	0.09	0.21	0.30	1	5	6	141	0.7	
Amal Heights	107	0.96	0.22	0.11	0.33	4	4	8	65	0.2	
Ansley Park	1,856	0.95	0.22	0.14	0.35	4	4	8	51	0.34	
Arden/Habersham	299	1.00	0.24	0.00	0.24	4	3	7	109	0.57	
Ardmore	986	0.93	0.14	0.20	0.34	2	5	7	93	0.34	
Argonne Forest	253	1.00	0.12	0.00	0.12	1	3	4	227	0.54	
Arlington Estates	3,117	1.00	0.15	0.00	0.15	2	3	5	200	0.63	
Ashley Courts	506	0.96	0.14	0.11	0.25	2	4	6	147	0.82	
Ashview Heights	1,087	0.75	0.24	0.72	0.96	4	5	9	12	0.32	
Atkins Park	885	0.99	0.21	0.03	0.24	4	3	7	111	0.24	
Atlanta Industrial Park	747	1.00	0.17	0.00	0.17	3	3	6	172	0.4	
Atlanta University Center	5,019	0.68	0.06	0.91	0.96	1	5	6	135	0.16	
Atlantic Station	1,416	1.00	0.17	0.00	0.17	3	3	6	171	0.04	
Audobon Forest	774	1.00	0.32	0.00	0.32	5	3	8	68	0.78	
Audobon Forest West	304	1.00	0.37	0.00	0.37	5	3	8	49	0.7	
Baker Hills	657	0.99	0.20	0.02	0.22	3	3	6	150	0.64	
Baker Hills at Campbellton	802	1.00	0.07	0.00	0.07	1	3	4	245	0.62	
Bakers Ferry	340	1.00	0.35	0.00	0.35	5	3	8	52	0.82	
Bankhead Courts	46	ND	0.11	ND	ND	1	4	5	177	0.54	
Bankhead/Bolton	260	0.88	0.64	0.33	0.97	5	5	10	1	0.39	
Beecher Hills	629	0.98	0.22	0.07	0.28	4	4	8	79	0.76	
Ben Hill	3,610	0.99	0.17	0.03	0.21	3	3	6	155	0.67	
Ben Hill Acres	382	0.98	0.27	0.06	0.34	5	4	9	24	0.52	
Ben Hill Forest	461	1.00	0.11	0.00	0.11	1	3	4	230	0.73	
Ben Hill Pines	389	1.00	0.17	0.00	0.17	3	3	6	173	0.54	
Ben Hill Terrace	1,024	1.00	0.13	0.00	0.13	2	3	5	216	0.77	
Benteen Park	1,098	0.94	0.11	0.17	0.28	1	5	6	143	0.48	
Berkeley Park	2,965	0.99	0.06	0.02	0.08	1	3	4	241	0.15	
Betmar LaVilla	557	1.00	0.16	0.00	0.16	2	3	5	191	0.3	
Blair Villa/Poole Creek	1,432	1.00	0.15	0.00	0.15	[illegible]	3	5	203	0.33	
Blandtown	1,700	1.00	0.12	0.00	0.12	[illegible]	3	4	224	0.18	

but sharing datasets—an essential part of contextualization—is tricky, particularly when it comes to annotations.

*Annabel Rothschild, Amanda Meng, Carl DiSalvo, Britney Johnson, Ben Rydal Shapiro, and Betsy DiSalvo. 2022. "Interrogating Data Work as a Community of Practice". Proceedings of the ACM on Human-Computer Interaction 6, Article 307 (November 2022) (2022), 29.

Datum Fieldnotes

- Google Sheets add on
- Automates micro-documentation (per datum)
- Supports collaboration and local expertise

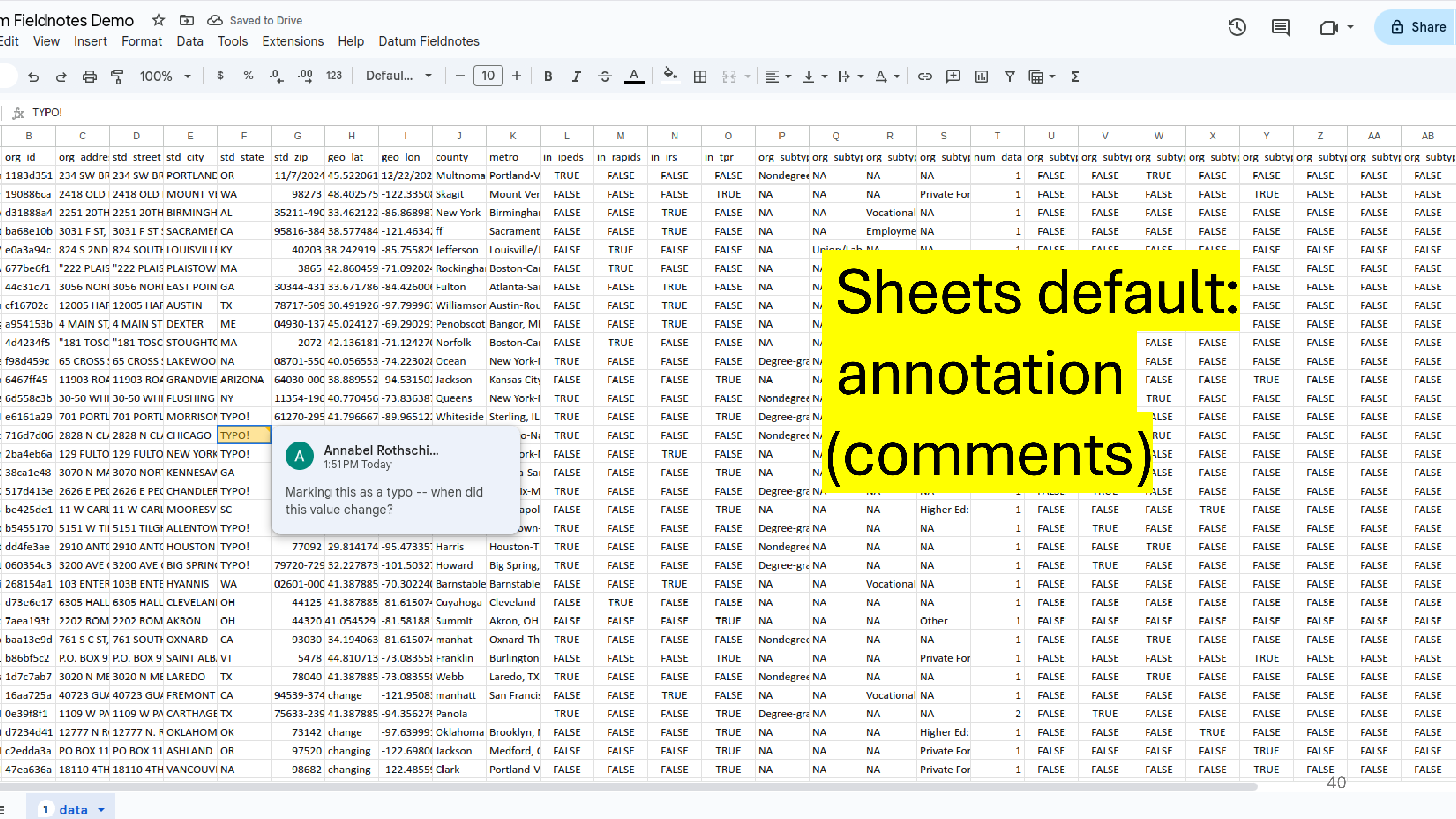
Paper in preparation: William Eickman*, Mukhlisa Nematova*, Annabel Rothschild, Carl DiSalvo, and Betsy DiSalvo. "Datum Fieldnotes: Automating and Archiving Data Workers' Contextualization Practices and Insights". CHI LBW, 2025.

(RQ1) Can we offload the labor of dataset micro-documentation from data workers?

(RQ2) How do data workers perform dataset contextualization practices in situ (in sheet)?

"Infrastructural inversion" – bringing background work to the forefront so that you can reflect on the social angles of production and the notion of quantification (p. 34) (Bowker & Star, 2008)

- **Needs to be cheap or free: Google Sheets**
  - Civic and non-profits have high staff turnover (Nault, 2020)
  - Build on existing features of accessibility, adaptability, and replicability (Shapiro & Oystrick, 2018)
  - Google's existing privacy infrastructure and cloud-hosting (Harmon et al., 2017)
  - No or little new organizational learning (Benjamin et al., 2018)
  - Ability to share and transfer between organizations (Voida et al., 2011; Erete et al., 2016)
- **Log, and in CSV format:**
  - Missing data is an ethical issue for civic and non-profit groups (Nault et al., 2020)
  - Operability between different organizations (Davies & Frank, 2013)
  - Losing control of dataset (Darian et al., 2023)
  - Assistive automation (Shapiro & Oystrick, 2018)


Fieldnotes Demo
Saved to Drive
Edit View Insert Format Data Tools Extensions Help Datum Fieldnotes
Share
TYPO!
Annabel Rothschi...
1:51 PM Today
Marking this as a typo -- when did this value change?
data
Sheets default: annotation (comments)

, 2:01PM

Sheets default: version history

B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X
org_id	org_addre	std_street	std_city	std_state	std_zip	geo_lat	geo_lon	county	metro	in_ipeds	in_rapids	in_irs	in_tpr	org_subtyp	org_subtyp	org_subtyp	org_subtyp	num_data	org_subtyp	org_subtyp	org_subtyp	org_subtyp
1183d351	234 SW BR	234 SW BR	PORTLAND	OR	11/7/2024	45.522061	12/22/202	Multnoma	Portland-V	TRUE	FALSE	FALSE	FALSE	Nondegree	NA	NA	NA	1	FALSE	FALSE	TRUE	FALSE
190886ca	2418 OLD	2418 OLD	MOUNT VI	WA	98273	48.402575	-122.3350	Skagit	Mount Ver	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Private For	1	FALSE	FALSE	FALSE	FALSE
d31888a4	2251 20TH	2251 20TH	BIRMINGH	AL	35211-490	33.462122	-86.86898	New York	Birminghai	FALSE	FALSE	TRUE	FALSE	NA	NA	Vocational	NA	1	FALSE	FALSE	FALSE	FALSE
ba68e10b	3031 F ST,	3031 F ST	SACRAMEI	CA	95816-384	38.577484	-121.4634	ff	Sacrament	FALSE	FALSE	TRUE	FALSE	NA	NA	Employme	NA	1	FALSE	FALSE	FALSE	FALSE
e0a3a94c	824 S 2ND	824 SOUTH	LOUISVILL	KY	40203	38.242919	-85.75582	Jefferson	Louisville/	FALSE	TRUE	FALSE	FALSE	NA	Union/Lab	NA	NA	1	FALSE	FALSE	FALSE	FALSE
677be6f1	"222 PLAIS	"222 PLAIS	PLAISTOW	MA	3865	42.860459	-71.09202	Rockingha	Boston-Ca	FALSE	TRUE	FALSE	FALSE	NA	NA	NA	NA	1	FALSE	FALSE	FALSE	FALSE
44c31c71	3056 NORI	3056 NORI	EAST POIN	GA	30344-431	33.671786	-84.42600	Fulton	Atlanta-Sa	FALSE	FALSE	TRUE	FALSE	NA	NA	Employme	NA	1	FALSE	FALSE	FALSE	FALSE
cf16702c	12005 HAF	12005 HAF	AUSTIN	TX	78717-509	30.491926	-97.79996	Williamsor	Austin-Rou	FALSE	FALSE	TRUE	FALSE	NA	NA	Vocational	NA	1	FALSE	FALSE	FALSE	FALSE
a954153b	4 MAIN ST,	4 MAIN ST	DEXTER	ME	04930-137	45.024127	-69.29029	Penobscot	Bangor, MI	FALSE	FALSE	TRUE	FALSE	NA	NA	Vocational	NA	1	FALSE	FALSE	FALSE	FALSE
4d4234f5	"181 TOSC	"181 TOSC	STOUGHTC	MA	2072	42.136181	-71.1242															
f98d459c	65 CROSS	65 CROSS	LAKEWOO	NA	08701-550	40.056553	-74.2230															
6467ff45	11903 ROA	11903 ROA	GRANDVIE	ARIZONA	64030-000	38.889552	-94.5315															
6d558c3b	30-50 WHI	30-50 WHI	FLUSHING	NY	11354-196	40.770456	-73.8363															
e6161a29	701 PORTL	701 PORTL	MORRISOI	NA	61270-295	41.796667	-89.96512	Whiteside	Sterling, IL	TRUE	FALSE	FALSE	TRUE	Degree-gra	NA	NA	NA	2	FALSE	TRUE	FALSE	FALSE
716d7d06	2828 N CL	2828 N CL	CHICAGO	IL	60657	41.933392	-87.64554	Cook	Chicago-Na	TRUE	FALSE	FALSE	FALSE	Nondegree	NA	NA	NA	1	FALSE	FALSE	TRUE	FALSE
2ba4eb6a	129 FULTO	129 FULTO	NEW YORK	NA	10038-271	40.710295	-74.00745	New York	New York-I	FALSE	FALSE	TRUE	FALSE	NA	NA	Employme	NA	1	FALSE	FALSE	FALSE	FALSE
38ca1e48	3070 N MA	3070 NOR	KENNESAV	GA	30144	34.029759	-84.62645	Cobb	Atlanta-Sa	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Other	1	FALSE	FALSE	FALSE	FALSE
517d413e	2626 E PEC	2626 E PEC	CHANDLEF	NA	85225-249	33.295398	-111.7963	KINGS	Phoenix-M	TRUE	FALSE	FALSE	FALSE	Degree-gra	NA	NA	NA	1	FALSE	TRUE	FALSE	FALSE
be425de1	11 W CARL	11 W CARL	MOORESV	SC	46158	39.616964	-86.37989	Morgan	Indianapol	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Higher Ed:	1	FALSE	FALSE	FALSE	TRUE
b5455170	5151 W TI	5151 TILGI	ALLENTOW	TYPO!	30516.5	40.591817	-75.56888	Lehigh	Allentown-	TRUE	FALSE	FALSE	FALSE	Degree-gra	NA	NA	NA	1	FALSE	TRUE	FALSE	FALSE
dd4fe3ae	2910 ANTC	2910 ANTC	HOUSTON	TYPO!	77092	29.814174	-95.47335	Harris	Houston-T	TRUE	FALSE	FALSE	FALSE	Nondegree	NA	NA	NA	1	FALSE	FALSE	TRUE	FALSE
060354c3	3200 AVE	3200 AVE	BIG SPRIN	TYPO!	79720-729	32.227873	-101.5032	Howard	Big Spring,	TRUE	FALSE	FALSE	FALSE	Degree-gra	NA	NA	NA	1	FALSE	TRUE	FALSE	FALSE
268154a1	103 ENTER	103B ENTE	HYANNIS	WA	02601-000	41.387885	-70.30224	Barnstable	Barnstable	FALSE	FALSE	TRUE	FALSE	NA	NA	Vocational	NA	1	FALSE	FALSE	FALSE	FALSE
d73e6e17	6305 HALL	6305 HALL	CLEVELANI	OH	44125	41.387885	-81.61507	Cuyahoga	Cleveland-	FALSE	TRUE	FALSE	FALSE	NA	NA	NA	NA	1	FALSE	FALSE	FALSE	FALSE
7aea193f	2202 ROM	2202 ROM	AKRON	OH	44320	41.054529	-81.58188	Summit	Akron, OH	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Other	1	FALSE	FALSE	FALSE	FALSE
baa13e9d	761 S C ST,	761 SOUTH	OXNARD	CA	93030	34.194063	-81.61507	manhat	Oxnard-Th	TRUE	FALSE	FALSE	FALSE	Nondegree	NA	NA	NA	1	FALSE	FALSE	TRUE	FALSE
b86bf5c2	P.O. BOX 9	P.O. BOX 9	SAINT ALB.	VT	5478	44.810713	-73.08355	Franklin	Burlington	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Private For	1	FALSE	FALSE	FALSE	FALSE
1d7c7ab7	3020 N ME	3020 N ME	LAREDO	TX	78040	41.387885	-73.08355	Webb	Laredo, TX	TRUE	FALSE	FALSE	FALSE	Nondegree	NA	NA	NA	1	FALSE	FALSE	TRUE	FALSE
16aa725a	40723 GU	40723 GU	FREMONT	CA	94539-374	change	-121.9508	manhatt	San Franci	FALSE	FALSE	TRUE	FALSE	NA	NA	Vocational	NA	1	FALSE	FALSE	FALSE	FALSE
0e39f8f1	1109 W PA	1109 W PA	CARTHAGE	TX	75633-239	41.387885	-94.35627	Panola		TRUE	FALSE	FALSE	TRUE	Degree-gra	NA	NA	NA	2	FALSE	TRUE	FALSE	FALSE
d7234d41	12777 N R	12777 N. F	OKLAHOM	OK	73142	change	-97.63999	Oklahoma	Brooklyn, I	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Higher Ed:	1	FALSE	FALSE	FALSE	TRUE
c2edda3a	PO BOX 11	PO BOX 11	ASHLAND	OR	97520	changing	-122.6980	Jackson	Medford, (	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Private For	1	FALSE	FALSE	FALSE	FALSE
47ea636a	18110 4TH	18110 4TH	VANCOUVI	NA	98682	changing	-122.4855	Clark	Portland-V	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Private For	1	FALSE	FALSE	FALSE	FALSE
f94b8bb3	1215 E ELN	1215 E. ELI	PHOENIX	AZ	94539-374	change	-112.0555		Phoenix-M	FALSE	FALSE	FALSE	TRUE	NA	NA	NA	Private For	1	FALSE	FALSE	FALSE	FALSE

Sheet1 | Log3 | in | Log5 | Log4 | Sheet99 | data | Log | Datasheet for Dataset Use and Distribution

Version history

All versions

Today

- November 7, 2:01PM — *Current version* — Annabel Rothschild
- November 7, 1:52PM — Annabel Rothschild
- November 7, 1:51PM — Annabel Rothschild
- November 7, 1:47PM — Annabel Rothschild
- November 7, 1:47PM — Annabel Rothschild
- November 7, 1:46PM — Annabel Rothschild
- November 7, 1:45PM — Annabel Rothschild
- November 7, 1:45PM — Annabel Rothschild
- November 7, 1:45PM — Annabel Rothschild
- November 7, 1:42PM — Annabel Rothschild
- November 7, 1:37PM

41

Show changes

Fieldnotes Usability Testing - P4

File Edit View Insert Format Data Tools Extensions Help Datum Fieldnotes

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fx 110

A	B	C	D	E	F	G	H	I	J	K	L	M	N	
	org_id	org_address	std_street	std_city	std_state	std_zip	geo_lat	geo_lon	county	metro	in_ipeds	in_rapids	in_irs	in_
ul Mitchell Th	1183d351	234 SW BROADV	234 SW BROADV	PORTLAND	OR	97205	45.5220611	-122.6777723	Multnomah	Portland-Vancou	TRUE	FALSE	FALSE	
agit City Truck	190886ca	2418 OLD HWY.	2418 OLD HWY.	MOUNT VERNOI	WA	98273	48.4025757	-122.3350808	Skagit	Mount Vernon-A	FALSE	FALSE	FALSE	
terans Village	d31888a4	2251 20TH ST SV	2251 20TH ST SV	BIRMINGHAM	AL	110	33.4621226	-86.8689877		Birmingham-Hoo	FALSE	FALSE	TRUE	
cramento Vall	ba68e10b	3031 F ST, SACR	3031 F ST STE 20	SACRAMENTO	CA	95816-3844	38.5774849	-121.4634271		Sacramento--Ro	FALSE	FALSE	TRUE	
uisville Machi	e0a3a94c	824 S 2ND ST, LC	824 SOUTH SECC	LOUISVILLE	KY	40203	38.242919	-85.7558298	Jefferson	Louisville/Jeffers	FALSE	TRUE	FALSE	
uette And Ho	677be6f1	"222 PLAISTOW	"222 PLAISTOW	PLAISTOW	MA	3865	42.8604594	-71.0920247	Rockingham	Boston-Cambrid	FALSE	TRUE	FALSE	
st Point Comm	44c31c71	3056 NORMAN I	3056 NORMAN I	EAST POINT	GA	30344-4312	33.6717867	-84.4260061	Fulton	Atlanta-Sandy Sp	FALSE	FALSE	TRUE	
lo-American S	**cf16702c**	12005 HARPSTEI	12005 HARPSTEI	AUSTIN	TX	78717-5091	30.4919266	-97.7999676	Williamson	Austin-Round Ro	FALSE	FALSE	TRUE	
xter Regional	a954153b	4 MAIN ST, DEXT	4 MAIN ST	DEXTER	ME	04930-1375	45.0241275	-69.2902918	Penobscot	Bangor, ME	FALSE	FALSE	TRUE	
H. Burg Corp.	4d4234f5	"181 TOSCA DRI	"181 TOSCA DRI	STOUGHTON	MA	2072	42.1361814	-71.1242706	Norfolk	Boston-Cambrid	FALSE	TRUE	FALSE	
hiva Gedola T	f98d459c	65 CROSS ST, LAI	65 CROSS STREE	LAKEWOOD	NJ	08701-5502	40.0565531	-74.2230286	Ocean	New York-Newar	TRUE	FALSE	FALSE	
admaster Driv	6467ff45	11903 ROAD GR.	11903 ROAD	GRANDVIEW	MO	64030	38.8895526	-94.5315029	Jackson	Kansas City, MO-	FALSE	FALSE	FALSE	
nsitions Care	6d558c3b	30-50 WHITESTC	30-50 WHITESTC	FLUSHING	NY	11354-1964	40.7704566	-73.8363875	Queens	New York-Newar	TRUE	FALSE	FALSE	
orrison Institu	e6161a29	701 PORTLAND /	701 PORTLAND /	MORRISON	IL	61270-2959	41.7966673	-89.9651228	Whiteside	Sterling, IL	TRUE	FALSE	FALSE	
eda Institute-(	716d7d06	2828 N CLARK ST	2828 N CLARK ST	CHICAGO	IL	60657	41.9333925	-87.645543	Cook	Chicago-Napervi	TRUE	FALSE	FALSE	
dge Homes In	2ba4eb6a	129 FULTON ST,	129 FULTON STR	NEW YORK	NY	10038-2716	40.7102958	-74.007457	New York	New York-Newar	FALSE	FALSE	TRUE	
e Edge Conne	38ca1e48	3070 N MAIN ST,	3070 NORTH MA	KENNESAW	GA	30144	34.029759	-84.6264509	Cobb	Atlanta-Sandy Sp	FALSE	FALSE	FALSE	
andler-Gilbert	517d413e	2626 E PECOS RI	2626 E PECOS RI	CHANDLER	AZ	85225-2499	33.295398	-111.7963497		Phoenix-Mesa-S	TRUE	FALSE	FALSE	
ncennes Unive	be425de1	11 W CARLISLE S	11 W CARLISLE S	MOORESVILLE	IN	46158	39.616964	-86.3798964	Morgan	Indianapolis-Car	FALSE	FALSE	FALSE	
coln Technica	b5455170	5151 W TILGHM	5151 TILGHMAN	ALLENTOWN	PA	18104-9889	40.5918177	-75.5688802	Lehigh	Allentown-Bethl	TRUE	FALSE	FALSE	
rthwest Educ	dd4fe3ae	2910 ANTOINE D	2910 ANTOINE E	HOUSTON	TX	77092	29.8141742	-95.4733576	Harris	Houston-The Wo	TRUE	FALSE	FALSE	
uthwest Colle	060354c3	3200 AVE C, BIG	3200 AVE C	BIG SPRING	TX	79720-7298	32.2278739	-101.503276	Howard	Big Spring, TX	TRUE	FALSE	FALSE	
itude Six Cera	268154a1	103 ENTERPRISE	103B ENTERPRIS								FALSE	FALSE	TRUE	
efitters Jatc, (	d73e6e17	6305 HALLE DR,	6305 HALLE DR.	CL							FALSE	TRUE	FALSE	
yond Expectat	7aea193f	2202 ROMIG RD	2202 ROMIG RD	AK							FALSE	FALSE	FALSE	
t-Oxnard	baa13e9d	761 S C ST, OXN	761 SOUTH C ST	OX							TRUE	FALSE	FALSE	
atford Career	b86bf5c2	P.O. BOX 917 05	P.O. BOX 917 05	SAINT ALBANS	VT	5478	44.8107132	-73.0835582	Franklin	Burlington-Soutl	FALSE	FALSE	FALSE	
Data, Inc.	eada32c3	14 WALL ST, NEV	14 WALL STREET	NEW YORK	NY	10005	40.7076193	-74.0105948	New York	New York-Newar	FALSE	FALSE	FALSE	
edo Beauty C	1d7c7ab7	3020 N MEADOV	3020 N MEADOV	LAREDO	TX	78040	27.5237548	-99.480774	Webb	Laredo, TX	TRUE	FALSE	FALSE	
ffs	16aa725a	40723 GUALALA	40723 GUALALA	FREMONT	CA	94539-3748	37.5472898	-121.9508366		San Francisco-Oa	FALSE	FALSE	TRUE	

Tool version 1: sidebar

Part 0 | Part 1 - full dataset | Part 1.1 - dataset section | Part 2 - VLOOKUP | Part 3 - HLOOKUP | Log

DataWorks Tool

Row 9, Column 1

Current Value: 110

View Notes

Log Number: 12

1/2/2024, 11:05:20

Value Right Now: 1

Function: Manual E

Previous Value: 111

Add Notes

Log Number: 11

1/2/2024, 11:04:57

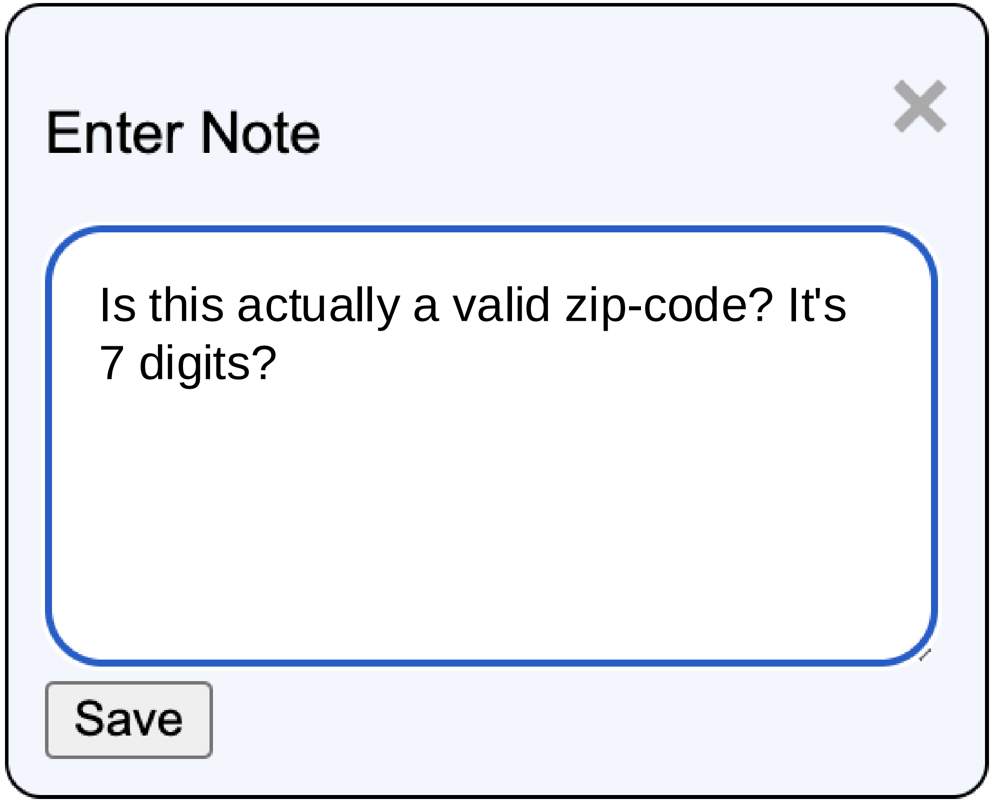
Value Right Now: 1

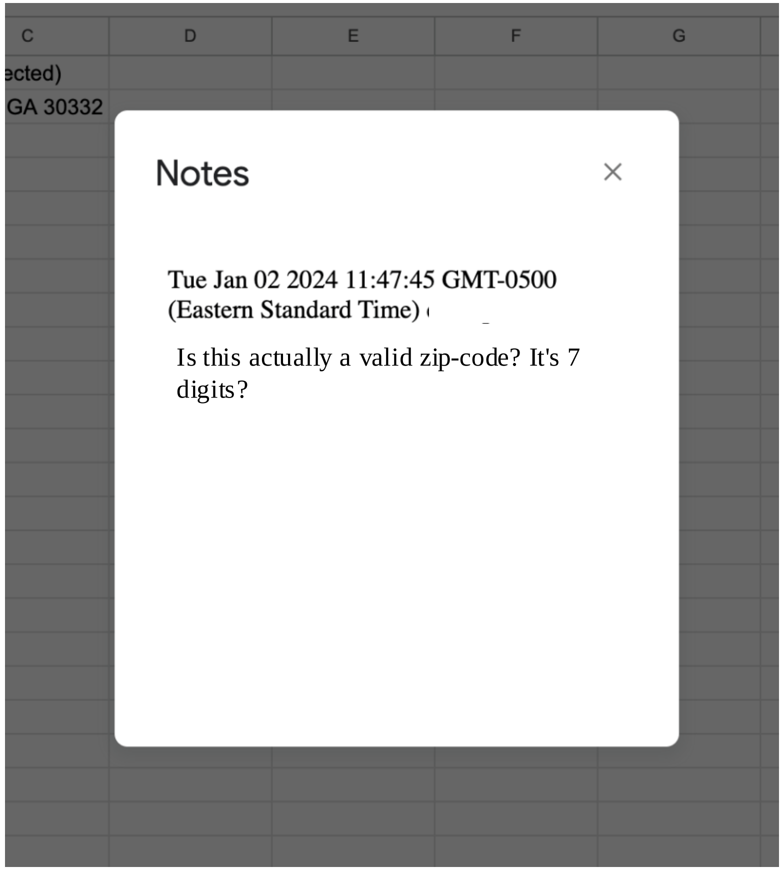
Function: Manual E

Previous Value: 10.

Add Notes

Tool Version 1: Add Notes





Timestamp	Cell	Sheet	Previous Val	New Value	Formula	User	Notes
11/16/2023 11:00:56	A13	Examples		change	Manual Entry		
11/16/2023 11:01:09	A13	Examples	change	boo	Manual Entry		Thu Nov 16 2023 11:01:33 G boo
11/16/2023 11:02:25	A13	Examples	boo	bool	Manual Entry		
11/16/2023 11:03:01	A13	Examples	bool	hi	Manual Entry		
11/16/2023 11:03:56	A13	Examples	hi	fff	Manual Entry		
11/16/2023 11:05:13	A13	Examples	fff		Manual Entry		
11/16/2023 11:06:34	A13	Examples		add	Manual Entry		
1/2/2024 10:09:43	A1	Sheet4		hi	Manual Entry		
1/2/2024 10:10:04	A1	Sheet4	hi	1	Manual Entry		Tue Jan 02 2024 10:10:27 GI We shifted from text to using
1/2/2024 11:04:58	A9	Examples	10	111	Manual Entry		
1/2/2024 11:05:21	A9	Examples	111	110	Manual Entry		

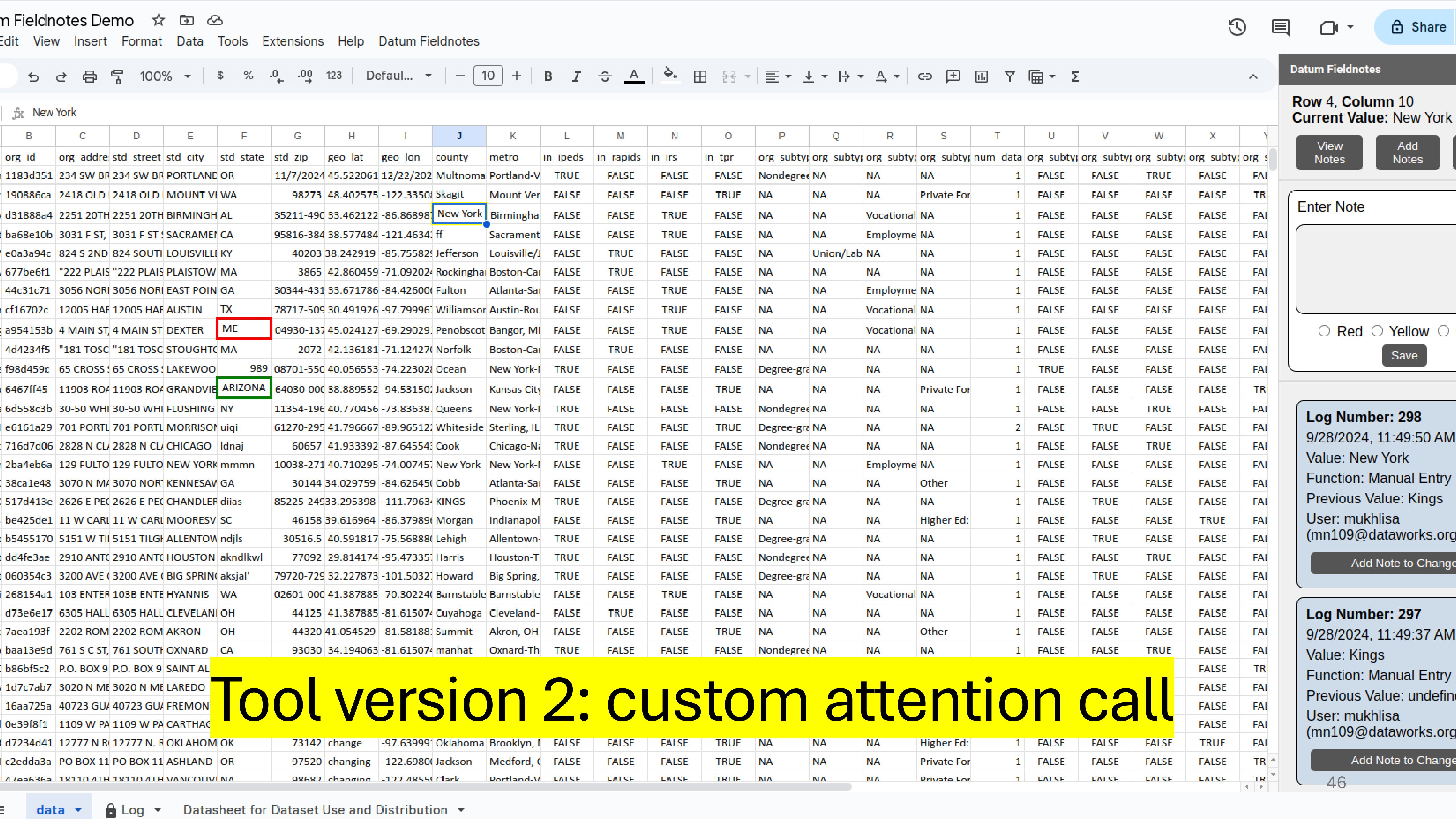
Tool version 1: Log

12 interviewees: 7 Data Fellows, 5 civic and non-profit data workers from around the United States

Follow the Data[1] **protocol**: use LLM to generate synthetic dataset, researchers markup as if colleagues, then ask participants to reconstruct a calculation or trace a concern. End with D4D questions.

Major findings: color coding (as visual indicators), need for localized definitions for D4D[2] terminology, additional security and privacy features.

1. Sands, A., Borgman, C. L., Wynholds, L., & Traweek, S. (2012). Follow the data: How astronomers use and reuse data. *Proceedings of the American Society for Information Science and Technology*, *49*(1), 1–3. https://doi.org/10.1002/meet.14504901341
2. Timnit Gebru, Jamie Morgenstern, Briana Vecchione, Jennifer Wortman Vaughan, Hanna Wallach, Hal Daumé Iii, and Kate Crawford. 2021. Datasheets for datasets. Communications of the ACM 64, 12: 86–92. https://doi.org/10.1145/3458723



Tool version 2: custom attention call

m Fieldnotes Demo

Edit View Insert Format Data Tools Extensions Help Datum Fieldnotes

Share

100% $ % .0 .00 123 Arial 12

fx Datasheet for Dataset Use and Distribution

Tool version 2: robust D4D

A	B
eet for Dataset Use and Distribution	
contents	
a Workers	2 - Datasheets for Datasets questions
mation	Motivation
er Reflections	Composition
	Collection process
	Preprocessing/cleaning/labeling
	Uses
	Distribution
	Maintenance
ns for Data Workers	
	Basic Information
this dataset created?	
vorked on this dataset?	mukhlisa (mn109@data.org), arothschild@gatech.edu, Annabel (annabel@dataworks.hq.com)
ld you contact if you have questions about this dataset?	
data use contract or agreement that someone accessing this dataset must ? Where can potential dataset users access that contract?	
	Data Worker Reflections
any ways you feel this dataset should not be used?	
otice any interesting patterns or surprising entries in this dataset?	
ncounter difficulty working on this dataset? What kinds?	
ets for Datasets Questions	
	Motivation
ourpose was the dataset created? Was there a specific task in mind? Was ecific gap that needed to be filled? Please provide a description.	
ed the dataset (e.g., which team, research group) and on behalf of which ., company, institution, organization)?	
ed the creation of the dataset? If there is an associated grant, please provide of the grantor and the grant name and number.	

Datum Fieldnotes

Row 1, **Column** 1
Current Value: Timestamp

View Notes | Add Notes

No session history

47 Privacy

data | Log | Datasheet for Dataset Use and Distribution

Five participants (Data Fellows)
How do you talk about data?

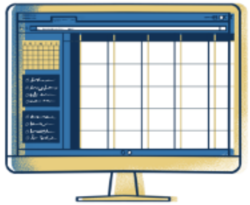
Findings:

- "Pre-processing" collapses several distinct data labor types into one
- Dealing with harmful or anxiety-provoking content cannot be made universal

Additional Suite of Learning Resources

Datum Fieldnotes

Datum Fieldnotes is an open-source Google Sheets extension that transforms how you work with data. It empowers you to track changes, add context-rich notes, and document your dataset's purpose and usage, all within the familiar Google Sheets environment. By providing a comprehensive view of your data's evolution, Datum Fieldnotes fosters transparency, encourages responsible data practices, and enhances collaboration among team members.



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User Guide

Tool Setup

Getting started with Datum Fieldnotes is quick and easy! Follow these simple steps to install the extension and set up your spreadsheet for enhanced data documentation.

Getting Started

Now that you have Datum Fieldnotes set up, let's explore how to use its core features to track changes, add notes, and document your dataset effectively.

Exploring the Tool

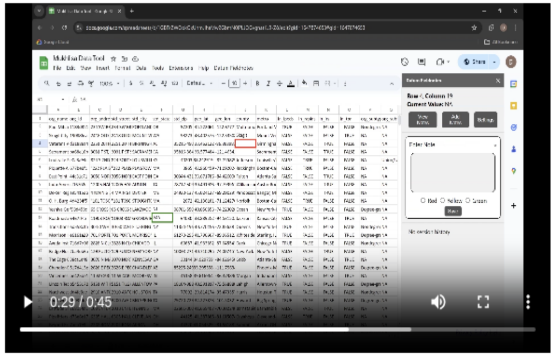
Datum Fieldnotes offers advanced features to help you analyze your data's evolution and ensure its quality. Let's delve into these capabilities.

FAQ

- What is Datum Fieldnotes and what is its purpose?
- Is Datum Fieldnotes a standalone tool or an extension only?
- Can I use Datum Fieldnotes offline?
- Is there a way to export or backup my notes and change log data?
- Does the tool support multi-user collaboration on the same sheet or workbook?
- What is the datasheet for dataset use and distribution?
- Where are the notes and change history data stored? Is it within the

Exploring/Querying the Log

Aside from the tools sidebar, Datum Fieldnotes Log sheet allows for further data analysis and understanding of your tool. Here are some examples in ways you can use the Log Sheet of the tool to further understand your data.



Accessing the Log sheet

Learn how to quickly locate and open the Datum Fieldnotes log sheet, your central hub for tracking and understanding changes in your spreadsheet.

Filtering the Log sheet

Discover how to use powerful filters to zero in on specific information within your change log, whether you're looking for edits by a certain user, within a

See more: https://dataworkforce.gatech.edu/datum-fieldnotes/

Human-AI collaboration around the conference table

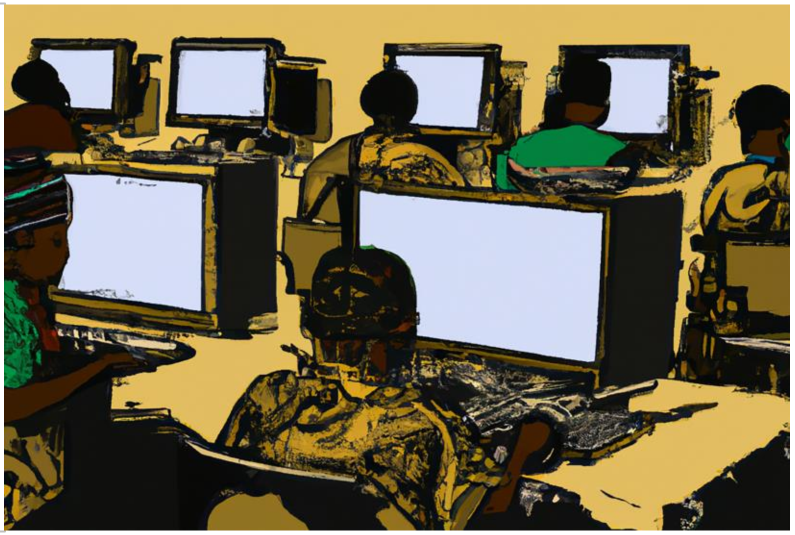
The Content Moderation Problem

- We can ask data workers about how they performed a task, but we can't do the same for computational (AI) approaches...
- However, human-AI collaboration can offload some of the difficulties of data annotation.

BUSINESS • TECHNOLOGY

Exclusive: OpenAI Used Kenyan Workers on Less Than $2 Per Hour to Make ChatGPT Less Toxic

15 MINUTE READ



What are the costs of data annotation across different methods?

- Paying a fair wage
- Opportunities for professional growth
- Financial cost

amazon mechanical turk

- Paying a fair wage
- Constructing tasks correctly to ensure feedback mechanisms
- Creating labor conditions that are pro-social

ChatGPT

- Environmental harms
- Auditing for perspective
- How to balance need for human review

Grace Kim, Annabel Rothschild, Carl DiSalvo, and Betsy DiSalvo. 2024. “What’s Your Stake in Sustainability of AI?: An Informed Insider’s Guide”. AIES (Conference on Artificial Intelligence, Ethics, and Society).

Building safe datasets requires partnering with the people who know and can best contextualize dataset entries in the wider socio-technical world.

My work:
(1) Partnering with data workers to channel their observations and feedbacks into dataset audits, resulting in safe datasets.
(2) Building tools and processes for the formalization of dataset audits by data workers.

The value of safe dataets?

Priceless!

DataWorks Fellows past and present, especially Dana Priest, Justin Booker, and Christa Davoll.

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Link to slides, citations and further reading

OR
(QR code and
Bit.ly point to
same link)

https://bit.ly/40RYp5E