

A photograph of a formal Senate hearing room. A long wooden U-shaped conference table is filled with numerous people in professional attire, mostly men in suits. The room has dark wood paneling and ornate gold-colored wall sconces. In the foreground, the back of two audience members is visible, looking towards the table. A small white sign on the table reads "PRESS ONLY" and "Senate Finance Committee".

Machine Learning in Production Transparency and Accountability

More Explainability, Policy, and Politics

Fundamentals of Engineering AI-Enabled Systems

Holistic system view: AI and non-AI components, pipelines, stakeholders, environment interactions, feedback loops

Requirements:

System and model goals
User requirements
Environment assumptions
Quality beyond accuracy
Measurement
Risk analysis
Planning for mistakes

Architecture + design:

Modeling tradeoffs
Deployment architecture
Data science pipelines
Telemetry, monitoring
Anticipating evolution
Big data processing
Human-AI design

Quality assurance:

Model testing
Data quality
QA automation
Testing in production
Infrastructure quality
Debugging

Operations:

Continuous deployment
Contin. experimentation
Configuration mgmt.
Monitoring
Versioning
Big data
DevOps, MLOps

Teams and process: Data science vs software eng. workflows, interdisciplinary teams, collaboration points, technical debt

Responsible AI Engineering

Provenance,
versioning,
reproducibility

Safety

Security and
privacy

Fairness

Interpretability
and explainability

Transparency
and trust

Ethics, governance, regulation, compliance, organizational culture

Readings

Required reading:

- Google PAIR. People + AI Guidebook. Chapter: [Explainability and Trust](#). 2019.

Recommended reading:

- Metcalf, Jacob, and Emanuel Moss. "[Owning ethics: Corporate logics, silicon valley, and the institutionalization of ethics](#)." *Social Research: An International Quarterly* 86, no. 2 (2019): 449-476.

Learning Goals

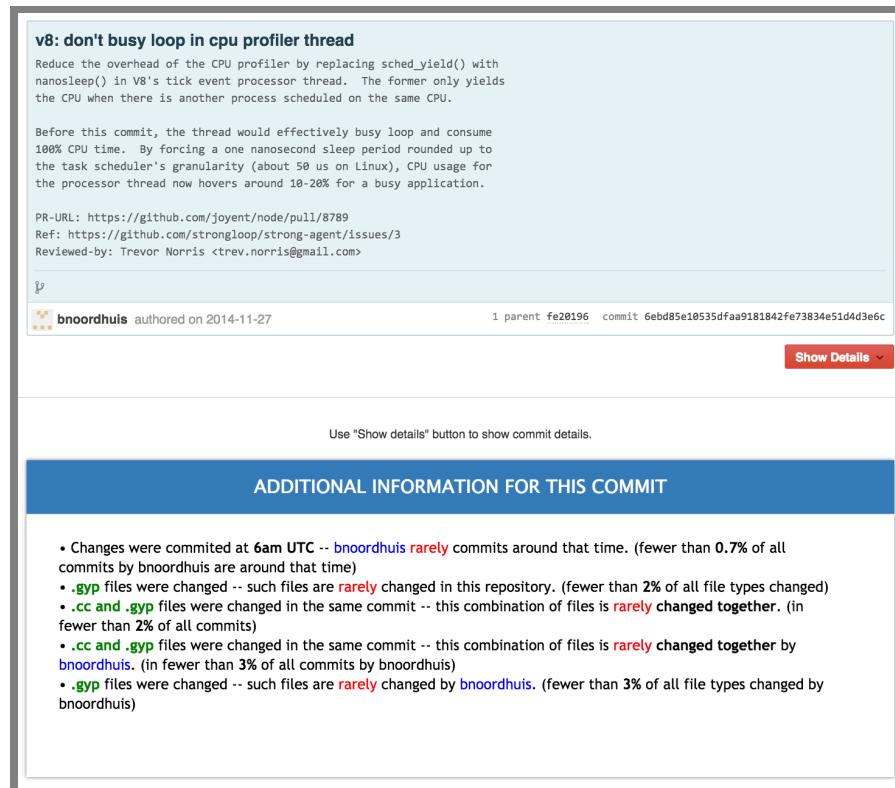
- Explain key concepts of transparency and trust
- Discuss whether and when transparency can be abused to game the system
- Design a system to include human oversight
- Understand common concepts and discussions of accountability/culpability
- Critique regulation and self-regulation approaches in ethical machine learning

Explainability vs Transparency

- Explainability & Interpretability: Tools to understand the model, mostly debugging, mostly developer-focused
- Transparency: Users know that algorithm exists and how the algorithm works

Transparency is focused on users -- Human-AI interaction, oversight, appeals, audits

Recall: Explaining for Human-AI Interaction, Trust



Goyal, Raman, Gabriel Ferreira, Christian Kästner, and James Herbsleb. "[Identifying unusual commits on GitHub](#)." Journal of Software: Evolution and Process 30, no. 1 (2018): e1893.

Recall: Explainability for Auditing

- Understand safety implications
- Ensure predictions use objective criteria and reasonable rules
- Inspect fairness properties
- Reason about biases and feedback loops
- Validate "learned specifications/requirements" with stakeholders

```
IF age between 18-20 and sex is male THEN predict arrest  
ELSE IF age between 21-23 and 2-3 prior offenses THEN predict  
ELSE IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Transparency of the Model's Existance



Listening to The Cure and thinking about the Bomb

@TheWrongNoel · [Follow](#)



A friend of mine has been trying to hire a new employee for her department in a medium-sized org. After advertising several times with few applicants, and a couple of rounds of interviews, the new employee is less than great. Then she discovered there were other applicants ...

5:01 AM · Nov 14, 2019



11K

Reply

[Copy link](#)

[Read 347 replies](#)

Case Study: Facebook's Feed Curation



Eslami, Motahhare, et al. [I always assumed that I wasn't really that close to \[her\]: Reasoning about Invisible Algorithms in News Feeds](#). In Proc. CHI, 2015.

Case Study: Facebook's Feed Curation

- 62% of interviewees were not aware of curation algorithm
- Surprise and anger when learning about curation

"Participants were most upset when close friends and family were not shown in their feeds [...] participants often attributed missing stories to their friends' decisions to exclude them rather than to Facebook News Feed algorithm."

- Learning about algorithm did not change satisfaction level
- More active engagement, more feeling of control

Transparency of How the Model Works

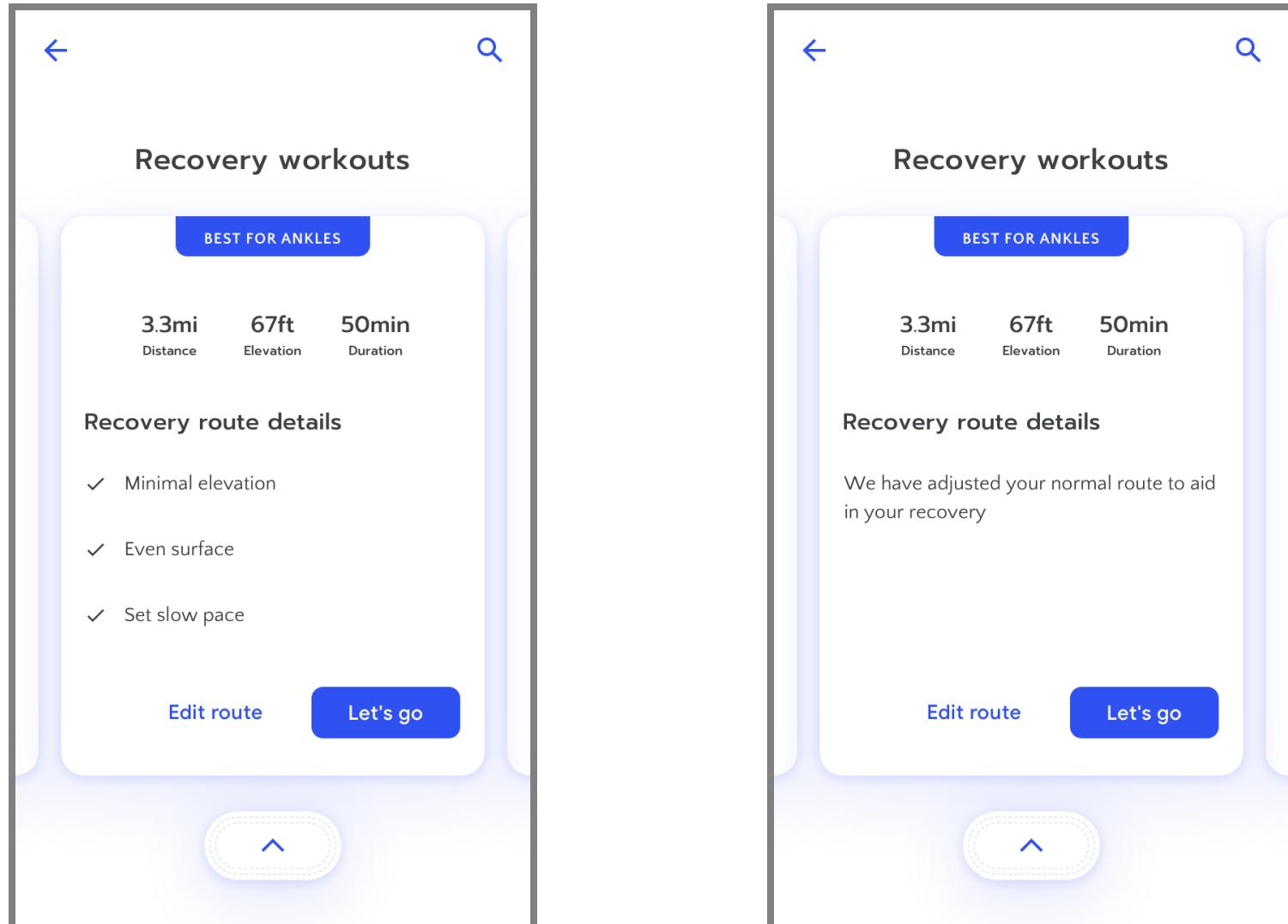
Enabling Oversight and Appeals

- What is this figure showing?
- Who want to get what information from this plot?
- Who can read this plot? What kinds of expertise? Training?

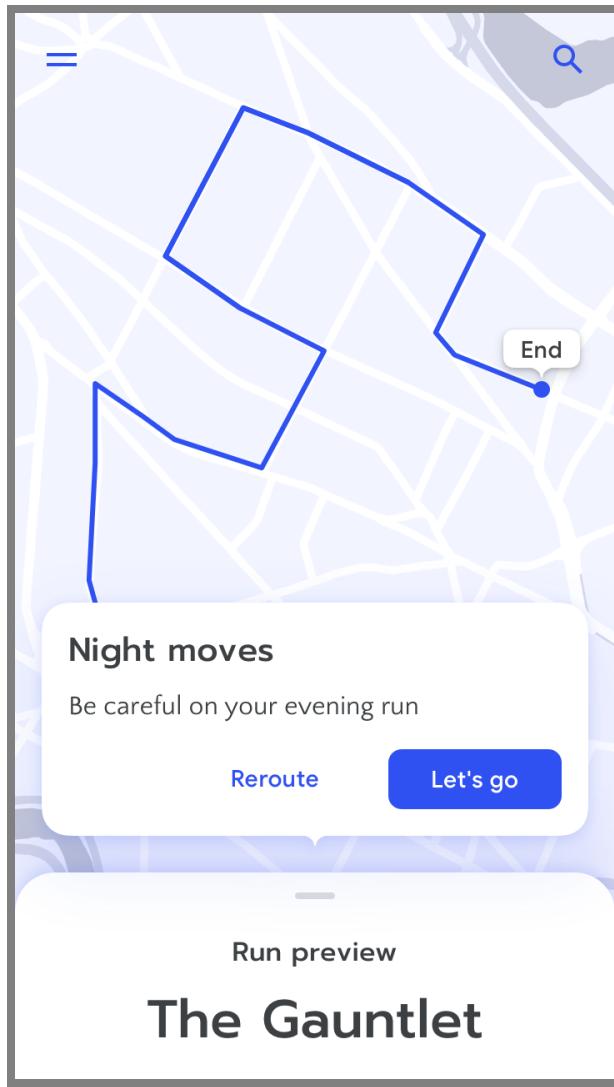
Human is the key!



Expl. for Human-AI Interaction



Give the user details about why a prediction was made in a high stakes scenario. Here, the user is exercising after an injury and needs confidence in the app's recommendation.



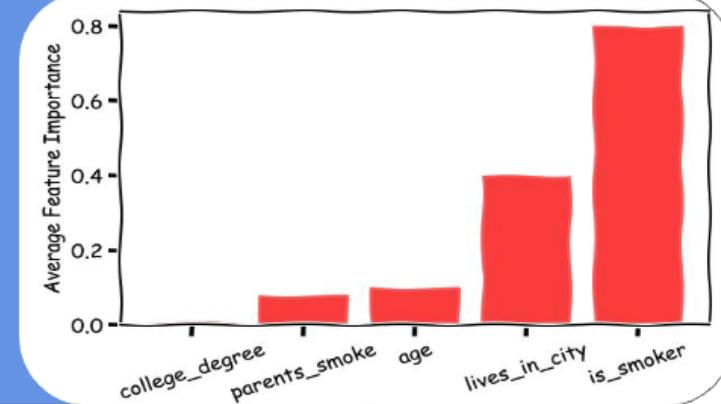
Tell the user when a lack of data might mean they'll need to use their own judgment. Don't be afraid to admit when a lack of data could affect the quality of the AI recommendations.

Express Explanation Intuitively



FOR WOMEN PREDICTED HIGH RISK FOR LUNG CANCER THAT ARE OLDER THAN 65, WHY DID THE MODEL DECIDE TO PREDICT THEM AS HIGH RISK?

GOOD QUESTION! IT LOOKS LIKE THE MODEL PREDICTED THESE INDIVIDUALS AS HIGH RISK MOSTLY BECAUSE THEY WERE SMOKERS BUT ALSO BECAUSE THEY LIVE IN LARGE CITIES. I'M HIGHLY CONFIDENT THESE ARE THE REASONS BECAUSE THE EXPLANATIONS HAVE HIGH FIDELITY. HERE'S THE AVERAGE FEATURE IMPORTANCE FOR THESE PEOPLE (HIGHER MEANS MORE IMPORTANT).

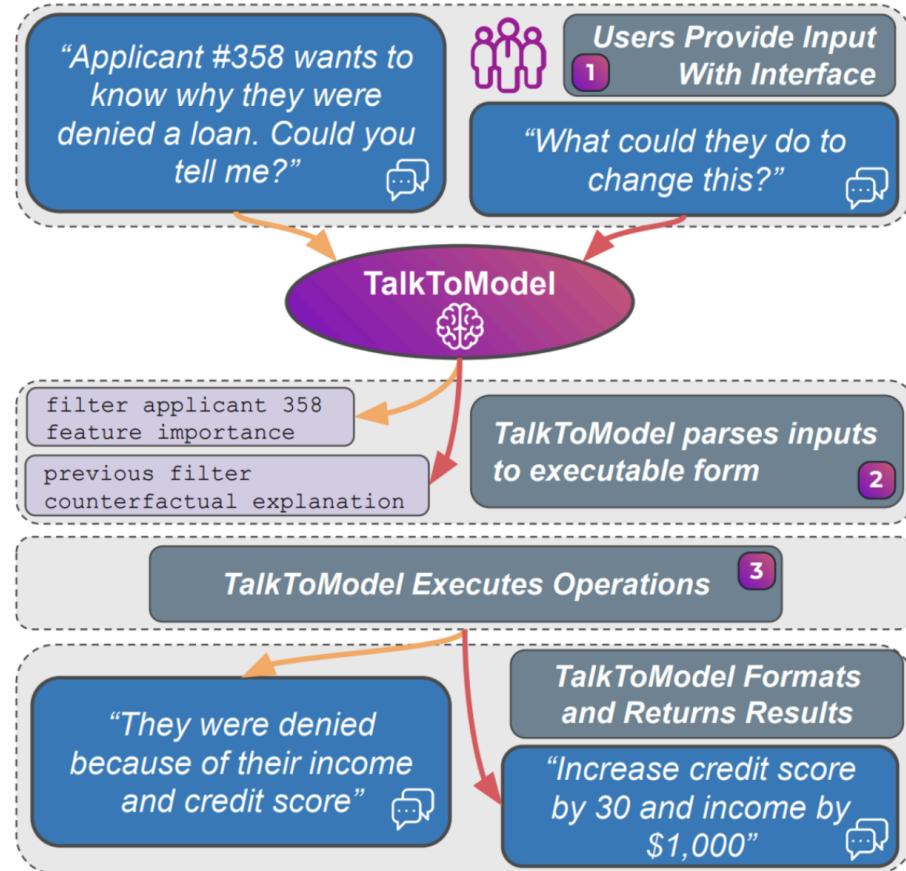


Wow, it's surprising that whether the person lives in a city is so important.

Yes, `LIVES_IN_CITY` has a significant effect on the predictions for these individuals. Perturbing this feature can flip the prediction for 4 of 15 of the instances in this group.



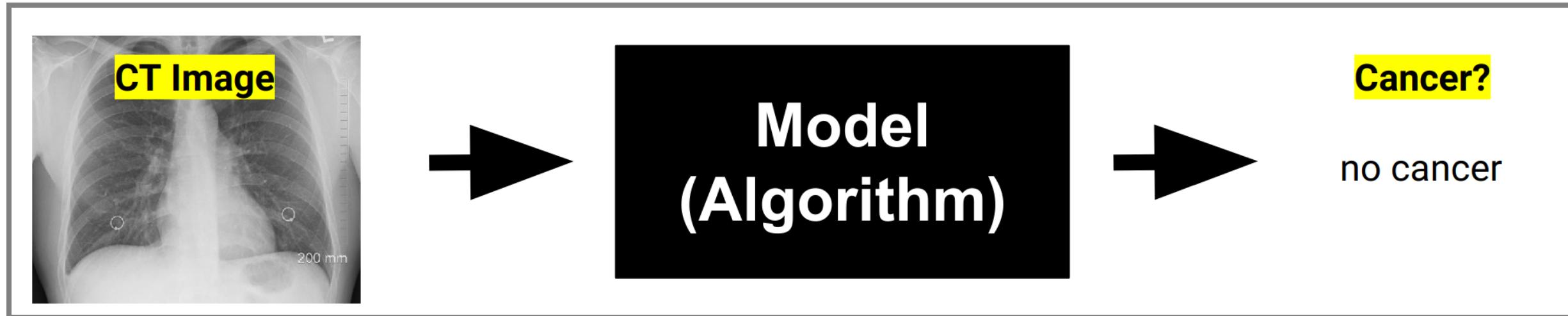
Express Explanation Intuitively



Slack, Dylan, et al. "TalkToModel: Explaining Machine Learning Models with Interactive Natural Language Conversations." (2022).

	operation, arguments, and description
Data	<code>filter(dataset, feature, value, comparison)</code> : filters <code>dataset</code> by using value and comparison operator <code>change(dataset, feature, value, variation)</code> : Changes <code>dataset</code> by increasing, decreasing, or setting feature by <code>value</code> <code>show(list)</code> : Shows items in list in the conversation <code>statistic(dataset, metric, feature)</code> : Computes summary statistic for <code>feature</code> <code>count(list)</code> : Length of list <code>and(op1, op2)</code> : Logical “and” of two operations <code>or(op1, op2)</code> : Logical “or” of two operations
Explainability	<code>explain(dataset, method, class=predicted)</code> : Feature importances on <code>dataset</code> <code>cfe(dataset, number, class=opposite)</code> : Gets <code>number</code> counterfactual explanations <code>topk(dataset, k)</code> : Top <code>k</code> most important features <code>important(dataset, feature)</code> : Importance ranking of <code>feature</code> <code>interaction(dataset)</code> : Interaction effects between features <code>mistakes(dataset)</code> : Patterns in the model’s errors on <code>dataset</code>
ML	<code>predict(dataset)</code> : Model predictions on <code>dataset</code> <code>likelihood(dataset)</code> : Prediction probabilities on <code>dataset</code> <code>incorrect(dataset)</code> : Incorrect predictions <code>score(dataset, metric)</code> : Scores the model with <code>metric</code>
Conv.	<code>prev_filter(conversation)</code> : Gets last filters <code>prev_operation(conversation)</code> : Gets last non-filtering operations <code>followup(conversation)</code> : Respond to system followups
Description	<code>function()</code> : Overview of the system’s capabilities <code>data(dataset)</code> : Summary of dataset <code>model()</code> : Description of <code>model</code> <code>define(term)</code> : Defines <code>term</code>

Setting Cancer Imaging -- What explanations do radiologists want?



- *Past attempts often not successful at bringing tools into production. Radiologists do not trust them. Why?*
- **Wizard of oz study** to elicit requirements



Radiologists' questions

- How does it perform compared to human experts?
- "What is difficult for the AI to know? Where is it too sensitive? What criteria is it good at recognizing or not good at recognizing?"
- What data (volume, types, diversity) was the model trained on?
- "Does the AI have access to information that I don't have? Does it have access to ancillary studies?" Is all used data shown in the UI?
- What kind of things is the AI looking for? What is it capable of learning? ("Maybe light and dark? Maybe colors? Maybe shapes, lines?", "Does it take into consideration the relationship between gland and stroma? Nuclear relationship?")
- "Does it have a bias a certain way?" (compared to colleagues)

Radiologists' questions

- Capabilities and limitations: performance, strength, limitations; e.g. how does it handle well-known edge cases
- Functionality: What data used for predictions, how much context, how data is used
- Medical point-of-view: calibration, how liberal/conservative when grading cancer severity
- Design objectives: Designed for few false positives or false negatives? Tuned to compensate for human error?
- Other considerations: legal liability, impact on workflow, cost of use

Radiologists Study Insights

- AI literacy important for trust
- Be transparent about data used
- Describe training data and capabilities
- Give mental model, examples, human-relatable test cases
- Communicate the AI's point-of-view and design goal

Cai, Carrie J., Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. ""Hello AI": Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making." Proceedings of the ACM on Human-computer Interaction 3, no. CSCW (2019): 1-24.

Designing Transparency

- Be explicit about the goal
- Tailor explanation to specific user needs and user's AI literacy
- Partial explanations or justifications often sufficient
- Test effectiveness of transparency mechanisms

The Dark Side of Transparency

Many explanations are wrong

Approximations of black-box models, often unstable

Explanations necessarily partial, social

Often multiple explanations possible (Rashomon effect)

Possible to use inherently interpretable models instead?

When explanation desired/required: What quality is needed/acceptable?

Explanations foster Trust

Users are less likely to question the model when explanations provided

- Even if explanations are unreliable
- Even if explanations are nonsensical/incomprehensible

Danger of overtrust and intentional manipulation

Stumpf, Simone, Adrian Bussone, and Dympna O'sullivan. "Explanations considered harmful? user interactions with machine learning systems." In Proceedings of the ACM SIGCHI Conference on



The graphic above displays the output from an algorithm that assesses the positivity/negativity of your writing as you answer the question below.

1. For each of the past 3 days: Choose one event that affected you emotionally and write a paragraph about how and why it affected you.

I went to the vet and got some really good news. Baxter is going to be okay after all.

Springer, Aaron, Victoria Hollis, and Steve Whittaker. "Dice in the black box: User experiences with an inscrutable algorithm." In 2017 AAAI Spring Symposium Series. 2017.



(a) Rationale, (b) Stating the prediction, (c) Numerical internal values

Observation: Both experts and non-experts overtrust numerical explanations, even when inscrutable.

Illusion of Control

Users may feel influence and control, even with placebo controls

Real —— (a) News Feeds —— Random —— (b) Control Setting —

The figure displays two Twitter timelines side-by-side. The left timeline, labeled 'Real' and '(a) News Feeds', shows tweets from xoNecole (@xonecole) and RI (@hyori_sunie). The right timeline, labeled 'Random' and '(b) Control Setting', shows tweets from Vogue Magazine (@voguemagazine), Monica Kim (@monicamkim), and Chloe (@chloesw). A 'Popularity' scale is shown, ranging from 'Less popular' to 'More popular'. Two quotes are highlighted in speech bubbles: 'The popularity also seemed to be working as much as it is, because I'm seeing content that seems highly either re-shared or liked. In fact, I'm not seeing anything that has zero for both...' (P27) and 'I'm not seeing very much of my friends or people that I went to school with. I see one, but everything else is pretty much a verified account, or an account that has multiple thousand followers...' (P28).

The popularity also seemed to be working as much as it is, because I'm seeing content that seems highly either re-shared or liked. In fact, I'm not seeing anything that has zero for both... (P27)

I'm not seeing very much of my friends or people that I went to school with. I see one, but everything else is pretty much a verified account, or an account that has multiple thousand followers... (P28)

Popularity

Less popular More popular

Users engage in complex sensemaking, whether controls are real or random

Vaccaro, Kristen, Dylan Huang, Motahhare Eslami, Christian Sandvig, Kevin Hamilton, and Karrie Karahalios. "The illusion of control: Placebo effects of control settings." In Proc CHI, 2018.

Regulatory Compliance

Companies give vague generic explanations to appease regulators

Checkbox compliance: Provide some mechanism without ensuring effectiveness

Example: FairCredit act requires explanation for declined credit applications -- Explanations generic and ineffective for fighting discrimination, at most ensure that input data was correct

Selbst, Andrew D., and Solon Barocas. "The intuitive appeal of explainable machines." Fordham L. Rev. 87 (2018): 1085.

Gaming/Attacking the Model with Explanations?

Does providing an explanation allow customers to 'hack' the system?

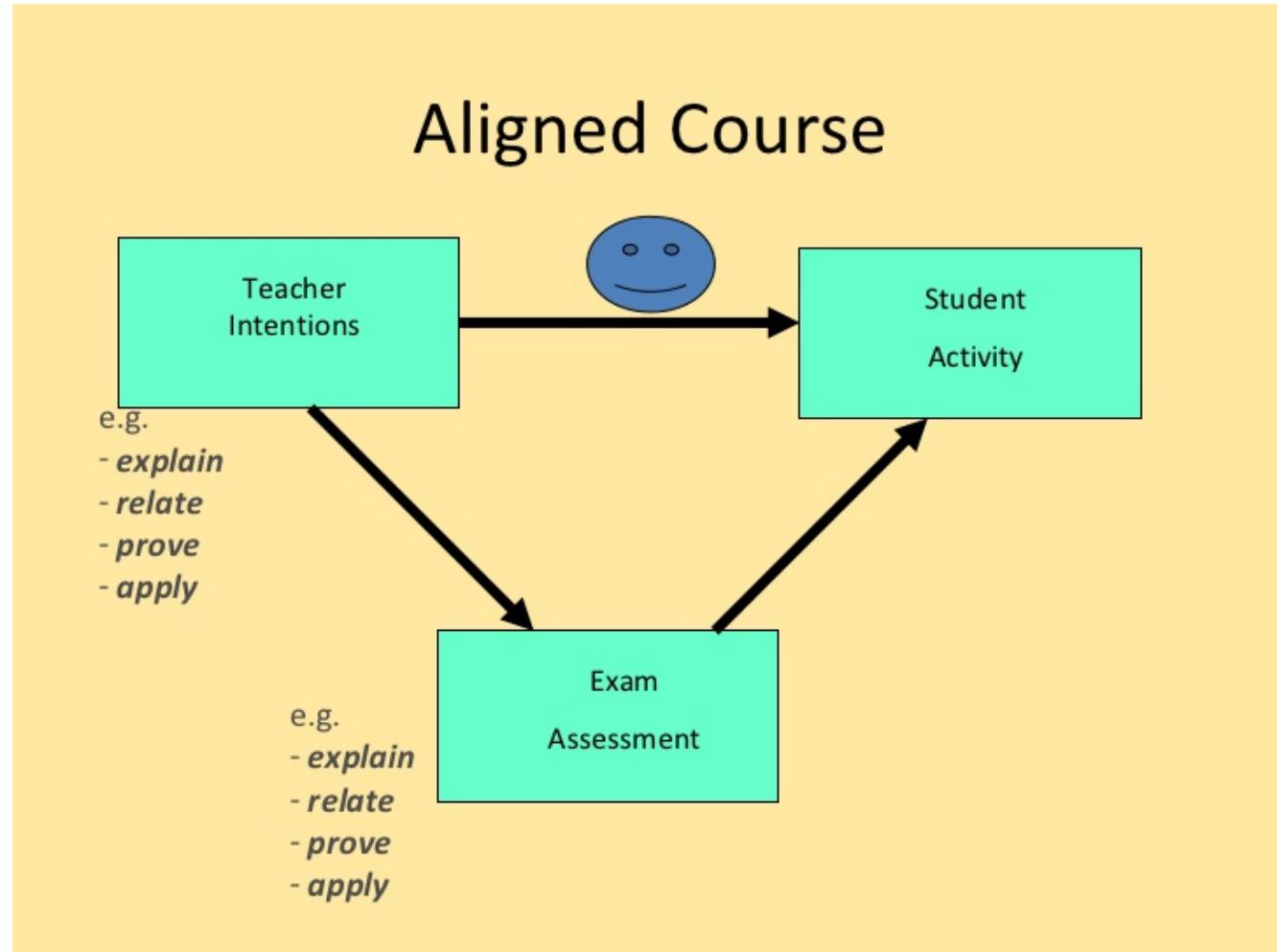
- Loan applications?
- Apple FaceID?
- Recidivism?
- Auto grading?
- Cancer diagnosis?
- Spam detection?

Gaming the Model with Explanations?



≡ see also Claus Brabrand. [Teaching & Understanding](#). Youtube 2009

Constructive Alignment in Teaching



≡ see also Claus Brabrand. [Teaching & Understanding](#). Youtube 2009

Gaming the Model with Explanations?

- A model prone to gaming uses **weak proxy features**
- Protections require to make the model hard to observe (e.g., expensive to query predictions)
- Protecting models akin to "security by obscurity"
- *Good models rely on hard facts that relate causally to the outcome <- hard to game*

```
IF age between 18-20 and sex is male THEN predict arrest
ELSE IF age between 21-23 and 2-3 prior offenses THEN predict
ELSE IF more than three priors THEN predict arrest
ELSE predict no arrest
```

Human Oversight and Appeals

Human Oversight and Appeals

- Unavoidable that ML models will make mistakes
- Users knowing about the model may not be comforting
- Inability to appeal a decision can be deeply frustrating

DHH · Nov 8, 2019
@dhh · Follow
Replying to @dhh

I wasn't even pessimistic to expect this outcome, but here we are:
@AppleCard just gave my wife the VIP bump to match my credit limit, but continued to be an utter fucking failure of a customer service experience. Let me explain...

DHH · Nov 8, 2019
@dhh · Follow

She spoke to two Apple reps. Both very nice, courteous people representing an utterly broken and reprehensible system. The first person was like "I don't know why, but I swear we're not discriminating, IT'S JUST THE ALGORITHM". I shit you not. "IT'S JUST THE ALGORITHM!".

11:20 PM · Nov 8, 2019

3.7K · Reply · Copy link

Read 54 replies

Capacity to keep humans in the loop?

ML used because human decisions as a bottleneck

ML used because human decisions biased and inconsistent

Do we have the capacity to handle complaints/appeals?

Wouldn't reintroducing humans bring back biases and inconsistencies?

Designing Human Oversight

Consider the entire system and consequences of mistakes

Deliberately design mitigation strategies for handling mistakes

Consider keeping humans in the loop, balancing harms and costs

- Provide pathways to appeal/complain? Respond to complains?
- Review mechanisms? Can humans override tool decision?
- Tracking telemetry, investigating common mistakes?
- Audit model and decision process rather than appeal individual outcomes?

Breakout: Transparency in Admissions

For a automated Master's admission support system, consider what you would make transparent and to whom.

In groups, tagging group members, respond in #lecture:

- What information (global, local) would you provide to applicants? What's the purpose?
- What information (global, local) would you provide to the admissions committee? What's the purpose?

Accountability and Culpability

Who is held accountable if things go wrong?

On Terminology



- accountability, responsibility, liability, and culpability all overlap in common use
- often about assigning *blame* -- responsible for fixing or liable for paying for damages
 - liability, culpability have *legal* connotation
 - responsibility tends to describe *ethical* aspirations
 - accountability often defined as oversight relationship, where actor is accountable to some "forum" that can impose penalties
 - see also legal vs ethical earlier

On Terminology



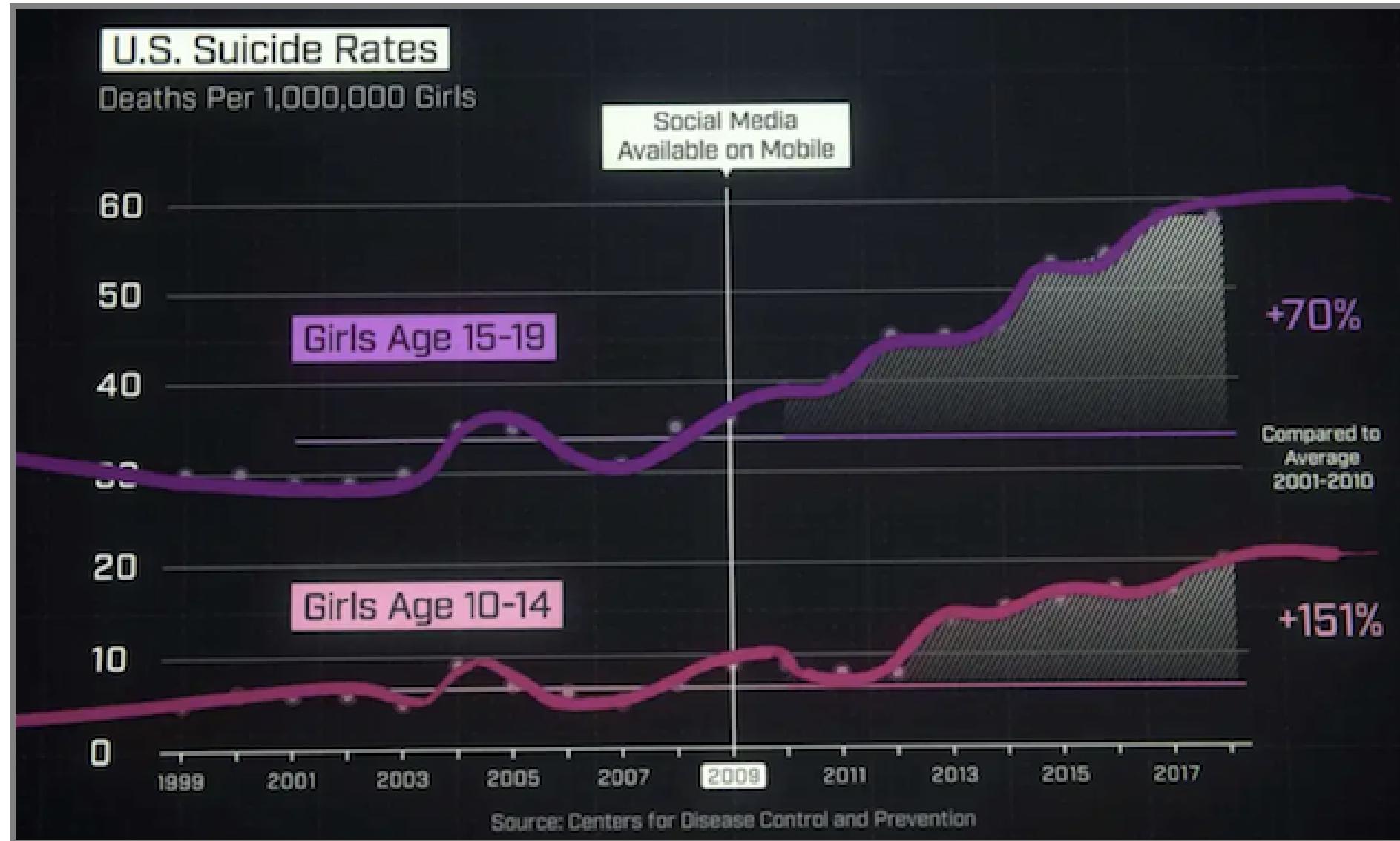
Academic definition of accountability:

*A relationship between an **actor** and a **forum**, in which the actor has an obligation to explain and to justify his or her conduct, the forum can pose questions and pass judgement, and the actor **may face consequences**.*

That is accountability implies some oversight with ability to penalize

Wieringa, Maranke. "What to account for when accounting for algorithms: a systematic literature review on algorithmic accountability." In *Proceedings of the Conference on Fairness, Accountability, and Transparency*, pp. 1-18. 2020.

Who is responsible?



Who is responsible?

Who is responsible?



Who is responsible?

Who is responsible for Faceswap / Deepfake?



Faceswap's README "FaceSwap has ethical uses"

[...] as is so often the way with new technology emerging on the internet, it was immediately used to create inappropriate content.

[...] it was the first AI code that anyone could download, run and learn by experimentation without having a Ph.D. in math, computer theory, psychology, and more. Before "deepfakes" these techniques were like black magic, only practiced by those who could understand all of the inner workings as described in esoteric and endlessly complicated books and papers.

[...] the release of this code opened up a fantastic learning opportunity.

Are there some out there doing horrible things with similar software? Yes. And because of this, the developers have been following strict ethical standards. Many of us don't even use it to create videos, we just tinker with the code to see what it does. [...]

FaceSwap is not for creating inappropriate content. FaceSwap is not for changing faces without consent or with the intent of hiding its use. FaceSwap is not for any illicit, unethical, or questionable purposes. [...]

THE SOFTWARE IS PROVIDED “AS IS”, WITHOUT WARRANTY OF ANY KIND, EXPRESS OR IMPLIED, INCLUDING BUT NOT LIMITED TO THE WARRANTIES OF MERCHANTABILITY, FITNESS FOR A PARTICULAR PURPOSE AND NONINFRINGEMENT. IN NO EVENT SHALL THE AUTHORS OR COPYRIGHT HOLDERS BE LIABLE FOR ANY CLAIM, DAMAGES OR OTHER LIABILITY, WHETHER IN AN ACTION OF CONTRACT, TORT OR OTHERWISE, ARISING FROM, OUT OF OR IN CONNECTION WITH THE SOFTWARE OR THE USE OR OTHER DEALINGS IN THE SOFTWARE.

Speaker notes

Software engineers got (mostly) away with declaring not to be liable

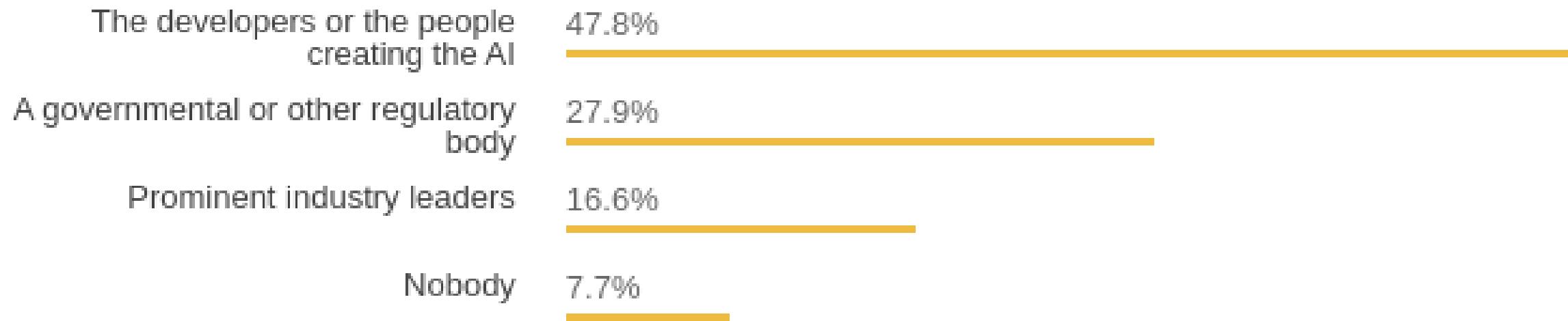


Easy to Blame "The Algorithm" / "The Data" / "Software"

"Just a bug, things happen, nothing we could have done"

- But system was designed by humans
- But humans did not anticipate possible mistakes, did not design to mitigate mistakes
- But humans made decisions about what quality was good enough
- But humans designed/ignored the development process
- But humans gave/sold poor quality software to other humans
- But humans used the software without understanding it
- ...

Who is Primarily Responsible for Considering the Ramifications of AI?



65,553 responses

Results from the 2018 StackOverflow Survey

What to do?

- Responsible organizations embed risk analysis, quality control, and ethical considerations into their process
- Establish and communicate policies defining responsibilities
- Work from aspirations toward culture change: baseline awareness + experts
- Document tradeoffs and decisions (e.g., datasheets, model cards)
- Continuous learning
- Consider controlling/restricting how software may be used, whether it should be built at all
- And... follow the law
- Get started with existing guidelines, e.g., in [AI Ethics Guidelines](#)

(Self-)Regulation and Policy



[DONATE](#)



Play Live Radio

[HOURLY NEWS](#) [LISTEN LIVE](#) [PLAYLIST](#)



SUBSCRIBE

SHORT WAVE

Tech Companies Are Limiting Police Use of Facial Recognition. Here's Why

June 23, 2020 · 4:00 AM ET



14-Minute Listen

[+ PLAYLIST](#)



Microsoft AI principles

We put our responsible AI principles into practice through the Office of Responsible AI (ORA) and the AI, Ethics, and Effects in Engineering and Research (Aether) Committee. The Aether Committee advises our leadership on the challenges and opportunities presented by AI innovations. ORA sets our rules and governance processes, working closely with teams across the company to enable the effort.

[Learn more about our approach >](#)

Fairness

AI systems should treat all people fairly

[▷ Play video on fairness](#)

Reliability & Safety

AI systems should perform reliably and safely

[▷ Play video on reliability](#)

Privacy & Security

AI systems should be secure and respect privacy

[▷ Play video on privacy](#)

Inclusiveness

AI systems should empower everyone and engage people

[▷ Play video on inclusiveness](#)

Transparency

AI systems should be understandable

[▷ Play video on transparency](#)

Accountability

People should be accountable for AI systems

[▷ Play video on accountability](#)

Policy Discussion and Frameing

- Corporate pitch: "Responsible AI" ([Microsoft](#), [Google](#), [Accenture](#))
- Counterpoint: Ochigame "[The Invention of 'Ethical AI': How Big Tech Manipulates Academia to Avoid Regulation](#)", The Intercept 2019
 - *"The discourse of “ethical AI” was aligned strategically with a Silicon Valley effort seeking to avoid legally enforceable restrictions of controversial technologies."*

Self-regulation vs government regulation? Assuring safety vs fostering innovation?



@emilymbender@dair-community.social on Mastodon

@emilymbender · [Follow](#)



Okay, so that AI letter signed by lots of AI researchers calling for a "Pause [on] Giant AI Experiments"? It's just dripping with [#Aihype](#). Here's a quick rundown.

>>

3:36 AM · Mar 29, 2023



1.4K Reply Copy link

[Read 38 replies](#)



Arvind Narayanan
@random_walker · [Follow](#)



This open letter — ironically but unsurprisingly — further fuels AI hype and makes it harder to tackle real, already occurring AI harms. I suspect that it will benefit the companies that it is supposed to regulate, and not society. Let's break it down.



Pause Giant AI Experiments: An Open Letter

We call on all AI labs to immediately pause for at least 6 months the training of AI systems more powerful than GPT-4.

futureoflife.org

Pause Giant AI Experiments: An Open Letter - Future of Life Institute

We call on all AI labs to immediately pause for at least 6 months the training of AI systems more powerful than GPT-4.

1:58 PM · Mar 29, 2023



1.2K Reply Copy link

[Read 35 replies](#)



"Wishful Worries"

We are distracted with worries about fairness and safety of hypothetical systems

Most systems fail because they didn't work in the first place; don't actually solve a problem or address impossible tasks

Wouldn't help even if they solved the given problem (e.g., predictive policing?)

Raji, Inioluwa Deborah, I. Elizabeth Kumar, Aaron Horowitz, and Andrew Selbst. "The fallacy of AI functionality." In 2022 ACM Conference on Fairness, Accountability, and Transparency, pp. 959-

4,576 views | Mar 1, 2020, 01:00am EST

This Is The Year Of AI Regulations



Kathleen Walch Contributor

COGNITIVE WORLD Contributor Group ⓘ

AI

-
- f The world of artificial intelligence is constantly evolving, and certainly so is the legal and regulatory environment.

“Accelerating America’s Leadership in Artificial Intelligence”

“the policy of the United States Government [is] to sustain and enhance the scientific, technological, and economic leadership position of the United States in AI.” -- [White House Executive Order Feb. 2019](#)

Tone: "When in doubt, the government should not regulate AI."

Speaker notes

- 3. Setting AI Governance Standards: "*foster public trust in AI systems by establishing guidance for AI development. [...] help Federal regulatory agencies develop and maintain approaches for the safe and trustworthy creation and adoption of new AI technologies. [...] NIST to lead the development of appropriate technical standards for reliable, robust, trustworthy, secure, portable, and interoperable AI systems.*"



EU AI Act

Broad regulatory framework, passed March 13, 2024

Risk-based framework:

2023 WH Executive Order on the Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence

Instructs agencies to study risks and develop standards

Broad scope, touches on quality assurance standards (incl. red teaming) and marking AI-generated content

Domain-specific guidelines for chemical, biological, radiological, nuclear, and cybersecurity risks to be explored

Committees, reports, guidance, research instead of enforceable rules

Call for Transparent and Audited Models

"no black box should be deployed when there exists an interpretable model with the same level of performance"

For high-stakes decisions

- ... with government involvement (recidivism, policing, city planning, ...)
- ... in medicine
- ... with discrimination concerns (hiring, loans, housing, ...)
- ... that influence society and discourse? (algorithmic content amplifications, targeted advertisement, ...)

Regulate possible conflict: Intellectual property vs public welfare

Rudin, Cynthia. "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead." *Nature Machine Intelligence* 1.5 (2019): 206-215. ([Preprint](#))

Criticism: Ethics Washing, Ethics Bashing, Regulatory Capture



Summary

- Transparency goes beyond explaining predictions
- Plan for mistakes and human oversight
- Accountability and culpability are hard to capture, little regulation
- Be a responsible engineer, adopt a culture of responsibility
- Regulations may be coming

Further Readings

- Jacovi, Alon, Ana Marasović, Tim Miller, and Yoav Goldberg. [Formalizing trust in artificial intelligence: Prerequisites, causes and goals of human trust in AI](#). In Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency, pp. 624–635. 2021.
- Eslami, Motahhare, Aimee Rickman, Kristen Vaccaro, Amirhossein Aleyasen, Andy Vuong, Karrie Karahalios, Kevin Hamilton, and Christian Sandvig. [I always assumed that I wasn't really that close to her: Reasoning about Invisible Algorithms in News Feeds](#). In Proceedings of the 33rd annual ACM conference on human factors in computing systems, pp. 153–162. ACM, 2015.
- Rakova, Bogdana, Jingying Yang, Henriette Cramer, and Rumman Chowdhury. "[Where responsible AI meets reality: Practitioner perspectives on enablers for shifting organizational practices](#)." Proceedings of the ACM on Human-Computer Interaction 5, no. CSCW1 (2021): 1–23.
- Greene, Daniel, Anna Lauren Hoffmann, and Luke Stark. "[Better, nicer, clearer, fairer: A critical assessment of the movement for ethical artificial intelligence and machine learning](#)." In *Proceedings of the 52nd Hawaii International Conference on System Sciences* (2019).
- Metcalf, Jacob, and Emanuel Moss. "[Owning ethics: Corporate logics, silicon valley, and the institutionalization of ethics](#)." *Social Research: An International Quarterly* 86, no. 2 (2019): 449-476.
- Raji, Inioluwa Deborah, I. Elizabeth Kumar, Aaron Horowitz, and Andrew Selbst. "[The fallacy of AI functionality](#)." In 2022 ACM Conference on Fairness, Accountability, and Transparency, pp. 959-972. 2022.

