Ethics in Data Science

CSCI 4360/6360 Data Science II

Source: http://ai.stanford.edu/blog/ethical-best-practices/

What is "technical debt"?

- Coined by Ward Cunningham in 1992
 - Refers to long-term costs incurred by moving quickly in software engineering
- Debt metaphor
 - Not necessarily a bad thing, but always needs to be serviced
- Goal: NOT to add new functionality
 - Enable future improvements, reduce errors, improve maintainability

What is "technical debt"?

Technical debt

From Wikipedia, the free encyclopedia

Technical debt (also known as **design debt**^[1] or **code debt**) is "a concept in programming that reflects the extra development work that arises when code that is easy to implement in the short run is used instead of applying the best overall solution^[2]".

Technical debt can be compared to monetary debt.^[3] If technical debt is not repaid, it can accumulate 'interest', making it harder to implement changes later on. Unaddressed technical debt increases software entropy. Technical debt is not necessarily a bad thing, and sometimes (e.g., as a proof-of-concept) technical debt is required to move projects forward. On the other hand, some experts claim that the "technical debt" metaphor tends to minimize the impact, which results in insufficient prioritization of the necessary work to correct it.^{[4][5]}

What is "technical debt"?



Technical Debt and Machine Learning

- All the maintenance problems of "traditional" code
 - Plus an additional set of ML-specific concerns
- Debt can exist at system level, instead of [strictly] code level
 - Data influences ML system behavior!
 - "Traditional" abstractions and boundaries can be corrupted
- "Traditional" methods for paying down code-level debt are not sufficient to address ML-specific issues at system level

Causes of Technical Debt

- MANY
 - Model complexity
 - Data dependencies
 - ML anti-patterns
 - Configuration debt
 - Changes in external world
- Feedback loops
 - Key feature of ML: the system influencing its own behavior
 - "Analysis debt": Difficult to predict the behavior of a given model before release



Anyone?

- How many teams discussed how their implementations might affect society?
- Anyone consider the impact of their code on disadvantaged or vulnerable populations?
- Were any tests written to determine if the datasets were biased?
- Did any team discussions center around transparency of the trained model?
- Any time spent considering other ethical hypotheticals?



- Fairness, Accountability, and Transparency
 - FATML
 - ► FAT*
- More informal chatter (following some high-profile blunders)
- General scientific ethics courses

200 intelligence")
AND "ethics"

150

100

50

0

2014
2015
2016
2017
2018

CBINSIGHTS

Quarterly news mentions of ("AI OR artificial intelligence") AND "ethics" 2014 – Q3 2018

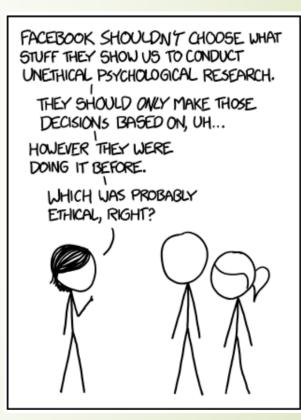
Talk of AI and ethics is on the rise

News Coverage

This lecture: some best practices to know

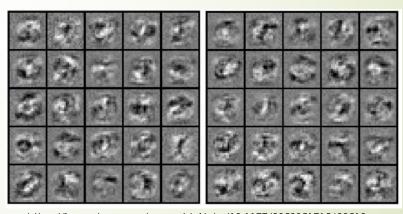
Unintended consequences

- The primary goal of ethical thinking in data science (and everywhere, really) is to avoid unintended consequences of your work
 - (of course, this assumes the actor is intentionally good... we don't have time to cover how to handle intentionally bad actors)
- Hows
- Education
- Communication
- Distribution
- Advocacy



https://xkcd.com/1390/

- Basics of Al Ethics
- Legal and policy communities have thought about ethics in AI at least as much as AI researchers have thought about its development
- Consider: opacity of machine learning algorithms
 - What is "opacity"?
 - Opacity of secrecy (corporate, government)
 - Opacity of technical illiteracy (black box algorithms)
 - Opacity of scale (unavoidable algorithmic complexity)



https://journals.sagepub.com/doi/abs/10.1177/2053951715622512

Consider: potential harms of fully-automated decision-making

Individua	Collective /					
Illegal	Unfair	Societal Harms				
Loss of Liberty						
	Constraints of Suspicion E.g. Emotional, dignitary, and social impacts of increased surveillance	Increased Surveillance E.g. Use of "predictive policing" to police minority neighborhoods more				
Individual Ir E.g. Use of "recidivism scores" to o (legal status	Disproportionate Incarceration E.g. Incarceration of groups at higher rates based on historic policing data					
	Constraints of Bias E.g. Constrained conceptions of career prospects based on search results	Confirmation Bias E.g. All-male image search results for "CEO," all-female results for "teacher"				
Education D E.g. Denial of opportunity for a student in a certain ability category	iscrimination E.g. Presenting only ads on for-profit colleges to low-income individuals	Differential Access to Education				

https://fpf.org/2017/12/11/unfairness-by-algorithm-distilling-the-harms-of-automated-decision-making/

Potential mitigation strategies

Collective/Societal Harms (with illegal analog)

Differential Access to Job Opportunities
Differential Access to Insurance Benefits
Differential Access to Housing

Differential Access to Housing

Differential Access to Education

Differential Access to Credit

Differential Access to Goods & Services

Disproportionate Incarceration

Group level impacts that are not legally prohibited, though related individual impacts could be illegal

- Same as above section
- Laws & policies should consider offline analogies & whether it is appropriate for industry to identify & mitigate

Individual Harms – Unfair (without illegal analog)

Narrowing of Choice

Network Bubbles

Dignitary Harms

Constraints of Bias

Constraints of Suspicion

Individual impacts for which we do not have legal rules. Mitigation may be difficult or undesirable absent a defined set of societal norms

- Business processes to index concerns, ethical frameworks & best practices to monitor & evaluate outcomes
- Laws & policies should consider whether it is appropriate to expect industry to identify & enforce norms like DPIAS to measure impact or enable rights to explanation

Dimerential Pricing

Individual Incarceration

https://fpf.org/2017/12/11/unfairness-by-algorithm-distilling-the-harms-of-automated-decision-making/

- Consider: facial recognition in public places
 - City centers, airports
 - Concerns of error, function creep, and privacy
 - https://www.emeraldinsight.com/doi/pdfplus/10.1108/14779960480000246 (paywall)
 - Emotional privacy
 - Masking emotions
 - Social cohesion
 - http://blog.practicalethics.ox.ac.uk/2014/03/computer-vision-and-emotional-privacy/

Consider: societal impacts of natural language processing



- Exclusion and demographic bias
- Overgeneralization and confirmation bias
- Topic overexposure (availability heuristic) and underexposure
- http://aclweb.org/anthology/P16-2096
- NLP ethical best practices http://aclweb.org/anthology/W17-1604.pdf

Table 1: Remedies: Pyramid of Possible Responses to Unethical Behavior.				
Demonstration	to effect a change in society by public activism			
Disclosure	to document/to reveal injustice to regulators, the police, investigative journalists			
	("Look what they do!", "Stop what they do!")			
Resignation	to distance oneself III ("I should not/cannot be part of this.")			
Persuasion	to influence in order to halt non-ethical activity ("Our organization should not do this.")			
Rejection	to distance oneself II; to deny participation; conscientious objection ("I can't do this.")			
Escalation	raise with senior management/ethics boards ("You may not know what is going on here.")			
Voicing dissent	to distance oneself I ("This project is wrong.")			
Documentation	ensure all the facts, plans and potential and actual issues are preserved.			

- Consider: "dual-use" technologies
 - Technologies designed for civilian use but which may have military applications
 - Google's Project Maven, software for automated drone surveillance for the Pentagon

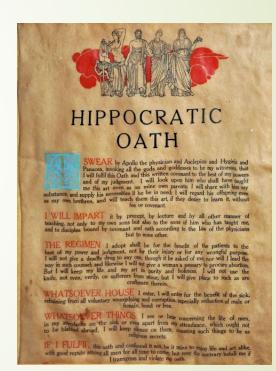
Sign this letter

Dear Sundar,

We believe that Google should not be in the business of war. Therefore we ask that Project Maven be cancelled, and that Google draft, publicize and enforce a clear policy stating that neither Google nor its contractors will ever build warfare technology.

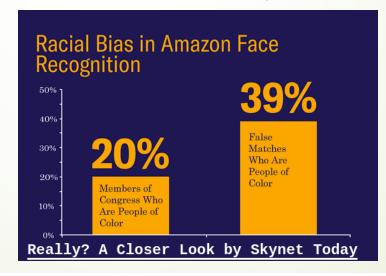
- Microsoft employees have protested the company's involvement in the same Department of Defense program
- Amazon's collaboration with the US Immigration and Customs Enforcement (ICE)

- Codes of Ethics
- Some have advocated for a "Data Science Hippocratic Oath"
- IEEE and ACM organizations have explicit codes of ethics
- Al research is arguably unique, but NeurIPS 2018 has a Code of Conduct and the ML Ally Pledge is similarly well constructed
- Many other institutions and "influencing" organizations have begun making their own



Communication

- Potential misuses and ethical considerations of new AI and data science algorithms / packages are rarely identified and pointed out, either in documentation or in academic papers
 - Amazon's Rekognition product for facial recognition did not warn about the high false positive rate associated with its default parameters



Communication

 New "Ethical Considerations" section in published works (academic, code documentation, blog posts, etc)

- Margaret Mitchell, Senior Research Scientist at Google, Tech Lead for Google's ML fairness effort
 - 2017 paper flagging patient suicide risk in clinical settings given their writings as input
 - Point out clear cases of potential ethical mis-use and how their study mitigated these concerns

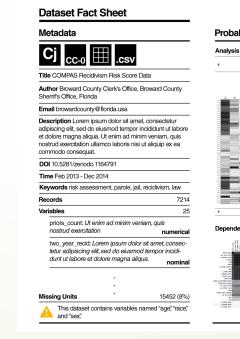
2 Ethical Considerations

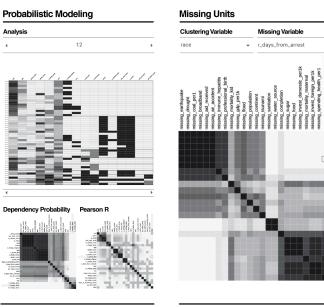
As with any author-attribute detection, there is the danger of abusing the model to single out people (overgeneralization, see Hovy and Spruit (2016)). We are aware of this danger, and sought to minimize the risk. For this reason, we don't provide a selection of features or representative examples. The experiments in this paper were performed with a clinical application in mind, and use carefully matched (but anonymized) data, so the distribution is not representative of the population as a whole. The results of this paper should therefore not be interpreted as a means to assess mental health conditions in social media in general, but as a test for the applicability of MTL in a well-defined clinical setting.

Communication

 Standardizing means of communicating aspects of new datasets and Al services

- Datasheets for datasets
- Data statements for NLP
- Policy certificates for RL
- Declarations of Al service conformity





Distribution

- Approval and Terms of Access for datasets, code, and models
- ImageNet
 - One of the most important computer vision datasets of the decade
 - Downloading it requires agreeing to terms of access!
 - Admittedly increases overhead for host lab or organization, but helps mitigate the dual-use problem
- A "Responsible Al License" for code and pre-trained models

Distribution

BOX 9

Ethical considerations in deciding whether to share Google Al advances

We generally seek to share Google research to contribute to growing the wider AI ecosystem. However we do not make it available without first reviewing the potential risks for abuse. Although each review is content-specific, key factors that we consider in making this judgment include:

- Risk and scale of benefit vs downside What is the primary purpose and likely use of a technology and application, and how beneficial is this? Conversely, how adaptable is it to a harmful use, and how likely is it that there are bad actors with the skills and motivation to deploy it? Overall, what is the magnitude of potential impact likely to be?
- Nature and uniqueness Is it a significant breakthrough or something that many people outside Google
 are also working on and close to achieving? Is sharing going to boost the capabilities of bad actors, or might
 it instead help to shift the playing field, so good actors are more able to offset the bad? What is the nature
 of Google's involvement are we openly publishing a research paper that anyone can learn from, or are we
 directly developing a custom solution for a contentious third-party application?
- Mitigation options Are there ways to detect and protect against bad actors deploying new techniques
 in bad ways? (If not, it might be necessary to hold back until a 'fix' has been found.) Would guidance on
 responsible use be likely to help, or more likely to alert bad actors?

Distribution

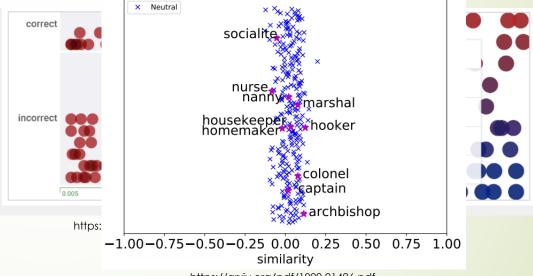
Use, share, and create emerging tools to detect bias and explore datasets

for ethical considerations

■ IBM's AI Fairness 360

Google's What-If

 gn_glove, a genderneutral word2veclike embedding



https://arxiv.org/pdf/1809.01496.pdf

- This is where we ALL come in
- Bring up concerns in talks and classrooms (like this one!)
- Dedicate part of the syllabus (like this one)
- Take an entire class on Al and Ethics, Ethics and Philosophy



Image from one of Stanford AI Lab's 'AI Salon' events on Best Practices in doing Ethical AI Research

- Obtain and promote more diverse research perspectives
- In 2017, Joy Buolamwini found facial recognition platforms at Microsoft, IBM, and Face++ did very poorly when identifying women and minorities



 While each service touted an excellent overall accuracy, certain subgroups performed very poorly

Gender Classifier	Darker Male	Darker Female	Lighter Male	Lighter Female	Largest Gap
Microsoft	94.0%	79.2%	100%	98.3%	20.8%
FACE**	99.3%	65.5%	99.2%	94.0%	33.8%
IBM	88.0%	65.3%	99.7%	92.9%	34.4%

She created http://gendershades.org/ and contacted each company regarding their inclusion and diversity practices during development

- Small and large-scale initiatives
- ► AI4ALL
- Women in Al
- Black in Al
- Al Now and NYU
- Human-Centered Al Institute at Stanford
- Ada Lovelace Institute
- AAAI/ACM Conference on AI, Ethics, and Society

- And don't forget: you
 - Take a stand against unethical decisions

Sign this letter

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We believe that Google should not be in the business of war. Therefore we ask that Project Maven be cancelled, and that Google draft, publicize and enforce a clear policy stating that neither Google nor its contractors will ever build warfare technology.

- Employees of Amazon and Microsoft have likewise worked to withdraw their respective companies from DoD contracts
- Expand your own intellectual and research circles to include other viewpoints

Conclusions

- Data science and artificial intelligence are only going to become more intertwined with our daily lives (self-driving cars, smart homes, internet-ofthings)
- Automated decision-making has the potential to shape our civilization on a large scale
- Understanding this technology and the strengths and limitations of its abilities is critical as we integrate it ever more deeply into our everyday routines
- Being able to interface not only with researchers, but with policymakers, legislators, and the public is going to be essential
- Can no longer afford to hide behind the ivory tower and ignore the implications of our work, and its unintended consequences

References

- Slides https://thegradient.pub/in-favor-of-developing-ethical-best-practices-in-ai-research/
- Gender Shades http://gendershades.org/index.html
- Stanford Sexual Orientation https://www.nytimes.com/2017/10/09/science/stanford-sexual-orientation-study.html
- Amazon Rekognition https://www.nytimes.com/2019/01/24/technology/amazon-facial-technology-study.html
- ACM FAT* Proceedings https://fatconference.org/2019/acceptedpapers.html
- AI Ethics Resources https://www.fast.ai/2018/09/24/ai-ethics-resources/

Questions?

