A Typology of Risks of Voice Technology

Emily M. Bender
University of Washington
@emilymbender

AAAS 2020
Seattle WA
14 February 2020

Goals

- Present a typology of the risks of adverse impacts of voice technology

Non-exhaustive, preliminary

- Present *data statements*: a positive step we can take to position ourselves to mitigate such risks

One tool, not a panacea!

- Reflect on which types of risks data statements help with

Some, not all

- Reflect on whose job it is to worry about these things

Everyone's; in different ways

Typology

- A systematic classification of phenomena, along one or more dimensions
- Helps to explore the space of possibilities
- Helps to understand relationships across categories

Prev work: Hovy & Spruitt 2016

Guiding principles: Sociolinguistics
(e.g. Labov 1966, Eckert & Rickford 2001)

- Variation is the natural state of language
    - Variation in pronunciation, word choice, grammatical structures
- Status as ‘standard’ language is a question of power, not anything inherent to the language variety itself
    - Language varieties & features associated with marginalized groups tend to be stigmatized
- Meaning, including social meaning, is negotiated in language use
- Our social world is largely constructed through linguistic behavior

Guiding principles: Value sensitive design

- Value sensitive design (Friedman et al 2006, Friedman & Hendry 2019):
    - Identify stakeholders
    - Identify stakeholders' values
    - Design to support stakeholders' values

Stakeholder-centered typology

Direct stakeholders	Indirect stakeholders
By choice	Subject of query
Not by choice	Contributor to broad corpus
	Subject of stereotypes

Direct stakeholders: By choice

- *I choose to use this voice assistant, dictation software, machine translation system…*
    - … but it doesn't work for my language or language variety
        - Suggests that my language/language variety is inadequate
        - Makes the product unusable for me
- … but the system doesn't indicate how reliable it is
    - Users reliant on machine translation/auto-captioning for important info left in the dark about what they might be missing

Direct stakeholders: Not by choice

- *My screening interview was conducted by a virtual agent*
- *I can only access my account information via a virtual agent*
- *Access to a 911 system requires interaction with a virtual agent first*

- … but it doesn’t work or doesn’t work well for my language variety
    - I scored poorly on the interview, even though the content of my answers was good
    - I can’t access my account information or 911

Indirect stakeholders: Subject of query

- *Someone searched for me online*
    - … but the search triggered display of negative ads including my name because of stereotypes about my ethnic identity (Sweeney 2013)
- *Someone searched for critics of the government*
    - … and found my blog post/tweet
- *Someone put my words into an MT system*
    - … which got the translation wrong and led the police to arrest me (*The Guardian*, 24 Oct 2017; https://bit.ly/2zyEetp)

Indirect stakeholders: Subject of query

- *Sor*
  - ative
- *Sor*
- *Sor*

Facebook

Facebook translates 'good morning' into 'attack them', leading to arrest

Palestinian man questioned by Israeli police after embarrassing mistranslation of caption under photo of him leaning against bulldozer

Indirect stakeholders: Subject of query

- *Someone designed a system to classify people by identity characteristics according to linguistic features*

    - Information I thought I was presenting only in some venues is made available in others

Indirect stakeholders: Contributor to broad corpus

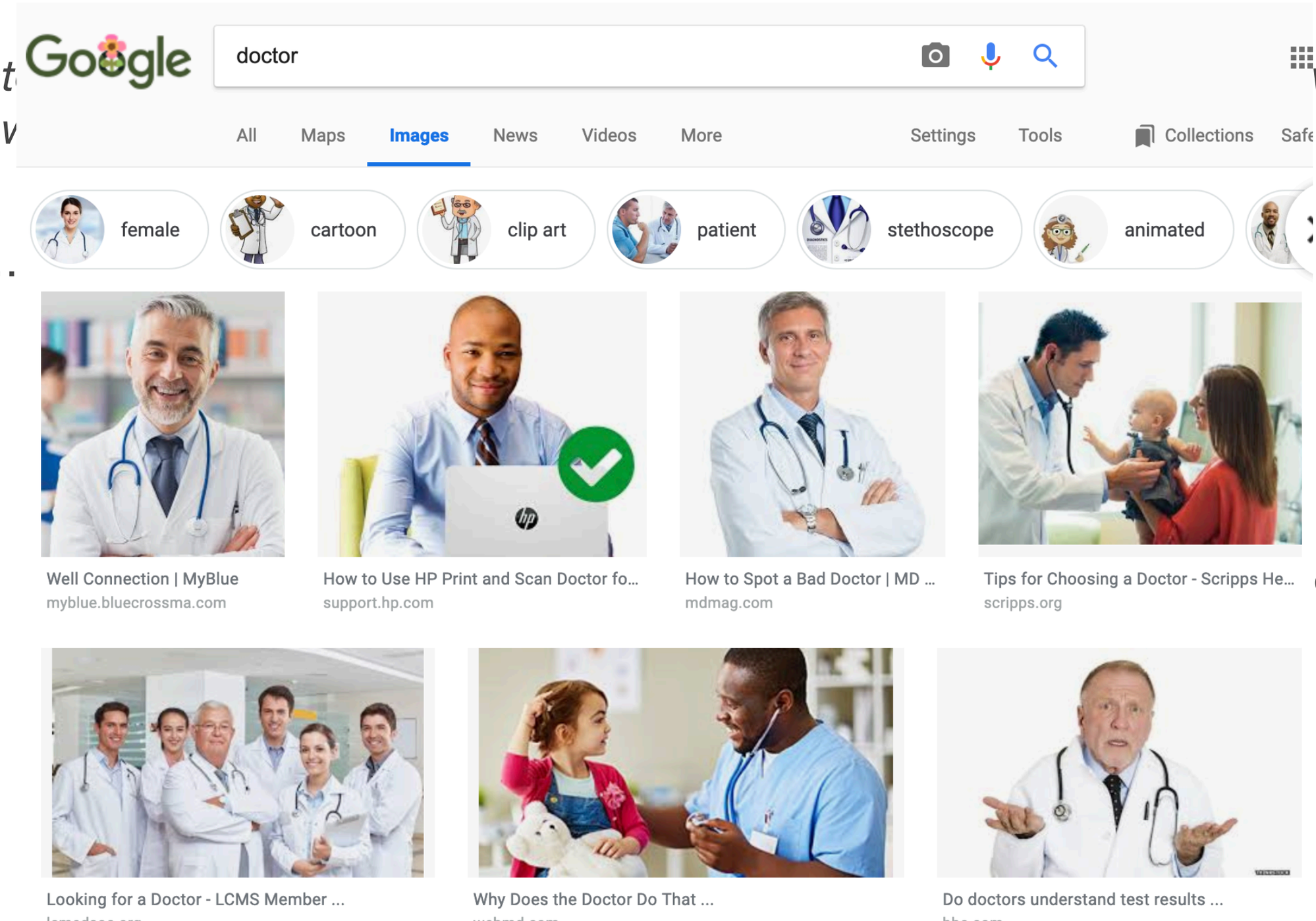
- *ASR doesn't caption my words as well as others*'
    - My contributions are rendered invisible to search engines
- *Language ID systems don’t identify my dialect*
    - Social-media based disease warning systems fail to work in my community (Jurgens et al 2017)

Indirect stakeholders: Subject of stereotypes

- *Virtual assistants are gendered as female and ordered around*
- *Systems are built using general webtext as a proxy for word meaning or world knowledge*
    - … but general web text reflects many types of bias (Bolukbasi et al 2016, Caliskan et al 2017, Gonen & Goldberg 2019)
        - My restaurant's positive reviews are underrated because of the name of the cuisine (Speer 2017)
        - My resume is rejected because the screening system has learned that typically "masculine" hobbies correlate with getting hired
        - My image search reflects stereotypes back to me

Indirect stakeholders: Subject of stereotypes

- *Syst* *world know*
  - ..



name

ed

Data Statements for NLP: Transparent documentation
(Bender & Friedman 2018)

- Foreground characteristics of our datasets (see also: AI Now Institute 2018, Gebru et al 2018, Mitchell et al 2019)

- Make it clear which populations & linguistic styles are and are not represented

- Support reasoning about what the possible effects of mismatches may be

- Recognize limitations of both training and test data:

  - Training data: effects on how systems can be appropriately deployed

  - Test data: effects on what we can measure & claim about system performance

Proposed Schema: Long Form

- A. Curation Rationale
- B. Language Variety
- C. Speaker Demographic
- D. Annotator Demographic
- E. Speech Situation
- F. Text Characteristics
- G. Recording Quality
- H. Other
- I. Provenance Appendix

What data? Why?

Whose language?

What kind of language behavior?

Who’s job is this?

- **Speech/language tech researchers & developers:** build better systems, promote systems appropriately, educate the public

- **Procurers:** choose systems/training data that match use case, align task assigned to speech/language tech system with goals

- **Consumers:** understand speech/language tech system output as the result of pattern recognition, trained on some dataset somewhere

- **Members of the public:** learn about benefits and impacts of speech/language tech and advocate for appropriate policy

- **Policy makers:** consider impacts of pattern matching on progress towards equity, require disclosure of characteristics of training data

Case: Direct stakeholders whose varieties aren't well represented

- **Speech/language tech researchers & developers:** Map out underrepresented language varieties and direct effort appropriately; test approaches more broadly

- **Procurers:** Is this trained model likely to work for our clientele?

- **Consumers:** Is this trained model likely to work for me?

- **Members of the public:** Advocate for models trained on datasets that are responsive to the community of users

- **Policy makers:** Require automated systems to be *accessible* to speakers of all language varieties in the community

Case: Indirect stakeholders whose varieties aren't well represented

- **Speech/language tech researchers & developers:** Map out underrepresented language varieties and direct effort appropriately; test approaches more broadly

- **Procurers:** What information is this system going to expose and what is it going to miss?

- **Consumers:** Is this software being transparent about how well it can work and under what circumstances it works better/worse?

- **Members of the public:** Advocate for transparency regarding system performance across representative samples

- **Policy makers:** Require broad testing of systems and transparency regarding system confidence/failure modes

Data statements are not a panacea!

- Mitigation of the negative impacts of speech/language technology will require on-going work and engagement (and cost/benefit analysis)

- Data statements are intended as one practice among others that position us (in various roles) to anticipate & mitigate some negative impacts

- Probably won't help with e.g.:
    - impacts of gendering virtual agents
    - privacy concerns around classification of identity characteristics

- Can help with problems stemming from lack of representative data sets and possibly also 'automation bias' (Skitka et al 2000)

Summary

- Variation is the natural state of language

- That variation is socially meaningful and varieties/features associated with marginalized groups get stigmatized

- Some of the risks of speech and language technology stem from uneven effectiveness across language varieties

- Such risks will be borne disproportionately by speakers of stigmatized varieties

- Transparency about language varieties represented in training data can position us to mitigate these risks

Thank you!

References

AI Now Institute (2018). Algorithmic impact assessments: Toward accountable automation in public agencies. Medium.com.

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

Bolukbasi, T., Chang, K.-W., Zou, J. Y., Saligrama, V., and Kalai, A. T. (2016). Man is to computer programmer as woman is to homemaker? Debiasing word embeddings. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems 29*, pages 4349–4357. Curran Associates, Inc.

Caliskan, A., Bryson, J. J., and Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. *Science*, **356**(6334), 183–186.

Eckert, P. and Rickford, J. R., editors (2001). *Style and Sociolinguistic Variation*. Cambridge University Press, Cambridge.

Friedman, B. and Hendry, D. (To appear). *Value Sensitive Design: A twenty-year synthesis and retrospective*.

Friedman, B., Kahn, Jr., P. H., and Borning, A. (2006). Value sensitive design and information systems. In P. Zhang and D. Galletta, editors, *Human–Computer Interaction in Management Information Systems: Foundations*, pages 348–372. M. E. Sharpe, Armonk NY.

Gebru, T., Morgenstern, J., Vecchione, B., Wortman Vaughan, J., Wallach, H., Daumé III, H., and Crawford, K. (2018). Datasheets for datasets. arXiv:1803.09010v1.

Gonen, H. and Goldberg, Y. (2019). Lipstick on a pig: Debiasing methods cover up systematic gender biases in word embeddings but do not remove them. arXiv:1903.03862v1.

Hovy, D. and Spruit, S. L. (2016). The social impact of natural language processing. In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 591–598, Berlin, Germany. Association for Computational Linguistics.

Hovy, D., Spruit, S., Mitchell, M., Bender, E. M., Strube, M., and Wallach, H., editors (2017). *Proceedings of the First ACL Workshop on Ethics in Natural Language Processing*. Association for Computational Linguistics, Valencia, Spain.

Jurgens, D., Tsvetkov, Y., and Jurafsky, D. (2017). Incorporating dialectal variability for socially equitable language identification. In *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 51–57, Vancouver, Canada. Association for Computational Linguistics.

Labov, W. (1966). *The Social Stratification of English in New York City*. Center for Applied Linguistics, Washington, DC.

Mitchell, M., Wu, S., Zaldivar, A., Barnes, P., Vasserman, L., Hutchinson, B., Spitzer, E., Raji, I. D., and Gebru, T. (2019). Model cards for model reporting. In *Proceedings of the Conference on Fairness, Accountability, and Transparency*, FAT* '19, pages 220–229, New York, NY, USA. ACM.

Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. (2019). Language models are unsupervised multitask learners. Unpublished MS, OpenAI San Francisco.

Schnoebelen, T. (2017). The carrots and sticks of ethical NLP. Blog post, `https://medium.com/@TSchnoebelen/ethics-and-nlp-some-further-thoughts-53bd7cc3ff69`, accessed 19 March 2019.

Skitka, L. J., Mosier, K., and Burdick, M. D. (2000). Accountability and automation bias. *International Journal of Human-Computer Studies*, **52**(4), 701 – 717.

Speer, R. (2017). Conceptnet numberbatch 17.04: better, less-stereotyped word vectors. Blog post, `https://blog.conceptnet.io/2017/04/24/conceptnet-numberbatch-17-04-better-less-stereotyped-word-vectors/`, accessed 6 July 2017.

Sweeney, L. (May 1, 2013). Discrimination in online ad delivery. *Communications of the ACM*, **56**(5), 44–54.