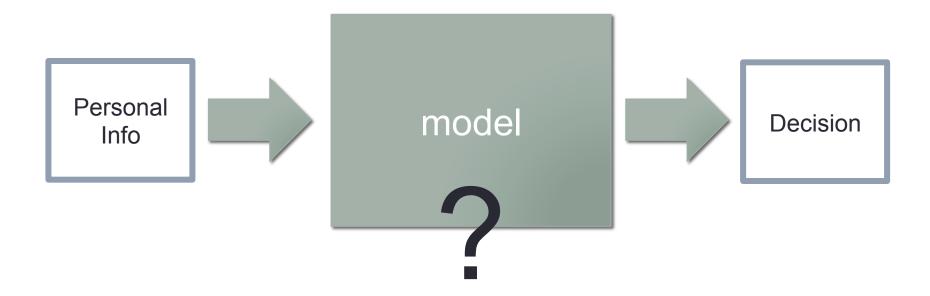
INTERPRETING AND AUDITING MACHINE-LEARNING ALGORITHMS

Sorelle Friedler

Haverford College

How is a model making its decision?



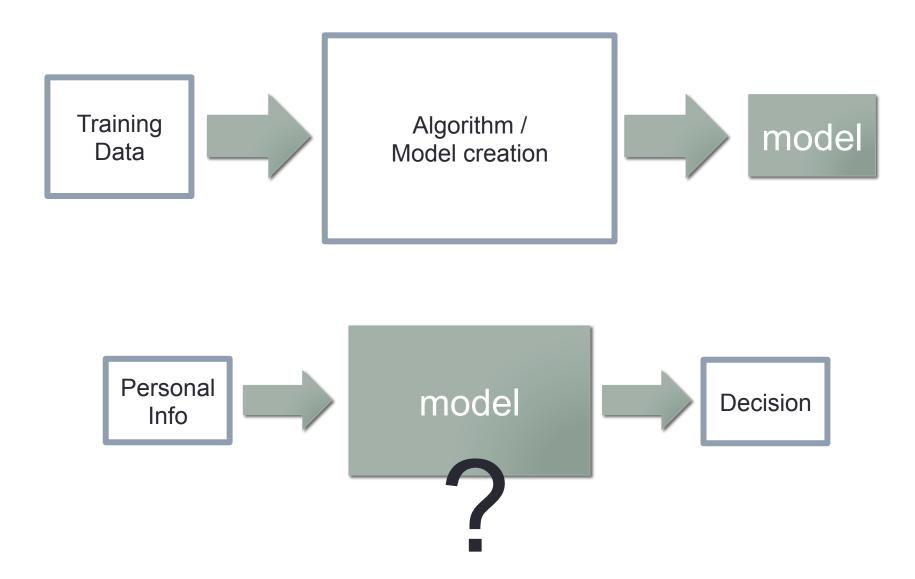
How is a model making its decision?



...for one person?

...for all people?

How is a model made?



How does bias happen in model creation?



Facebook challenges legitimacy of some Native names



By BBC Trending What's popular and why

() 3 March 2015





When Lance Browneyes of the Oglala Lakota community in South Dakota was blocked from Facebook for using a "fake" name, he submitted proof of his identification. Facebook then changed his name to Lance Brown.

http://www.bbc.com/news/blogs-trending-31699618

A hypothetical case study

Training Data

Name	Top 1000 baby name	Dictionary word?	Real Name?
Sorelle Friedler	no	no	yes
Lady Gaga	no	yes	no
Big Bird	no	yes	no
Barack Obama	no	no	yes

Dana Lone yes yes	???
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BBC Trending

Facebook challenges legitimacy of some Native names



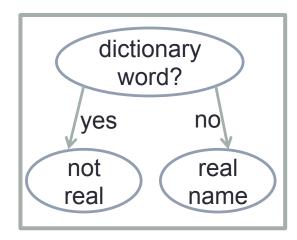
What's popular and w

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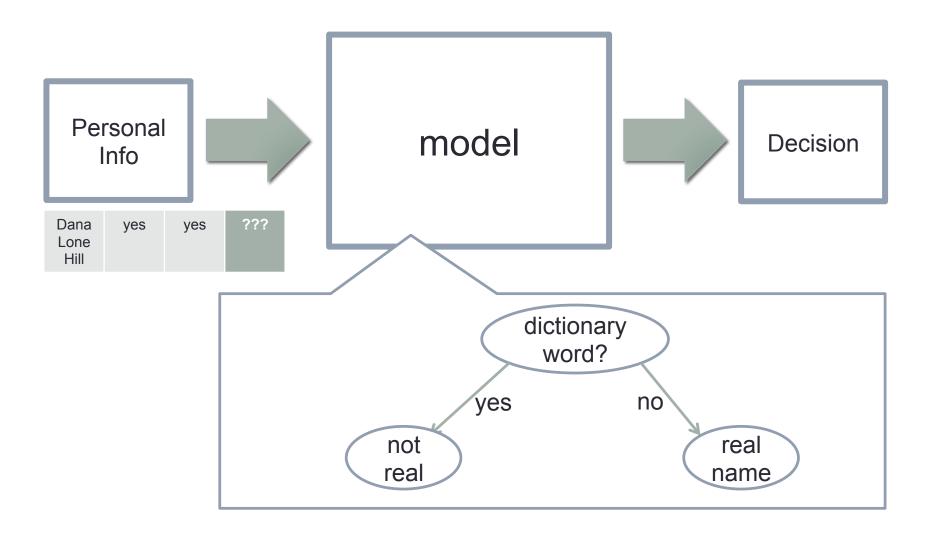




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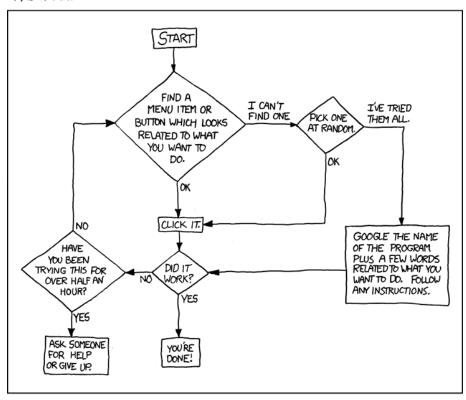
Interpretable models



Interpretable models – decision trees

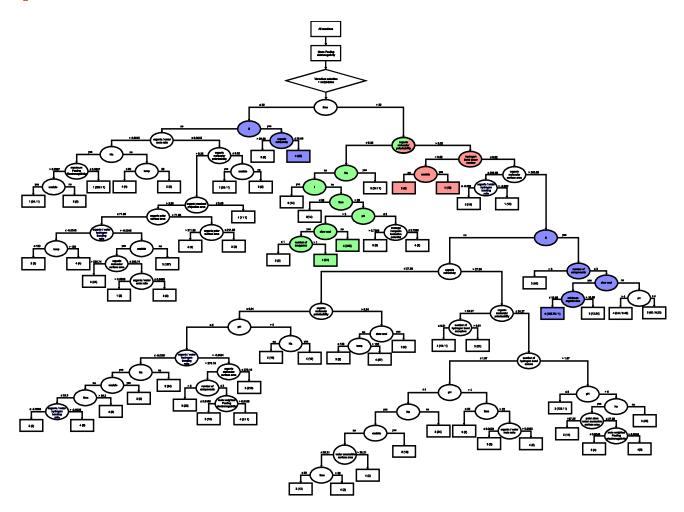
DEAR VARIOUS PARENTS, GRANDPARENTS, CO-WORKERS, AND OTHER "NOT COMPUTER PEOPLE."

WE DON'T MAGICALLY KNOW HOW TO DO EVERYTHING IN EVERY PROGRAM. WHEN WE HELP YOU, WE'RE USUALLY JUST DOING THIS:



PLEASE PRINT THIS FLOWCHART OUT AND TAPE IT NEAR YOUR SCREEN. CONGRATULATIONS; YOU'RE NOW THE LOCAL COMPUTER EXPERT!

Interpretable models?



Paul Raccuglia, Katherine C. Elbert, Philip D. F. Adler, Casey Falk, Malia B. Wenny, Aurelio Mollo, Matthias Zeller, Sorelle A. Friedler, Joshua Schrier, and Alexander J. Norquist. Machine-learning-assisted materials discovery using failed experiments. Nature, 533: 73 - 76, May 5, 2016. http://dx.doi.org/10.1038/nature17439

Interpretable models



Is Your BFF Really on Your Side?

- 1. If you and your friend meet a cute guy you're both into, what would she do after you declare that you like him?
- your wingwoman
- Suggest you go for him and offer to be Back off if he's you than her
- Say "Really? Hmm. He doesn't seem
- 2. When she bails on plans to hang out with you to get together with her boyfriend instead, you're:
- happened many
- Hurt but not exactly surprised. It's Shocked. She's always made such a big deal about putting friends first.
- both flaked
- 3. You just came up with the coolest idea for a blog. How would she react to it when you tell her?
- You don't usually share stuff like that b Enthusiastically, and she'll point out percent behind it with her because she can be critical of your ideas.
- possible snags that you haven't thought through yet.
- no questions
- 4. When you two have a disagreement, how does it usually get resolved?
- You both speak your piece then back off and forget about it.
 - You end up giving in—it's so much easier than arguing with her.
- Disagreement? You're such good friends, it never
- 5. What role does your BFF usually take on when you two are in public together?
- Number one fan. She tends to stay by your side and let you be the topic of conversation.
- Comedian to your take jabs at you to get a laugh, but it's all in good fun.
- straight man. She'll Partner in crime. at the hip but do check in with each

Frenemy in Disguise

0 TO 3 POINTS

Too-Faithful Friend

know what she's really thinking—something

SCORING: 1. a-0, b-1, c-2; 2. a-2, b-0, c-1; 3. a-2, b-1, c-0; 4. a-1, b-2, c-0; 5. a-0, b-2, c-1

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Interpretable models - SLIM

PREDICT ARREST FOR ANY OFFENSE IF SCORE > 1

1.	age_at_release_18_to_24	2 points		
2.	$prior_arrests \ge 5$	2 points	+	
3.	prior_arrest_for_misdemeanor	1 point	+	
4.	no_prior_arrests	-1 point	+	
5.	age_at_release≥40	-1 point	+	
	ADD POINTS FROM ROWS 1-5	SCORE	=	

Jiaming Zeng, Berk Ustun, and Cynthia Rudin. Interpretable Classification Models for Recidivism Prediction. Accepted to Journal of the Royal Statistical Society, 2016.

What if using an interpretable model doesn't make sense?

Interpretable models don't always achieve the same level of accuracy as other models – there may be a tradeoff.

Revealing the model isn't always possible.

If we have access to run the model, we can still find out some information about how it's making decisions!

Audit options

Assumes access to appropriate input data and the ability to run the model and examine the outputs.

- Create an interpretable model of the model use the predicted outputs as labels. Note: this is not the same model!
- Audit for direct influence replace the feature with random noise and test the deterioration of the model.
- Audit for *indirect* influence remove the feature and information about that feature contained in other features (e.g., proxy variables) and test the deterioration of the model.
- A. Henelius, K. Puolamäki, H. Boström, L. Asker, and P. Papapetrou. A peek into the black box: exploring classifiers by randomization. Data Min Knowl Disc, 28:1503–1529, 2014.
- A. Datta, S. Sen, and Y. Zick. Algorithmic transparency via quantitative input influence: Theory and experiments with learning systems. In Proceedings of 37th IEEE Symposium on Security and Privacy, 2016.
- P. Adler, C. Falk, S. Friedler, G. Rybeck, C. Scheidegger, B. Smith, and S. Venkatasubramanian. Auditing Black-box Models for Indirect Influence. In Proceedings of the IEEE International Conference on Data Mining (ICDM), 2016.

Direct and Indirect Influence Audits Synthetic Data (decision tree)

Synthetic Data:

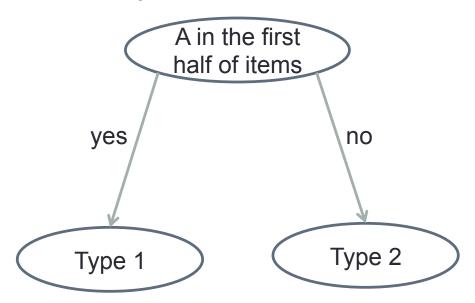
A: item i number

B: 2i, C: -i

Constant, Random

Outcome:

first half of items 1 second half 2



<u>Direct Influence:</u> <u>Indirect Influence:</u>

A: 0.5

B: 0 B: 0.5

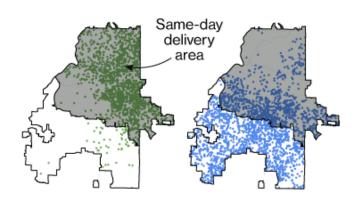
Constant: 0 Constant: 0

P. Adler, C. Falk, S. Friedler, G. Rybeck, C. Scheidegger, B. Smith, and S. Venkatasubramanian. Auditing Black-box Models for Indirect Influence. In Proceedings of the IEEE International Conference on Data Mining (ICDM), 2016.

Direct vs. Indirect Influence Audits



Zip code is a proxy for race.



Black residents

White residents

Audit specifically for non-discrimination

Theorem:

the information content of a feature can be estimated by trying to predict it from the remaining features

If a protected feature can't be predicted from the remaining features, then the information from that feature can't influence the outcome of the model.

Audit: Build a classifier to try to predict the protected feature from the remaining training data. If the error is high, any trained model is non-discriminatory.

Michael Feldman, Sorelle A. Friedler, John Moeller, Carlos Scheidegger, and Suresh Venkatasubramanian. Certifying and Removing Disparate Impact. *Proceedings of the 21st ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 2015.

Policy points

- It's possible to create interpretable models!
- Choosing interpretable models restricts model design choice, which *may* lower accuracy.
- We can audit a model even if it's not interpretable:
 - model the model
 - direct influence
 - indirect influence
 - goal-specific audit (e.g., non-discrimination)

THANKS!

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