

INTERPRETABILITY AND EXPLAINABILITY

Christian Kaestner

Required reading:  Data Skeptic Podcast Episode “Black Boxes are not Required” with Cynthia Rudin (32min) or
□ Rudin, Cynthia. "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead." Nature Machine Intelligence 1, no. 5 (2019): 206-215.

Recommended supplementary reading: □ Christoph Molnar. "Interpretable Machine Learning: A Guide for Making Black Box Models Explainable." 2019

LEARNING GOALS

- Understand the importance of and use cases for interpretability
- Explain the tradeoffs between inherently interpretable models and post-hoc explanations
- Measure interpretability of a model
- Select and apply techniques to debug/provide explanations for data, models and model predictions
- Eventuate when to use interpretable models rather than ex-post explanations

MOTIVATING EXAMPLES



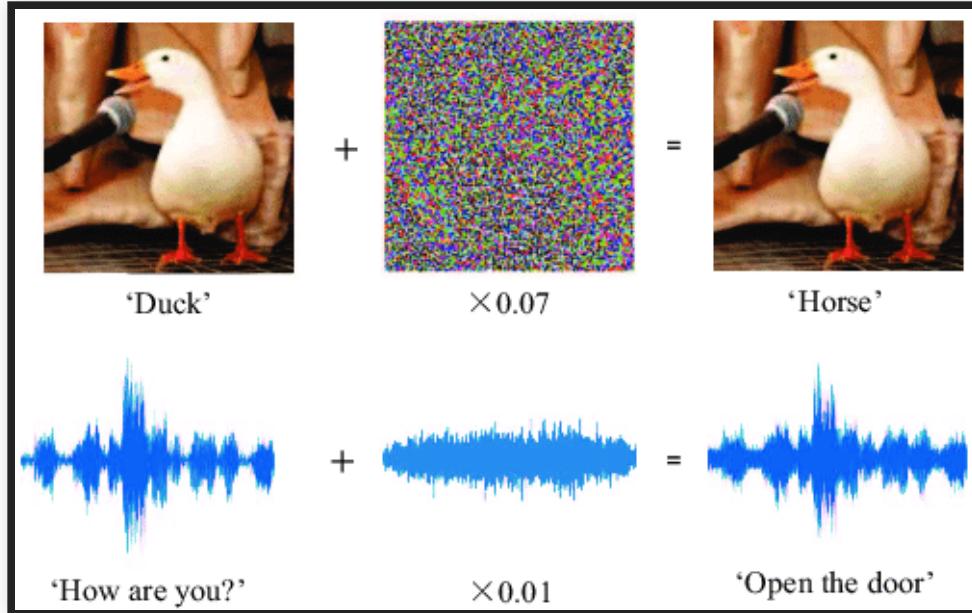


Image: Gong, Yuan, and Christian Poellabauer. "[An overview of vulnerabilities of voice controlled systems](#)." arXiv preprint arXiv:1803.09156 (2018).

DETECTING ANOMALOUS COMMITS

The screenshot shows a GitHub commit page for a Node.js pull request. The commit message is titled "v8: don't busy loop in cpu profiler thread". It describes a change to reduce CPU overhead by replacing `sched_yield()` with `nanosleep()`. The commit notes that before this, the thread would effectively be a busy loop. It includes links to a PR and an issue, and is reviewed by Trevor Norris.

Below the commit message, it shows the author as "bnoordhuis" from 2014-11-27, with a single parent commit and a specific hash. A "Show Details" button is present.

At the bottom of the commit page, there is a blue header "ADDITIONAL INFORMATION FOR THIS COMMIT" followed by a bulleted list of anomalies detected by the system:

- Changes were committed at 6am UTC -- **bnoordhuis rarely** commits around that time. (fewer than 0.7% of all commits by bnoordhuis are around that time)
- .gyp files were changed -- such files are **rarely** changed in this repository. (fewer than 2% of all file types changed)
- .cc and .gyp files were changed in the same commit -- this combination of files is **rarely changed together**. (in fewer than 2% of all commits)
- .cc and .gyp files were changed in the same commit -- this combination of files is **rarely changed together** by **bnoordhuis**. (in fewer than 3% of all commits by bnoordhuis)
- .gyp files were changed -- such files are **rarely** changed by **bnoordhuis**. (fewer than 3% of all file types changed by bnoordhuis)

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.

IS THIS RECIDIVISM MODEL FAIR?

```
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 arrest  
ELSE  
IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Rudin, Cynthia. "[Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead.](#)" Nature Machine Intelligence 1, no. 5 (2019): 206-215.

HOW TO INTERPRET THE RESULTS?

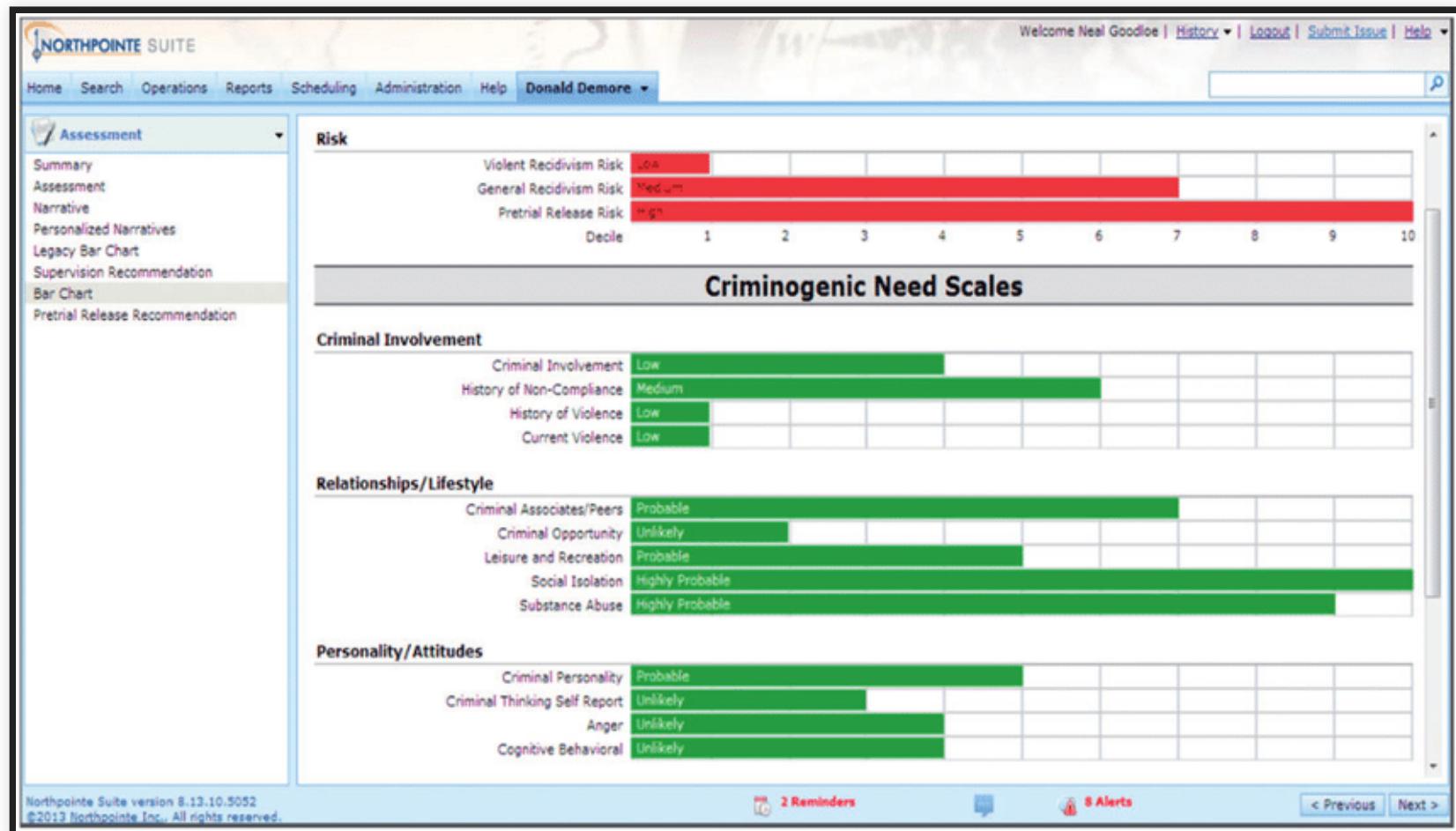


Image source (CC BY-NC-ND 4.0): Christin, Angèle. (2017). Algorithms in practice: Comparing web journalism and criminal justice. *Big Data & Society*. 4.

HOW TO JUDGE RELATIVE TO SERIOUSNESS OF THE CRIME?

1. Age at Release between 18 to 24	2 points	...
2. Prior Arrests ≥ 5	2 points	+ ...
3. Prior Arrest for Misdemeanor	1 point	+ ...
4. No Prior Arrests	-1 point	+ ...
5. Age at Release ≥ 40	-1 point	+ ...
	SCORE	= ...

PREDICT ARREST FOR ANY OFFENSE IF SCORE > 1

1. Prior Arrests ≥ 2	1 point	...
2. Prior Arrests ≥ 5	1 point	+ ...
3. Prior Arrests for Local Ordinance	1 point	+ ...
4. Age at Release between 18 to 24	1 point	+ ...
5. Age at Release ≥ 40	-1 points	+ ...
	SCORE	= ...

SCORE	-1	0	1	2	3	4
RISK	11.9%	26.9%	50.0%	73.1%	88.1%	95.3%

Rudin, Cynthia, and Berk Ustun. "[Optimized scoring systems: Toward trust in machine learning for healthcare and criminal justice.](#)" *Interfaces* 48, no. 5 (2018): 449-466.

WHAT FACTORS GO INTO PREDICTING STROKE RISK?

1. <i>Congestive Heart Failure</i>	1 point	...
2. <i>Hypertension</i>	1 point	+
3. <i>Age ≥ 75</i>	1 point	+
4. <i>Diabetes Mellitus</i>	1 point	+
5. <i>Prior Stroke or Transient Ischemic Attack</i>	2 points	+
ADD POINTS FROM ROWS 1–5	SCORE	= ...

SCORE	0	1	2	3	4	5	6
STROKE RISK	1.9%	2.8%	4.0%	5.9%	8.5%	12.5%	18.2%

Rudin, Cynthia, and Berk Ustun. "Optimized scoring systems: Toward trust in machine learning for healthcare and criminal justice." *Interfaces* 48, no. 5 (2018): 449-466.

IS THERE AN ACTUAL PROBLEM? HOW TO FIND OUT?

Tweet

Tweet

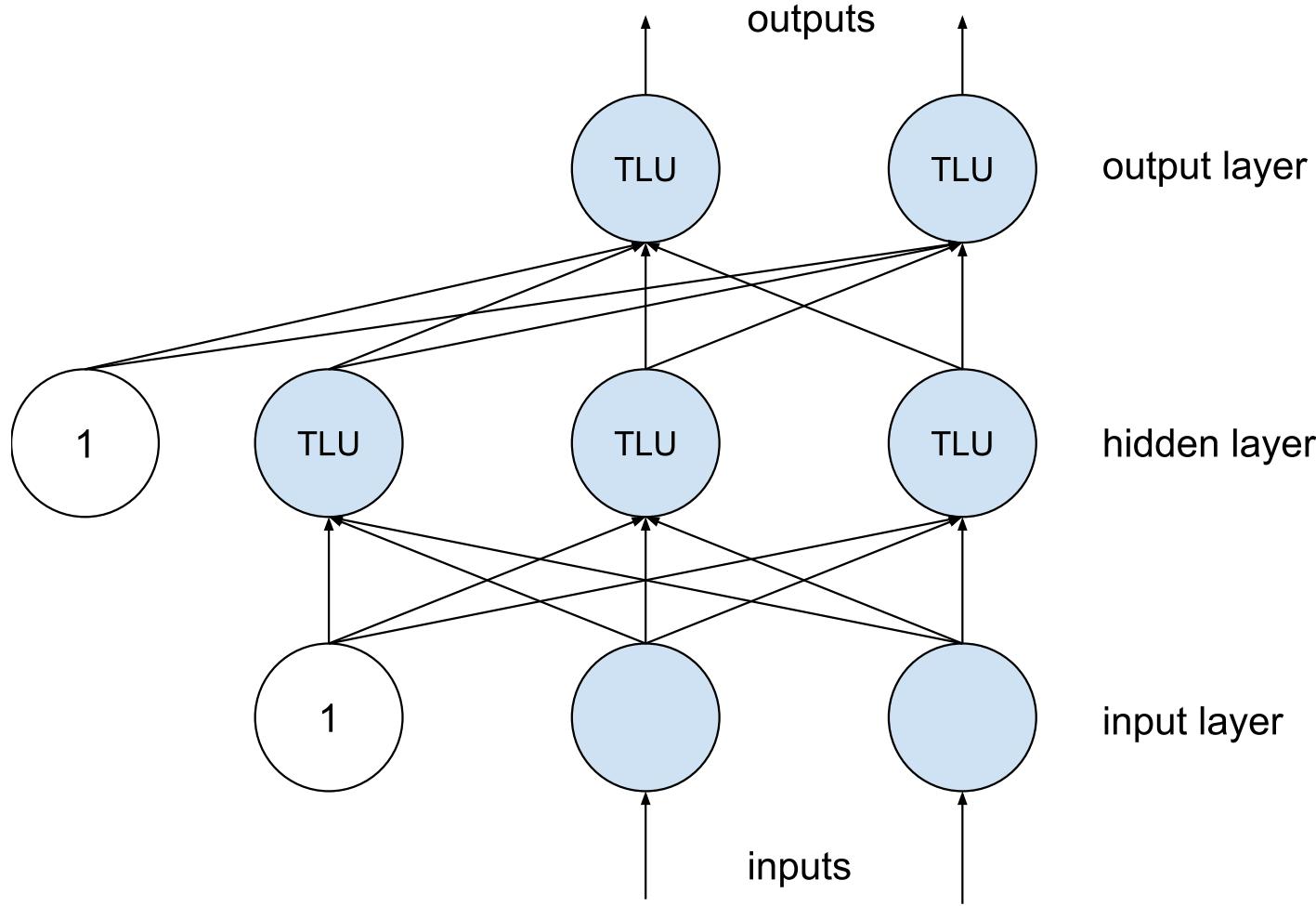
EXPLAINING DECISIONS

Cat? Dog? Lion?

Confidence? Why?



WHAT'S HAPPENING HERE?



EXTRACTING KNOWLEDGE FROM DATA

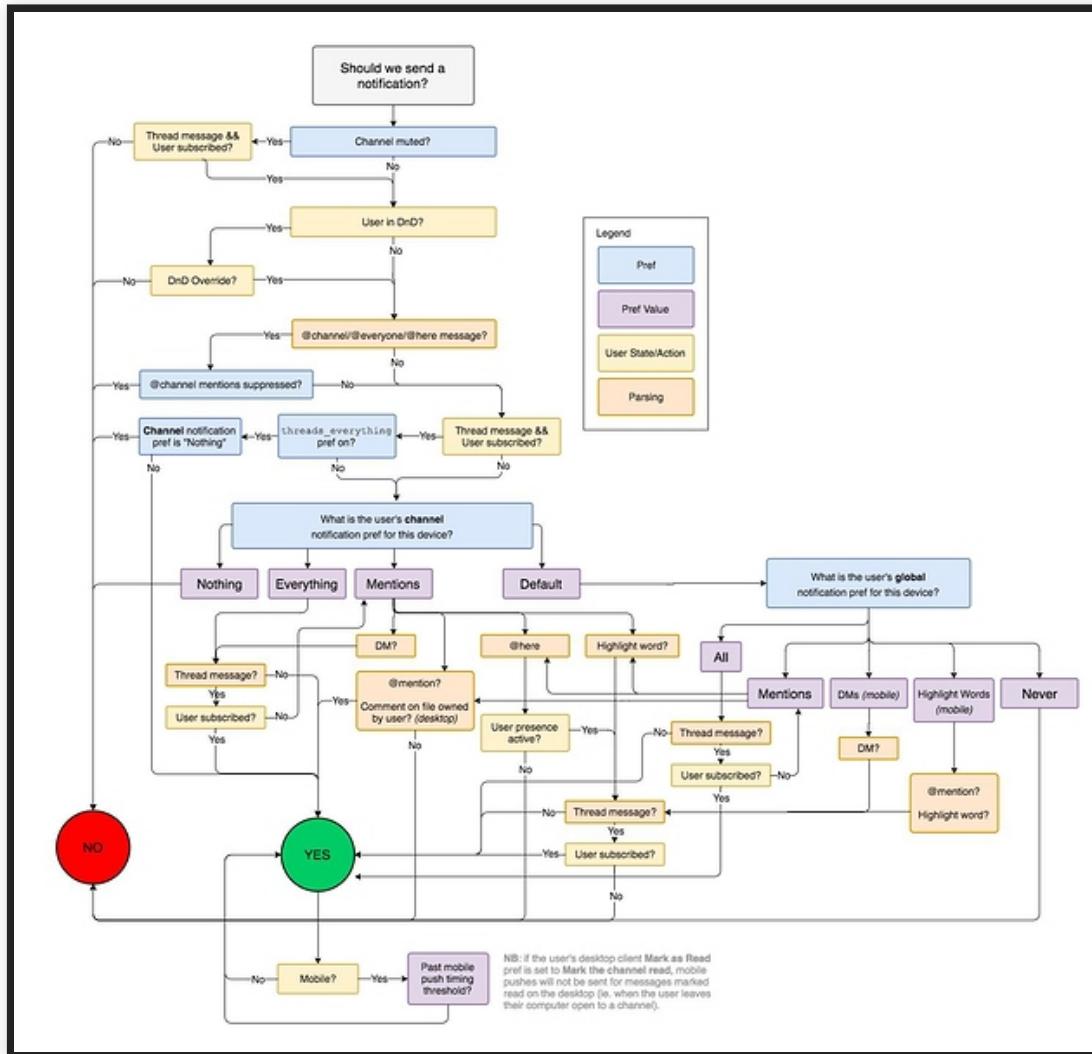
- Sale 1: Bread, Milk
- Sale 2: Bread, Diaper, Beer, Eggs
- Sale 3: Milk, Diaper, Beer, Coke
- Sale 4: Bread, Milk, Diaper, Beer
- Sale 5: Bread, Milk, Diaper, Coke

Rules

- $\{\text{Diaper, Beer}\} \rightarrow \text{Milk}$ (40% support, 66% confidence)
- $\text{Milk} \rightarrow \{\text{Diaper, Beer}\}$ (40% support, 50% confidence)
- $\{\text{Diaper, Beer}\} \rightarrow \text{Bread}$ (40% support, 66% confidence)

(see [association rule learning](#))

EXPLAINING DECISIONS



EXPLAINABILITY IN ML

- Explain how the model made a decision
 - Rules, cutoffs, reasoning?
 - What are the relevant factors?
 - Why those rules/cutoffs?
- Challenging because models too complex and based on data
 - Can we understand the rules?
 - Can we understand why these rules?

WHY EXPLAINABILITY?

LEGAL REQUIREMENTS

The European Union General Data Protection Regulation extends the automated decision-making rights in the 1995 Data Protection Directive to provide a legally disputed form of a right to an explanation: "[the data subject should have] the right ... to obtain an explanation of the decision reached"

US Equal Credit Opportunity Act requires to notify applicants of action taken with specific reasons: "The statement of reasons for adverse action required by paragraph (a)(2)(i) of this section must be specific and indicate the principal reason(s) for the adverse action."

See also https://en.wikipedia.org/wiki/Right_to_explanation

HELP CUSTOMERS ACHIEVE BETTER OUTCOMES

What can I do to get the loan?

How can I change my message to get more attention on Twitter?

Why is my message considered as spam?

DEBUGGING

- Why did the system make a wrong prediction in this case?
- What does it actually learn?
- What kind of data would make it better?
- How reliable/robust is it?
- How much does the second model rely on the outputs of the first?
- Understanding edge cases



Most common use case in practice according to recent study (Bhatt et al. "Explainable machine learning in deployment." In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, pp. 648-657. 2020.)

AUDITING

- Understand safety implications
- Ensure predictions are based on objective criteria and reasonable rules
- Inspect fairness properties
- Reason about biases and feedback loops
- ML as Requirements Engineering view: Validate "mined" 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 arrest  
ELSE  
IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

CURIOSITY, LEARNING, DISCOVERY, SCIENCE

- What drove our past hiring decisions? Who gets promoted around here?
- What factors influence cancer risk? Recidivism?
- What influences demand for bike rentals?
- Which organizations are successful at raising donations and why?

Basic Model response: <i>freshness</i> = 0 17.3% deviance explained		Full Model response: <i>freshness</i> = 0 17.4% deviance explained		RDD response: <i>log(freshness)</i> $R^2_m = 0.04, R^2_c = 0.35$	
Coeffs (Err.)	LR Chisq	Coeffs (Err.)	LR Chisq	Coeffs (Err.)	Sum sq.
(Inter.)	3.54 (0.03)***	3.50 (0.03)***		1.45 (0.09)***	
Dep.	-1.78 (0.01)***	32077.8***	-1.79 (0.01)***	32292.8***	-0.04 (0.02)
RDep.	0.22 (0.01)***	610.3***	0.21 (0.01)***	560.6***	-0.01 (0.02)
Stars	-0.08 (0.00)***	301.4***	-0.09 (0.00)***	311.2***	0.00 (0.01)
Contr.	-0.24 (0.01)***	500.5***	-0.25 (0.01)***	548.7***	-0.04 (0.02)*
lastU	-0.65 (0.01)***	12080.9***	-0.64 (0.01)***	11537.9***	0.01 (0.02)
hasDM		0.24 (0.03)***	116.1 ***	0.45 (0.08)***	2.43
hasInf		0.11 (0.02)***	48.3***	0.04 (0.05)	0.45
hasDM:hasInf		-0.05 (0.04)	1.9	-0.32 (0.10)**	
hasOther		0.01 (0.01)			
time				0.03 (0.00)***	82.99***
intervention				-0.93 (0.03)***	1373.22***
time_after_intervention				0.11 (0.00)***	455.56***
time_after_intervention:hasDM				-0.10 (0.01)***	230.36***
time_after_intervention:hasInf				-0.00 (0.01)	1.14
time_after_intervention:hasDM:hasInf				0.03 (0.01)**	10.62**

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$;

Dep: dependencies; RDep: dependents; Contr.: contributors; lastU: time since last update; hasDM: has dependency-manager badge; hasInf: has information badge; hasOther: adopts additional badges within 15 days

SETTINGS WHERE INTERPRETABILITY IS NOT IMPORTANT?



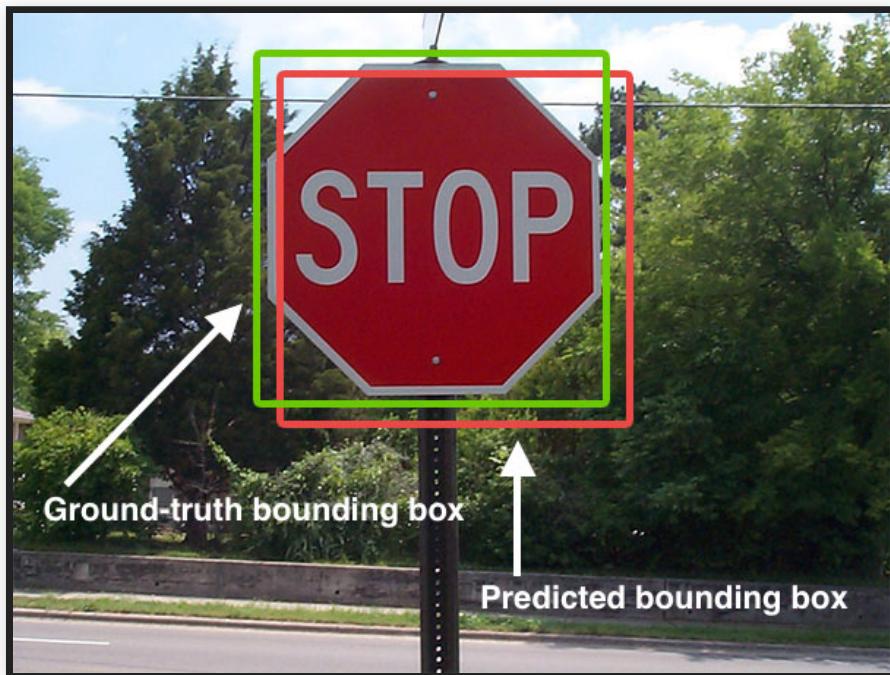
Speaker notes

- Model has no significant impact (e.g., exploration, hobby)
- Problem is well studied? e.g optical character recognition
- Security by obscurity? -- avoid gaming

EXERCISE: DEBUGGING A MODEL

Consider the following debugging challenges. In groups discuss how you would debug the problem. In 5 min report back to the group.

Algorithm bad at recognizing some signs in some conditions:



Graduate application system seems to rank applicants HBCUs lowly:



Left Image: CC BY-SA 4.0, Adrian Rosebrock

DEFINING AND MEASURING INTERPRETABILITY

Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable](#)." 2019

INTERPRETABILITY DEFINITIONS

Interpretability is the degree to which a human can understand the cause of a decision

Interpretability is the degree to which a human can consistently predict the model's result.

(No mathematical definition)

MEASURING INTERPRETABILITY?



Speaker notes

Experiments asking humans questions about the model, e.g., what would it predict for X, how should I change inputs to predict Y?

EXPLANATION

Understanding a single prediction for a given input

Your loan application has been declined. If your savings account had had more than \$100 your loan application would be accepted.

Answer **why** questions, such as

- Why was the loan rejected? (justification)
- Why did the treatment not work for the patient? (debugging)
- Why is turnover higher among women? (general data science question)

MEASURING EXPLANATION QUALITY?



THREE LEVELS OF EVALUATING INTERPRETABILITY

- Functionally-grounded evaluation, proxy tasks without humans (least specific and expensive)
 - Depth of a decision tree (assuming smaller trees are easier to understand)
- Human-grounded evaluation, simple tasks with humans
 - Ask crowd-worker which explanation of a loan application they prefer
- Application-grounded evaluation, real tasks with humans (most specific and expensive)
 - Would a radiologist explain a cancer diagnosis in a similar way?

Doshi-Velez, Finale, and Been Kim. “[Towards a rigorous science of interpretable machine learning](#),” 2017.

INTRINSIC INTERPRETABILITY VS POST-HOC EXPLANATION?

Models simple enough to understand
(e.g., short decision trees, sparse linear models)

1. Congestive Heart Failure		1 point	...				
2. Hypertension		1 point	+	...			
3. Age \geq 75		1 point	+	...			
4. Diabetes Mellitus		1 point	+	...			
5. Prior Stroke or Transient Ischemic Attack		2 points	+	...			
ADD POINTS FROM ROWS 1–5		SCORE	=	...			
SCORE	0	1	2	3	4	5	6
STROKE RISK	1.9%	2.8%	4.0%	5.9%	8.5%	12.5%	18.2%

Explanation of black-box models, local or global

Your loan application has been declined. If your savings account had more than \$100 your loan application would be accepted.

Load applications are always declined if the savings account has less than \$50.

ON TERMINOLOGY

- Rudin's terminology and this lecture:
 - Interpretable models: Intrinsily interpretable models
 - Explainability: Post-hoc explanations
- Interpretability: property of a model
- Explainability: ability to explain the workings/predictions of a model
- Explanation: justification of a single prediction
- Interpretability vs explainability often used inconsistently or interchangeable

INHERENTLY INTERPRETABLE MODELS

SPARSE LINEAR MODELS

$$f(x) = \alpha + \beta_1 x_1 + \dots + \beta_n x_n$$

Truthful explanations, easy to understand for humans

Easy to derive contrastive explanation and feature importance

Requires feature selection/regularization to minimize to few important features
(e.g. Lasso); possibly restricting possible parameter values

1. <i>Congestive Heart Failure</i>	1 point	...
2. <i>Hypertension</i>	1 point	+
3. <i>Age ≥ 75</i>	1 point	+
4. <i>Diabetes Mellitus</i>	1 point	+
5. <i>Prior Stroke or Transient Ischemic Attack</i>	2 points	+
ADD POINTS FROM ROWS 1–5	SCORE	= ...

SCORE	0	1	2	3	4	5	6
STROKE RISK	1.9%	2.8%	4.0%	5.9%	8.5%	12.5%	18.2%

DECISION TREES

Easy to interpret up to a size

Possible to derive counterfactuals and feature importance

Unstable with small changes to training data

```
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 ar  
ELSE IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

NOT ALL LINEAR MODELS AND DECISION TREES ARE INTERPRETABLE

- Models can be very big, many parameters (factors, decisions)
- Nonlinear interactions possibly hard to grasp
- Tool support can help (views)
- Random forests, ensembles no longer understandable ("average over multiple interpretations"?)

```
173554,681081086 * root + 318523,818532818 * heuristicUnit +
-103411,870761673 * eq + -24600,5000000002 * heuristicVsids +
-11816,7857142856 * heuristicVmtf + -33557,8961038976 *
heuristic + -95375,3513513509 * heuristicUnit * satPreproYes +
3990,79729729646 * transExt * satPreproYes + -136928,416666666
* eq * heuristicUnit + 12309,4990990994 * eq * satPreproYes +
33925,0833333346 * eq * heuristic + -643,428571428088 *
backprop * heuristicVsids + -11876,2857142853 * backprop *
heuristicUnit + 1620,24242424222 * eq * backprop +
-7205,2500000002 * eq * heuristicBerkmin + -2 * Num1 * Num2 +
10 * Num3 * Num4
```

Speaker notes

Example of a performance influence model from <http://www.fosd.de/SPLConqueror/> -- not the worst in terms of interpretability, but certainly not small or well formed or easy to approach.

DECISION RULES

if-then rules mined from data

easy to interpret if few and simple rules

see [association rule mining](#):

- {Diaper, Beer} -> Milk (40% support, 66% confidence)
- Milk -> {Diaper, Beer} (40% support, 50% confidence)
- {Diaper, Beer} -> Bread (40% support, 66% confidence)

K-NEAREST NEIGHBORS

- Instance-based learning
- Returns most common class among the k nearest training data points
- No global interpretability, because no global rules
- Interpret results by showing nearest neighbors
- Interpretation assumes understandable distance function and interpretable reference data points

example: predict & explain car prices by showing similar sales

RESEARCH IN INTERPRETABLE MODELS

- Several approaches to learn sparse constrained models (e.g., fit score cards, simple if-then-else rules)
- Often heavy emphasis on feature engineering and domain-specificity
- Possibly computationally expensive

Rudin, Cynthia. "[Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead.](#)" Nature Machine Intelligence 1, no. 5 (2019): 206-215.

POST-HOC EXPLANATIONS OF BLACK-BOX MODELS

(large research field, many approaches, much recent research)

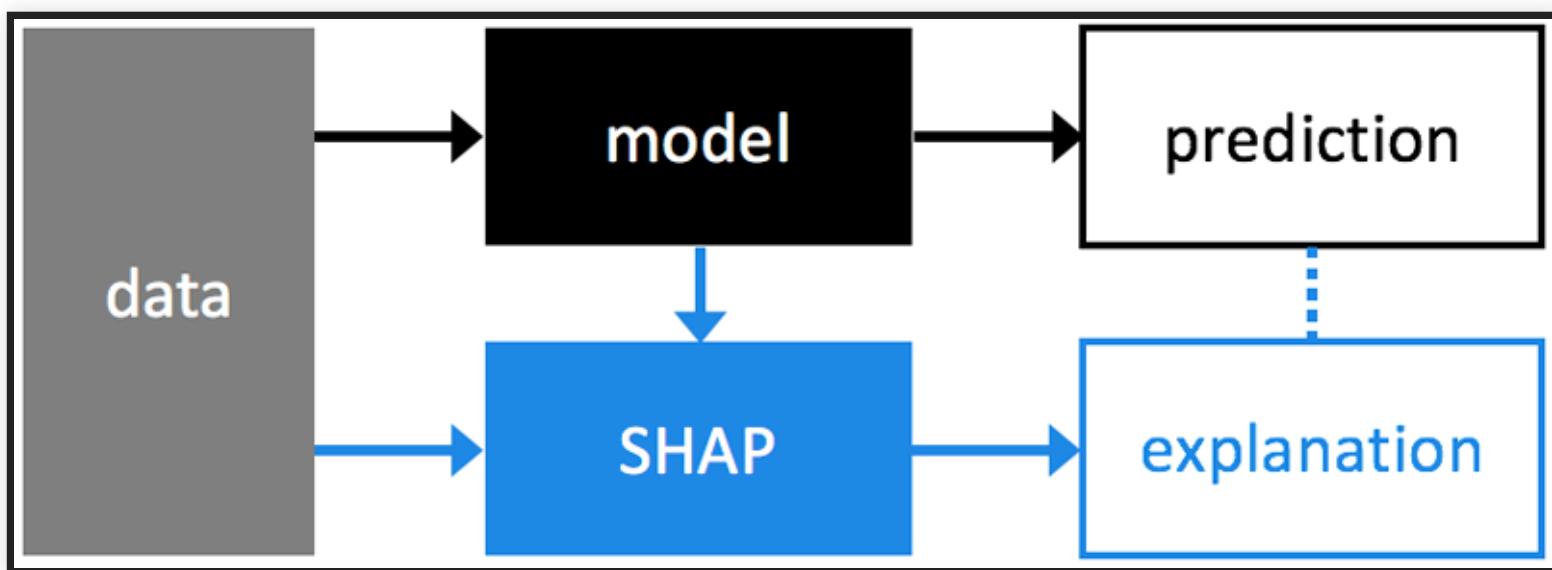


Figure: Lundberg, Scott M., and Su-In Lee. [A unified approach to interpreting model predictions](#). Advances in Neural Information Processing Systems. 2017.

EXPLAINING BLACK-BOX MODELS

Given model f observable by querying

No access to model internals or training data (e.g., own deep neural network,
online prediction service, ...)

Possibly many queries of f

GLOBAL SURROGATES

1. Select dataset X (previous training set or new dataset from same distribution)
2. Collect model predictions for every value ($y_i = f(x_i)$)
3. Train inherently interpretable model g on (X,Y)
4. Interpret surrogate model g

Can measure how well g fits f with common model quality measures, typically R^2

Advantages? Disadvantages?

Speaker notes

Flexible, intuitive, easy approach, easy to compare quality of surrogate model with validation data (R^2). But: Insights not based on real model; unclear how well a good surrogate model needs to fit the original model; surrogate may not be equally good for all subsets of the data; illusion of interpretability. Why not use surrogate model to begin with?

LOCAL SURROGATES (LIME)

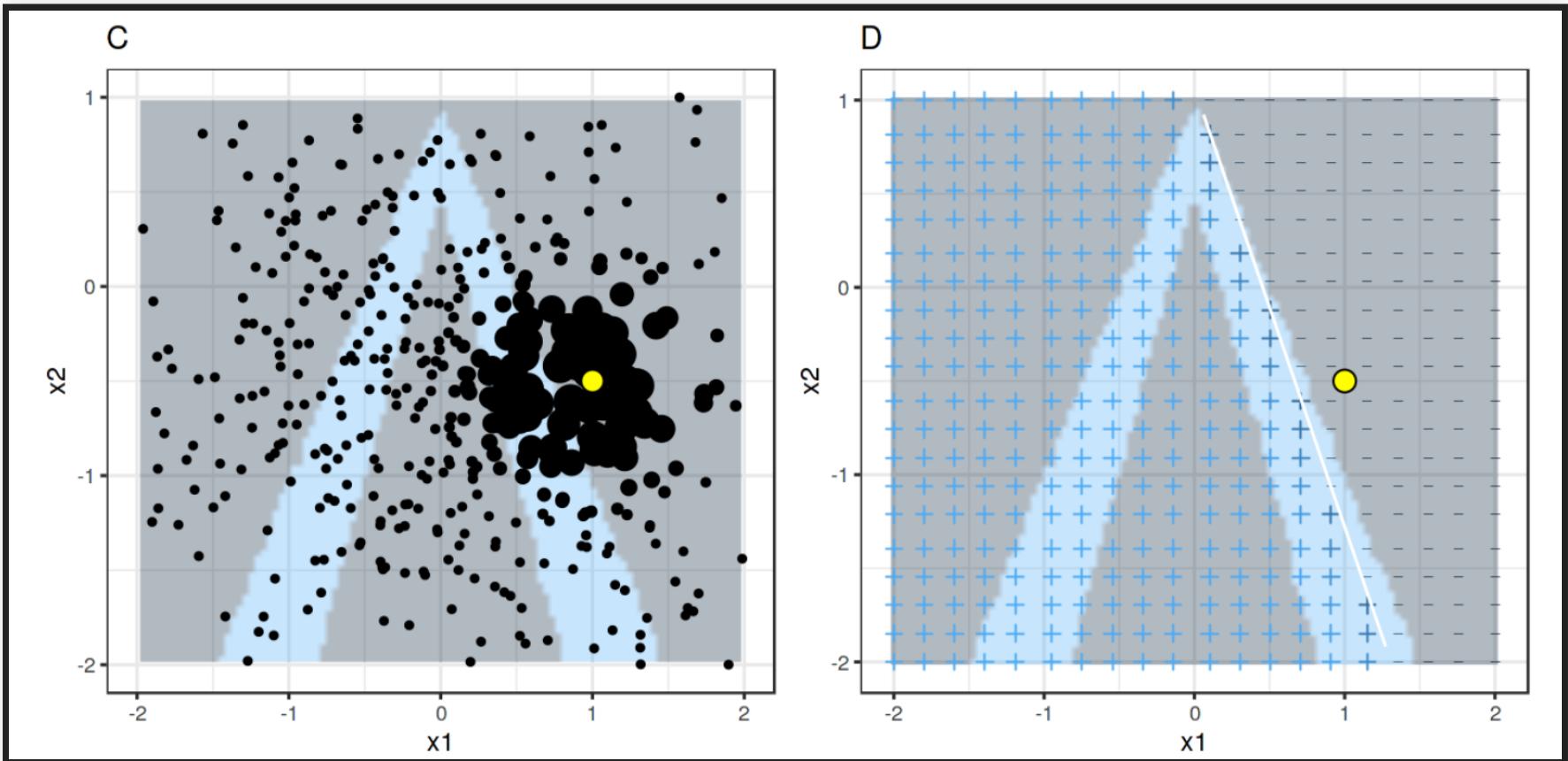
Create an inherently interpretable model (e.g. sparse linear model) for the area around a prediction

Lime approach:

- Create random samples in the area around the data point of interest
- Collect model predictions with f for each sample
- Learn surrogate model g , weighing samples by distance
- Interpret surrogate model g

Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "["Why should I trust you?" Explaining the predictions of any classifier.](#)" In Proc International Conference on Knowledge Discovery and Data Mining, pp. 1135-1144. 2016.

LIME EXAMPLE

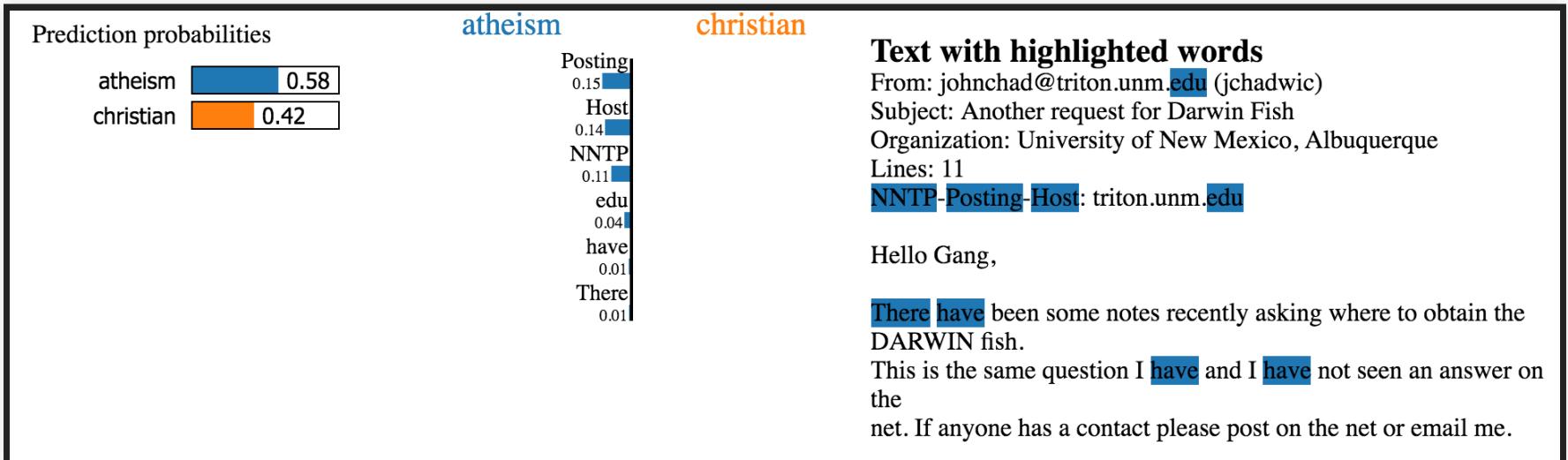


Source: Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable.](#)"
2019

Speaker notes

Model distinguishes blue from gray area. Surrogate model learns only a white line for the nearest decision boundary, which may be good enough for local explanations.

LIME EXAMPLE



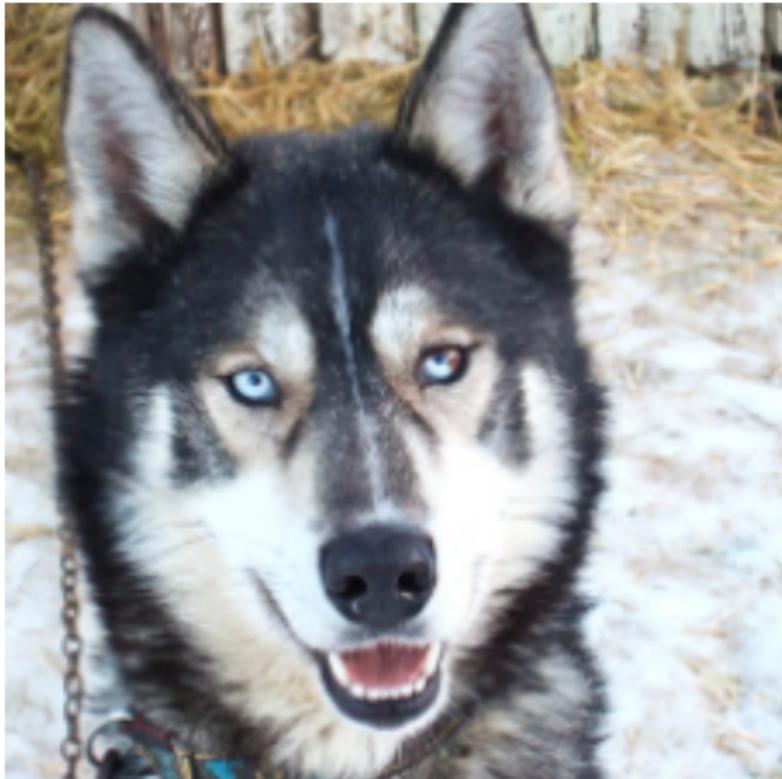
Source: <https://github.com/marcotcr/lime>

LIME EXAMPLE



Source: <https://github.com/marcotcr/lime>

LIME EXAMPLE



(a) Husky classified as wolf



(b) Explanation

Source: Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "["Why should I trust you?" Explaining the predictions of any classifier.](#)" In Proc International Conference on Knowledge Discovery and Data Mining, pp. 1135-1144. 2016.

ADVANTAGES AND DISADVANTAGES OF (LOCAL) SURROGATES?



ADVANTAGES AND DISADVANTAGES OF (LOCAL) SURROGATES?

- short, contrastive explanations possible
- useful for debugging
- easy to use; works on lots of different problems
- explanations may use different features than original model

- partial local explanation not sufficient for compliance scenario where full explanation is needed
- explanations may be unstable

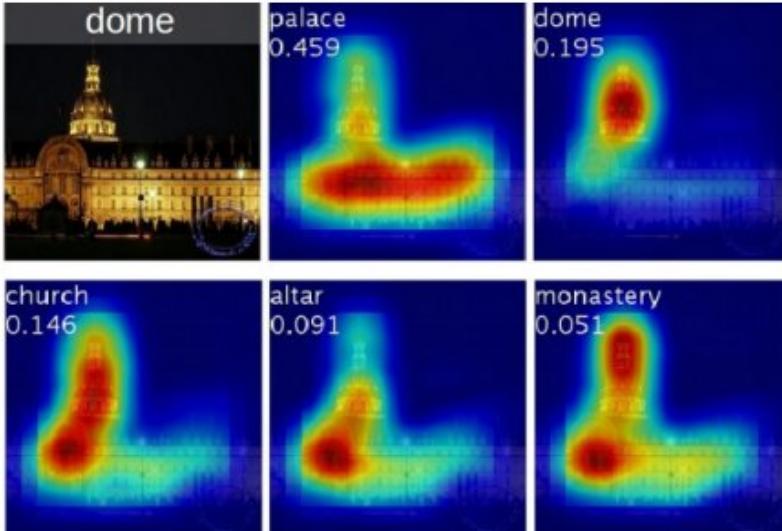
SHAPLEY VALUES

- Game-theoretic foundation for local explanations (1953)
- Explains contribution of each feature, over predictions with different subsets of features
 - "The Shapley value is the average marginal contribution of a feature value across all possible coalitions"
- Solid theory ensures fair mapping of influence to features
- Requires heavy computation, usually only approximations feasible
- Explanations contain all features (ie. not sparse)
- Influence, not counterfactuals
- Currently, most common local method used in practice

Lundberg, Scott M., and Su-In Lee. "[A unified approach to interpreting model predictions.](#)" In Advances in neural information processing systems, pp. 4765-4774. 2017.

Bhatt et al. "Explainable machine learning in deployment." In Proceedings of the 2020 Conference on Fairness, Accountability, and Transparency, pp. 648-657

ATTENTION MAPS



Class activation maps of top 5 predictions



Class activation maps for one object class

Identifies which parts of the input lead to decisions

Source: B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba. [Learning Deep Features for Discriminative Localization](#). CVPR'16

USER INTERFACE DESIGN

Message Predictor 1.0.5.28868

Move message to folder... Only show predictions that just changed OFF Search Stanley Clear

Folders

Unknown (1,180 messages) **A**
correct predictions
Baseball 8/8 correct predictions

Prediction totals

Hockey 278 ▼
Baseball 917 ▲

Messages containing "Stanley"

Baseball
Hockey
Unknown **E**

Messages in the 'Unknown' folder

Original order	Subject	Predicted topic	Prediction confidence
9287	Re: Playoff Predictions	Hockey	99%
9294	Re: Schedule...	Baseball	60% ▲
9306	Paul Kuryla and Canadian Wor...	Hockey	99%
9308	Re: My Predictions For 1993	Baseball	64% ▲
9312	Re: NHL Team Captains	Baseball	64% ▲
9316	Re: ugliest swing	Baseball	63% ▲
9319	Re: Octopus in Detroit?	Hockey	67% ▼
9339	Sparky Anderson Gets win #2000, Tigers beat A's	Baseball	99%
9347	Re: Goalie masks	Baseball	53%
9362	Re: Young Catchers	Baseball	82% ▲
9371	Re: Winning Streaks	Baseball	53%
9379	Royals	Baseball	64% ▲
9390	Phillies Mailing List?	Baseball	65% ▲
9410	Reds snap 5-game losing streak: RedReport 4-18	Baseball	98%
9423	Re: Juggling Dodgers	Baseball	57% ▲
9424	Re: Candlestick Park experience (long)	Baseball	99%
9433	Re: Notes on Jays vs. Indians Series	Baseball	53%
9434	Re: When did Dodgers move from NY to LA?	Baseball	53%
9439	Playoff pool	Hockey	96%
9441	Re: Hockey and the Hispanic community	Hockey	99%
9449	Re: Yoai-isms	Baseball	53%

Re: Octopus in Detroit?
From: georgeh@jhsun (George H)
Harold Zazula <DLMQC@CUNYVM.BITNET>
>I was watching the Detroit-Minnesota game last night and thought I saw an octopus on the ice after Ysebeart scored a goal at two. What gives? >(is there some custom to throw octopuses onto the ice in Detroit?)
It is a long standing good luck Redwing's tradition to throw an octopus on the ice during a **Stanley Cup** game. They say it dates back to '52 at the Olympia when the Wings became the 1st team (I think) to sweep the cup in 8 games. A lot harder to throw one from Joe Louis seats than from the old Olympia balcony, though.
Funniest I ever saw was when some **Tiger** fans threw one on the field during a Detroit/Toronto **baseball** game ... I was living in California and the folks I was watching with had never heard of **hockey** and were incredulous when I recognized the octopus BEFORE the camera closeup !!

Why Hockey?

Part 1: Important words
This message has important words about **Hockey** and **Baseball**
baseball **hockey**
stanley **tiger** **D**

The difference makes the computer think this message is 2.3 times more likely to be about Hockey than Baseball.

AND

Part 2: Folder size
The **Baseball** folder has more messages than the **Hockey** folder

Hockey:	7
Baseball:	8

The difference makes the computer thinks each Unknown message is 1.1 times more likely to be about Baseball than Hockey.

Important words

These are all of the words the computer used to make its prediction (click [here](#) for more).

Importance

baseball, bill, canadian, dave, david, hockey, player, players, prime, stanley, stats, tiger, time

Add a new word or phrase
Remove word
Undo importance adjustment **F**

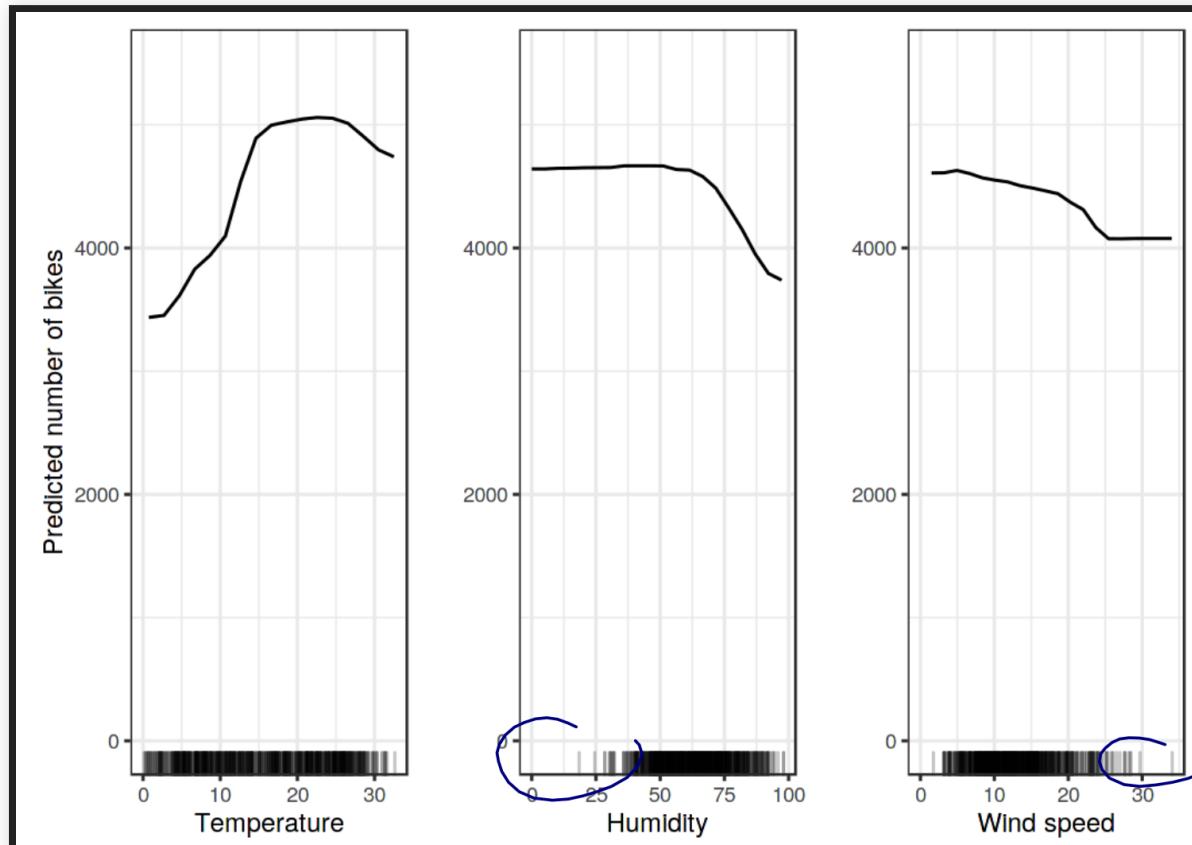
ulesza, T., Burnett, M., Wong, W-K. & Stumpf, S. (2015). Principles of Explanatory Debugging to personalize interactive machine learning. In: Proc. International Conference on Intelligent User Interfaces. (pp. 126-137)

PARTIAL DEPENDENCE PLOT (PDP)

- Computes marginal effect of feature on predicted outcome
- Identifies relationship between feature and outcome (linear, monotonous, complex, ...)
- Intuitive, easy interpretation
- Assumes no correlation among features

PARTIAL DEPENDENCE PLOT EXAMPLE

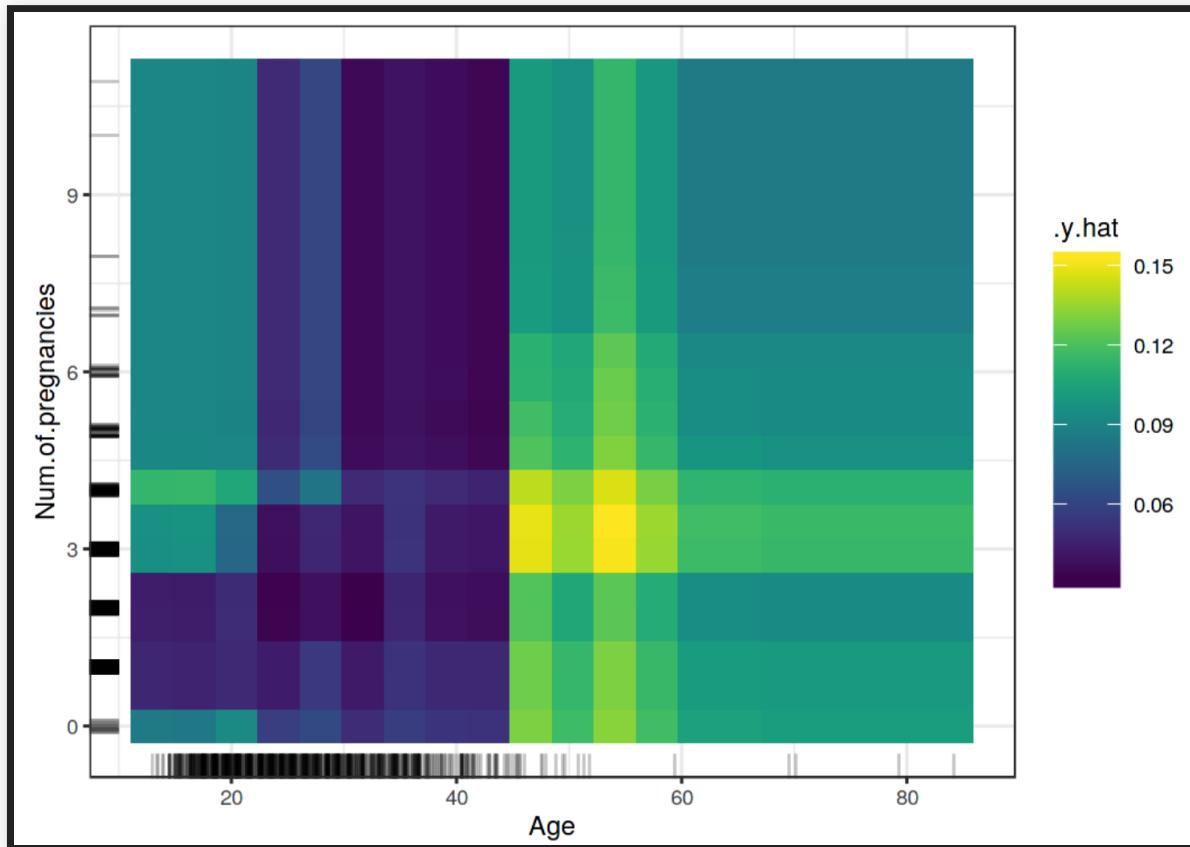
Bike rental in DC



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

PARTIAL DEPENDENCE PLOT EXAMPLE

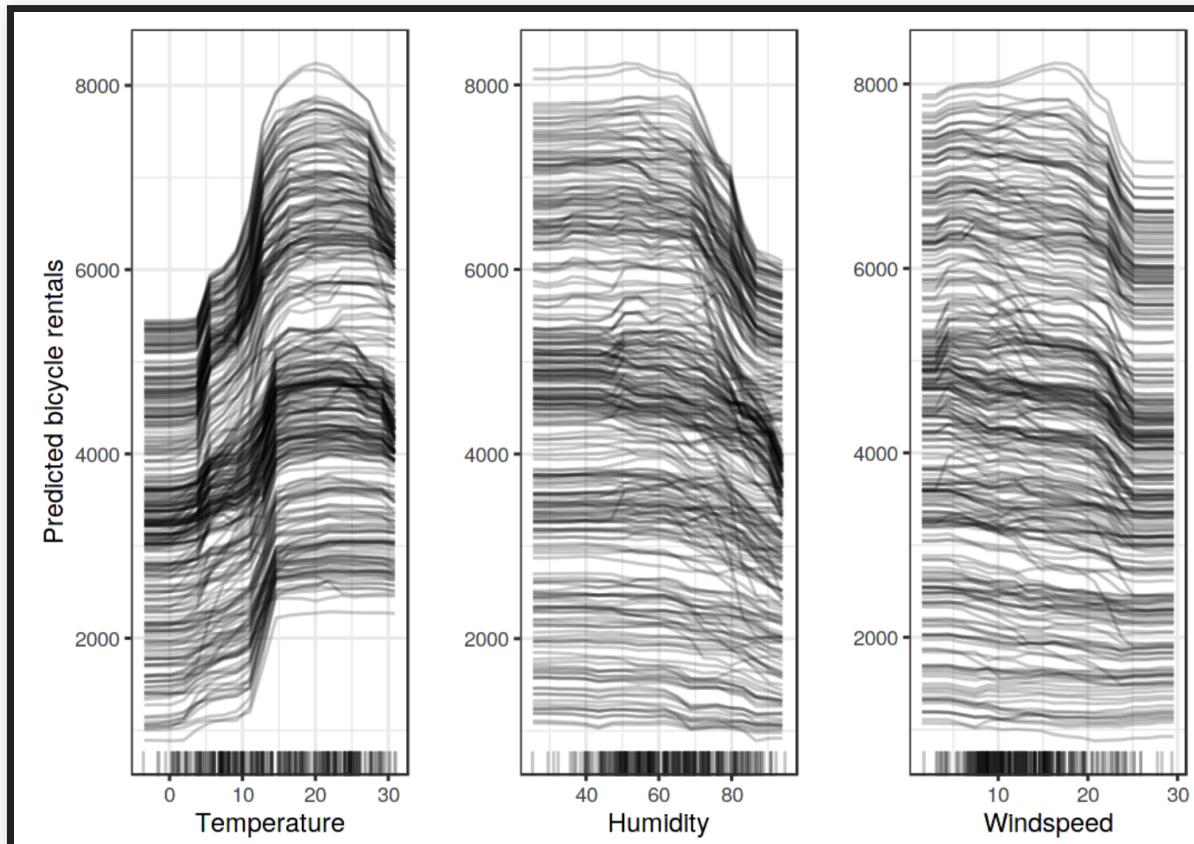
Probability of cancer



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

INDIVIDUAL CONDITIONAL EXPECTATION (ICE)

Similar to PDP, but not averaged; may provide insights into interactions



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

FEATURE IMPORTANCE

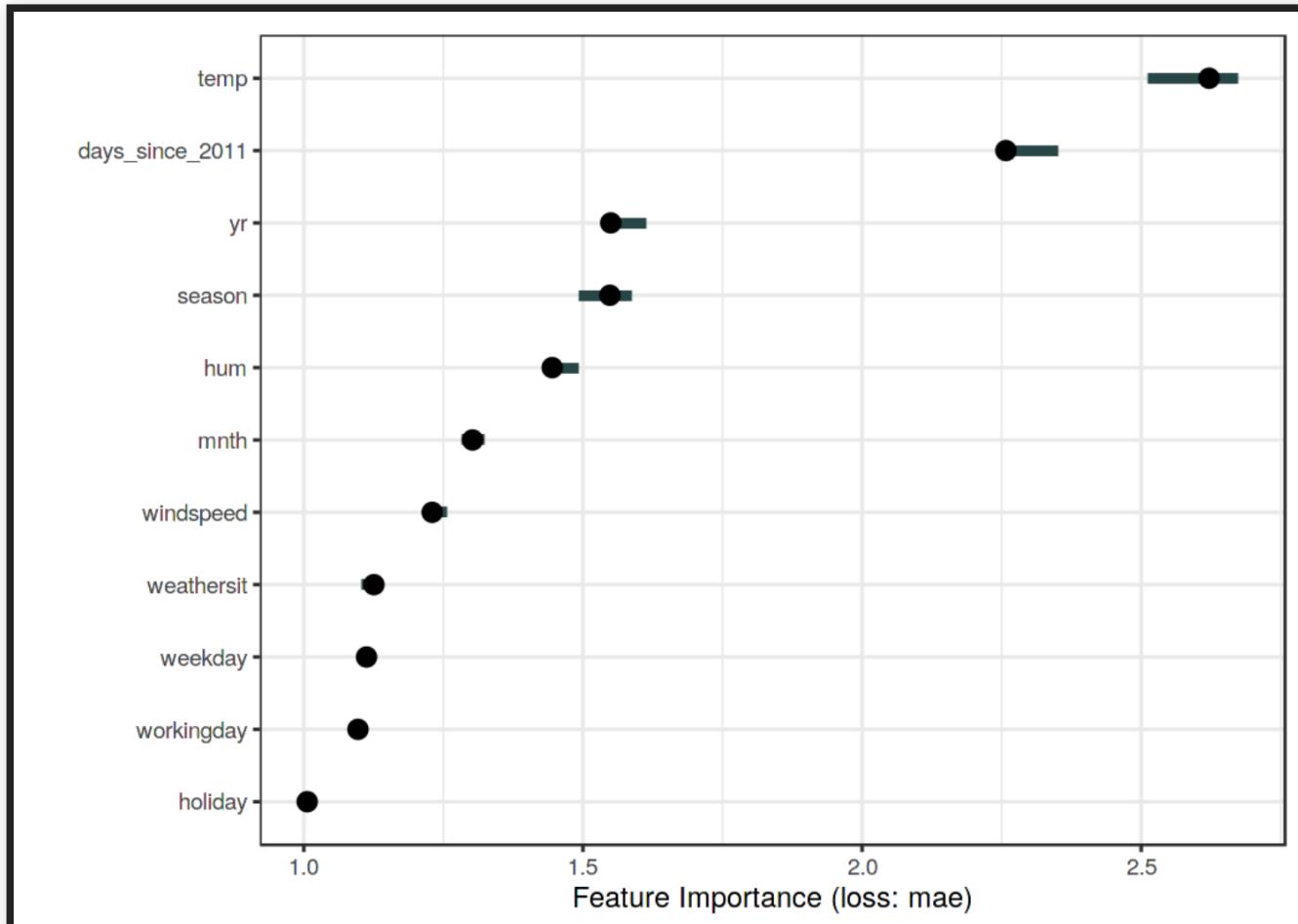
- Permute a features value in training or validation set to not use it for prediction
 - Measure influence on accuracy
 - i.e. evaluate feature effect without retraining the model
-
- Highly compressed, *global* insights
 - Effect for feature + interactions
 - Can only be computed on labeled data, depends on model accuracy, randomness from permutation
 - May produce unrealistic inputs when correlations exist

Feature importance on training or validation data?

Speaker notes

Training vs validation is not an obvious answer and both cases can be made, see Molnar's book. Feature importance on the training data indicates which features the model has learned to use for predictions.

FEATURE IMPORTANCE EXAMPLE



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

INVARIANTS AND ANCHORS

- Identify partial conditions that are sufficient for a prediction
- e.g. "*when income < X loan is always rejected*"
- For some models, many predictions can be explained with few mined rules

- Compare association rule mining and specification mining
- Rules mined from many observed examples

Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "[Anchors: High-precision model-agnostic explanations.](#)" In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

Ernst, Michael D., Jake Cockrell, William G. Griswold, and David Notkin. "[Dynamically discovering likely program invariants to support program evolution.](#)" IEEE Transactions on Software Engineering 27, no. 2 (2001): 99-123.

EXAMPLE: ANCHORS

	If	Predict
adult	No capital gain or loss, never married	$\leq 50K$
	Country is US, married, work hours > 45	$> 50K$
rcdv	No priors, no prison violations and crime not against property	Not rearrested
	Male, black, 1 to 5 priors, not married, and crime not against property	Re-arrested
lending	FICO score ≤ 649	Bad Loan
	$649 \leq$ FICO score ≤ 699 and $\$5,400 \leq$ loan amount $\leq \$10,000$	Good Loan

Source: Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "[Anchors: High-precision model-agnostic explanations](#)." In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

EXAMPLE: ANCHORS

Instance	If	Predict
I want to play(V) ball.	previous word is PARTICLE	play is VERB.
I went to a play(N) yesterday.	previous word is DETERMINER	play is NOUN.
I play(V) ball on Mondays.	previous word is PRONOUN	play is VERB.

Source: Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "[Anchors: High-precision model-agnostic explanations](#)." In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

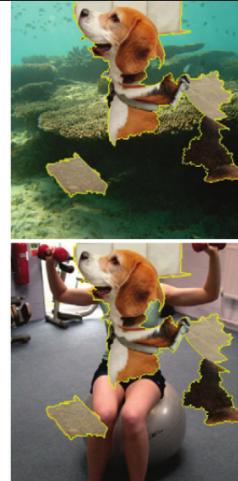
EXAMPLE: ANCHORS



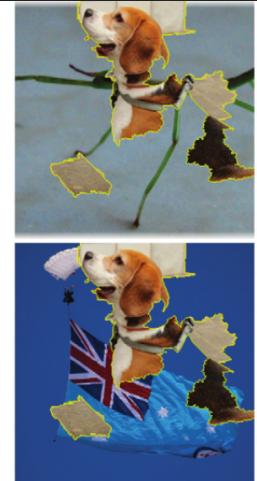
(a) Original image



(b) Anchor for “beagle”



(c) Images where Inception predicts $P(\text{beagle}) > 90\%$



Source: Ribeiro, Marco Tulio, Sameer Singh, and Carlos Guestrin. "[Anchors: High-precision model-agnostic explanations](#)." In Thirty-Second AAAI Conference on Artificial Intelligence. 2018.

EXCURSION: DAIKON FOR DYNAMIC DETECTION OF LIKELY INVARIANTS

- Software engineering technique to find invariants
 - e.g., `i>0, a==x, this.stack != null, db.query() after db.prepare()`
 - Pre- and post-conditions of functions, local variables
- Uses for documentation, avoiding bugs, debugging, testing, verification, repair
- Idea: Observe many executions (instrument code), log variable values, look for relationships (test many possible invariants)

DAIKON EXAMPLE

```
public class Stack {  
    private Object[] theArray;  
    private int topOfStack;  
    public StackAr(int c) {  
        theArray = new Object[c];  
        topOfStack = -1;  
    }  
    public Object top( ) {  
        if(isEmpty()) return null;  
        return theArray[topOfStack];  
    }  
    public boolean isEmpty( ) {  
        return topOfStack == -1;  
    }  
    ...  
}
```

Invariants found

```
StackAr:::OBJECT  
this.theArray != null  
this.theArray.getClass().getName() ==  
    java.lang.Object[].class  
this.topOfStack >= -1  
this.topOfStack <= size(this.theArray[  
  
StackAr.top():::EXIT75  
return ==  
    this.theArray[this.topOfStack]  
return ==  
    this.theArray[orig(this.topOfStack)]  
return ==  
    orig(this.theArray[this.topOfStack])  
this.topOfStack >= 0  
return != null
```

Speaker notes

many examples in <https://www.cs.cmu.edu/~aldrich/courses/654-sp07/tools/kim-daiikon-02.pdf>

DISCUSSION: ANCHORS AND INVARIANTS

- Anchors provide only partial explanations
- Help check/debug functioning of system
- Anchors usually probabilistic, not guarantees

EXAMPLE-BASED EXPLANATIONS

(thinking in analogies and contrasts)

Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable](#)." 2019

COUNTERFACTUAL EXPLANATIONS

if X had not occurred, Y would not have happened

Your loan application has been declined. If your savings account had had more than \$100 your loan application would be accepted.

-> Smallest change to feature values that result in given output

MULTIPLE COUNTERFACTUALS

Often long or multiple explanations

Your loan application has been declined. If your savings account ...

Your loan application has been declined. If you lived in

...

Report all or select "best" (e.g. shortest, most actionable, likely values)

(Rashomon effect)



SEARCHING FOR COUNTERFACTUALS?



SEARCHING FOR COUNTERFACTUALS

Random search (with growing distance) possible, but inefficient

Many search heuristics, e.g. hill climbing or Nelder–Mead, may use gradient of model if available

Can incorporate distance in loss function

$$L(x, x', y', \lambda) = \lambda \cdot (\hat{f}(x') - y')^2 + d(x, x')$$

(similar to finding adversarial examples)

EXAMPLE COUNTERFACTUALS

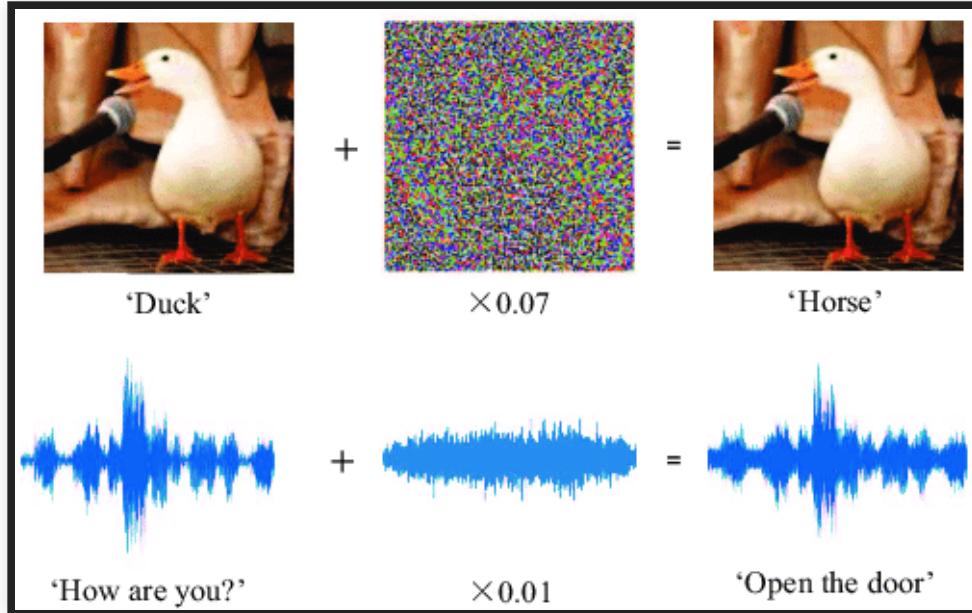
redicted risk of diabetes with 3-layer neural network

Which feature values must be changed to increase or decrease the risk score of diabetes to 0.5?

- Person 1: If your 2-hour serum insulin level was 154.3, you would have a score of 0.51
- Person 2: If your 2-hour serum insulin level was 169.5, you would have a score of 0.51
- Person 3: If your Plasma glucose concentration was 158.3 and your 2-hour serum insulin level was 160.5, you would have a score of 0.51

DISCUSSION: COUNTERFACTUALS





DISCUSSION: COUNTERFACTUALS

- Easy interpretation, can report both alternative instance or required change
- No access to model or data required, easy to implement
- Often many possible explanations (Rashomon effect), requires selection/ranking
- May require changes to many features, not all feasible
- May not find counterfactual within given distance
- Large search spaces, especially with high-cardinality categorical features

ACTIONABLE COUNTERFACTUALS

Example: Denied loan application

- Customer wants feedback of how to get the loan approved
- Some suggestions are more actionable than others, e.g.,
 - Easier to change income than gender
 - Cannot change past, but can wait
- In distance function, not all features may be weighted equally

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?



GAMING THE MODEL WITH EXPLANATIONS?

- A model prone to gaming uses weak proxy features
 - Protections requires 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 are hard to game and relate causally to the outcome

```
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 arrest  
ELSE  
IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

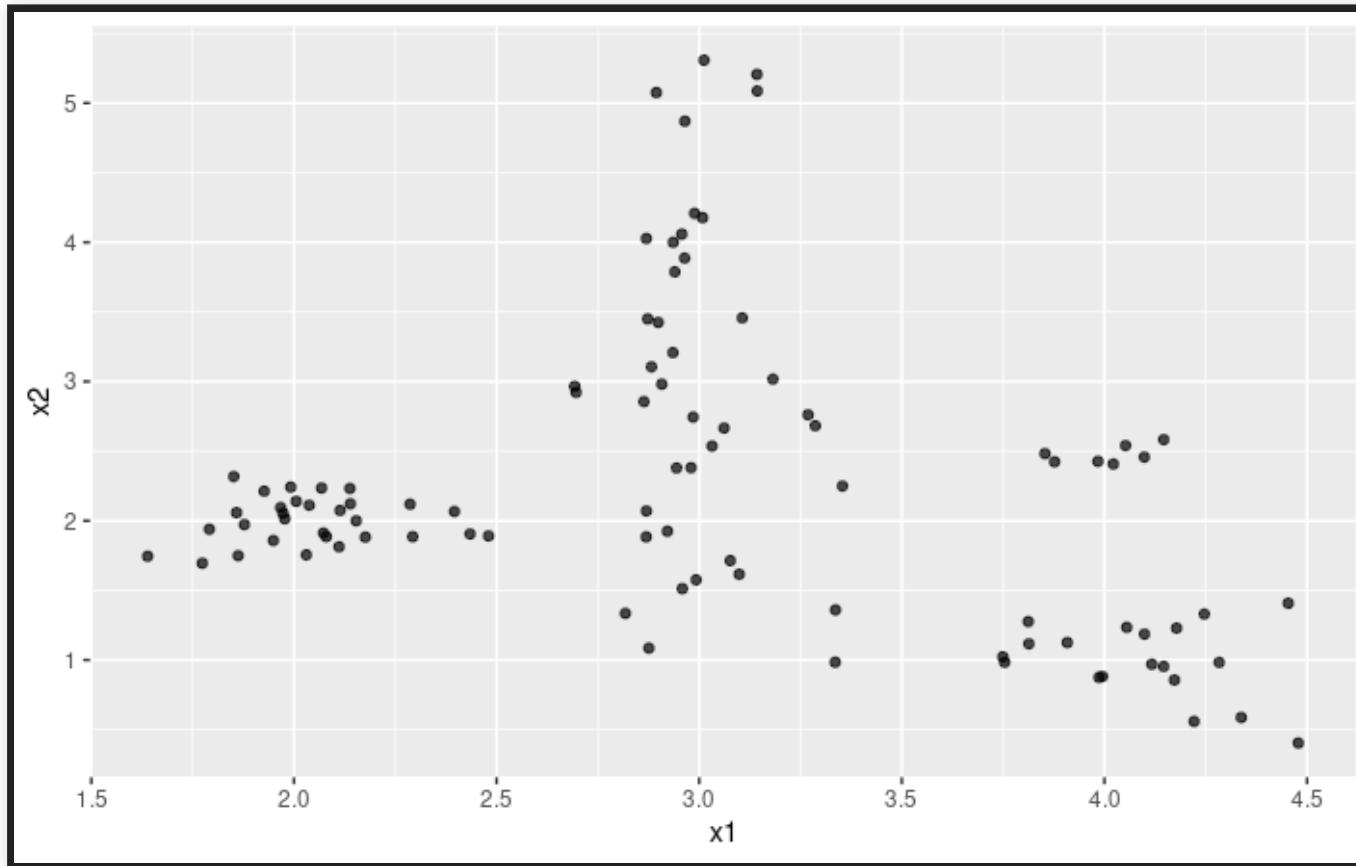
PROTOTYPES AND CRITICISMS

A prototype is a data instance that is representative of all the data.

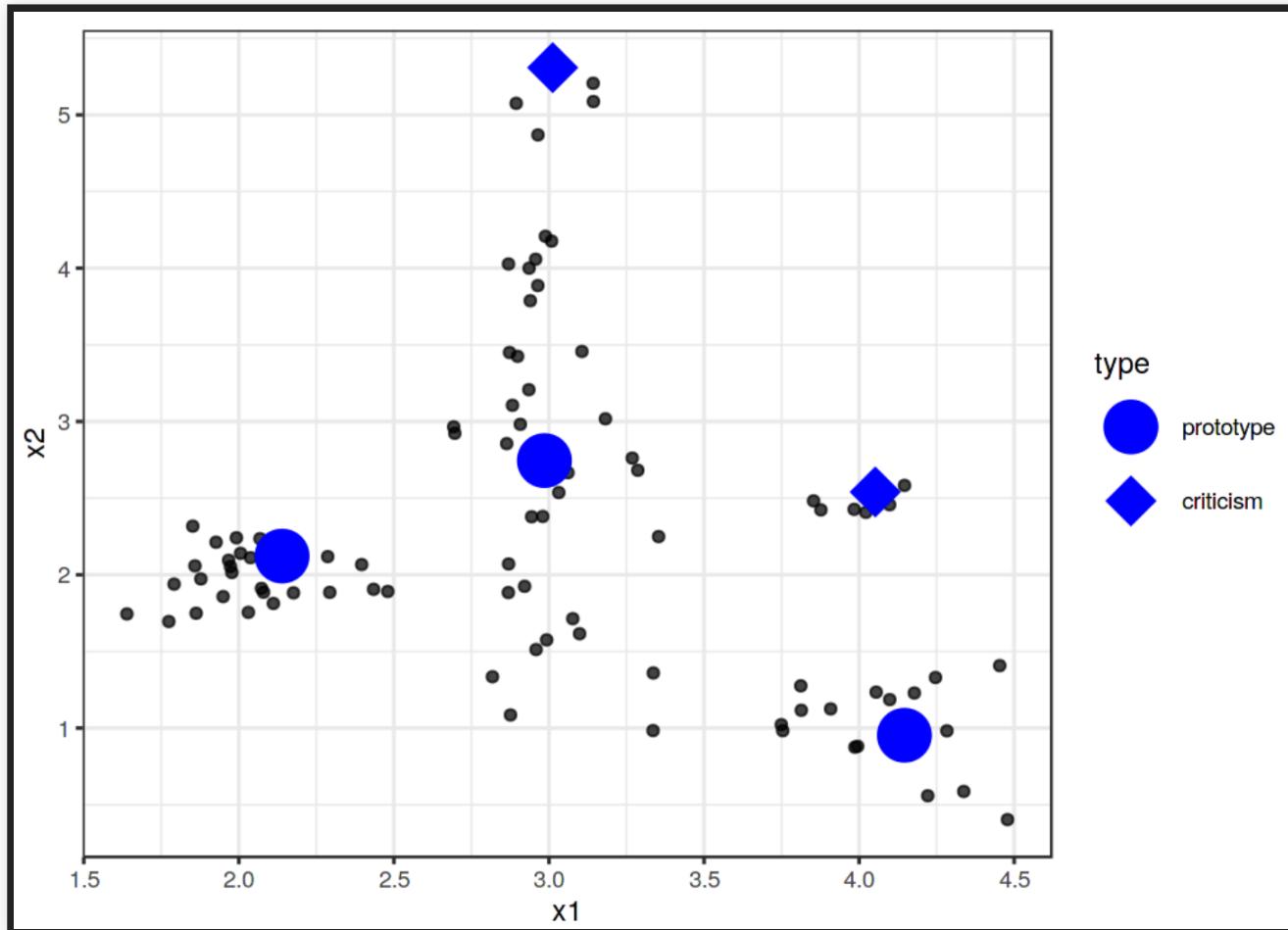
A criticism is a data instance that is not well represented by the set of prototypes.

How would you use this? (e.g., credit rating, cancer detection)

EXAMPLE: PROTOTYPES AND CRITICISMS?



EXAMPLE: PROTOTYPES AND CRITICISMS



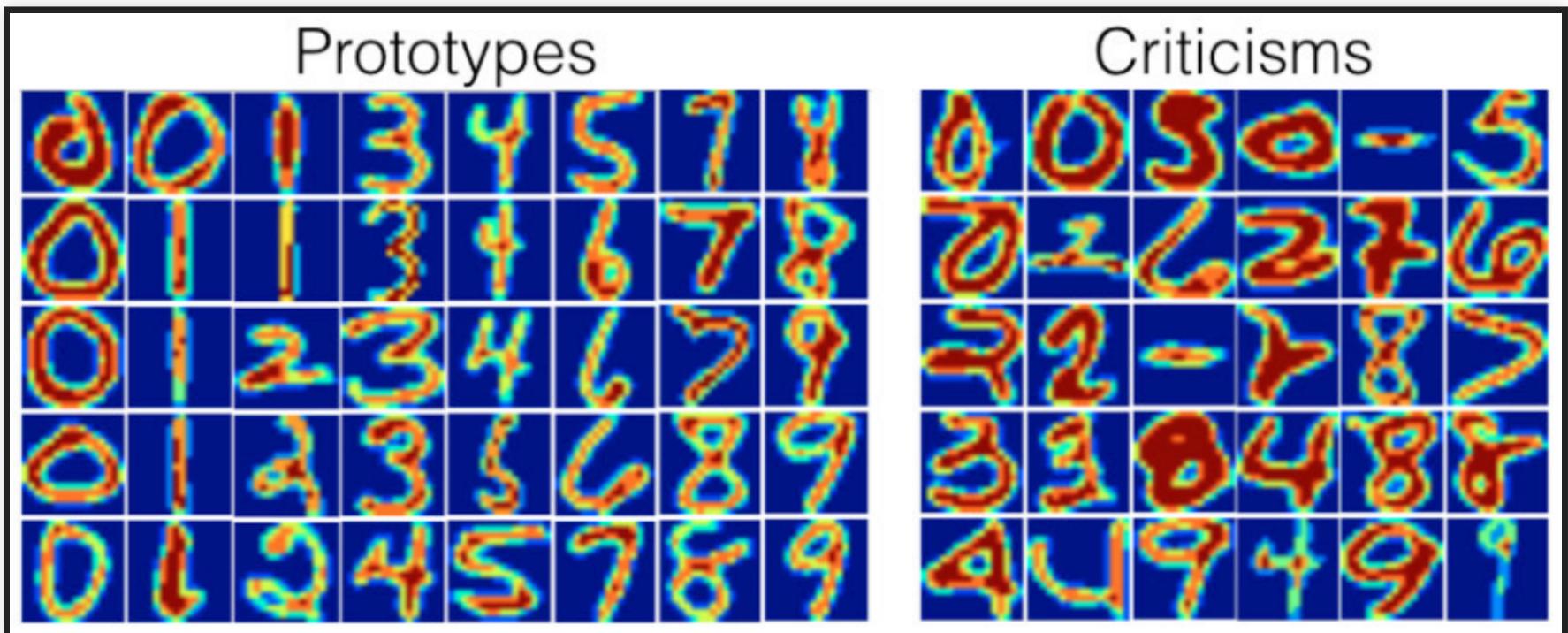
Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

EXAMPLE: PROTOTYPES AND CRITICISMS



Source: Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable.](#)"
2019

EXAMPLE: PROTOTYPES AND CRITICISMS



Source: Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable](#)."

2019

Speaker notes

The number of digits is different in each set since the search was conducted globally, not per group.

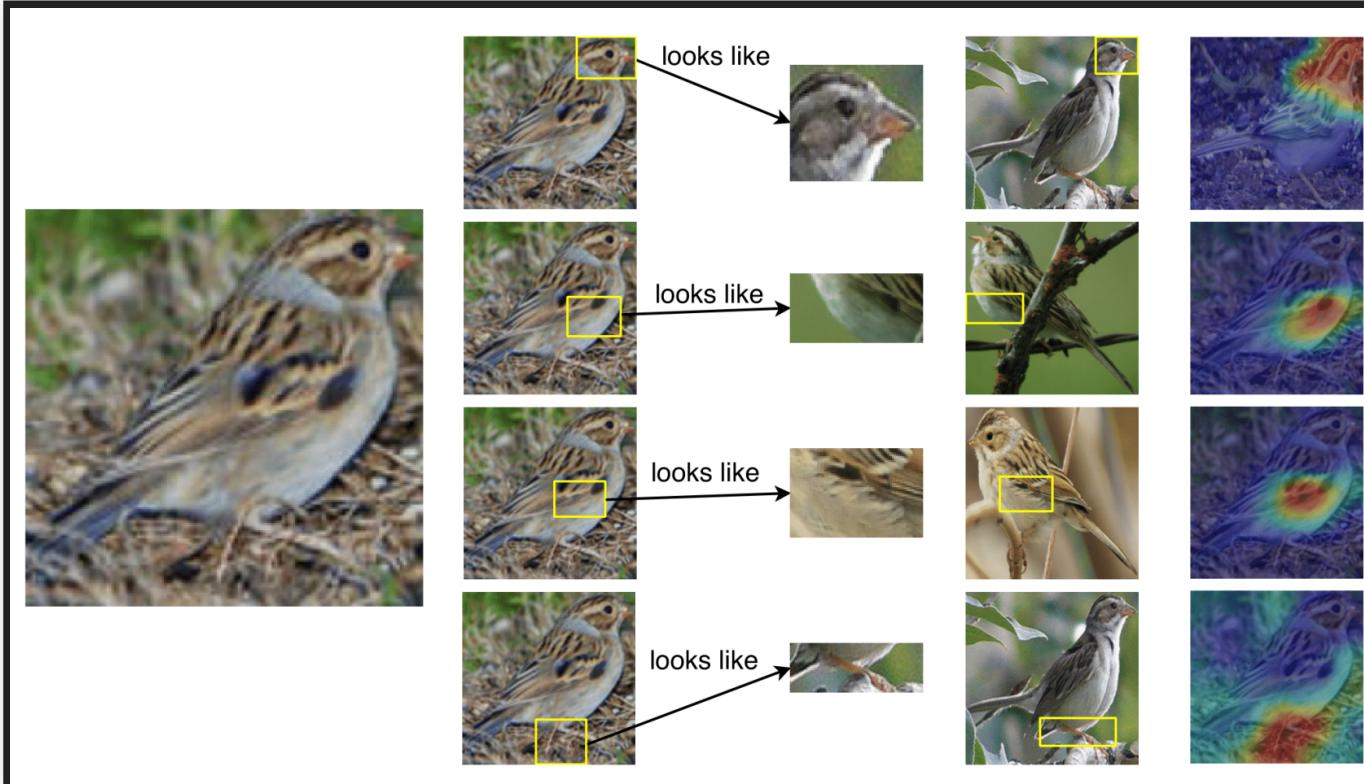
METHODS: PROTOTYPES AND CRITICISMS

- Usually identify number of prototypes and criticisms upfront
- Clustering of data (ala k-means)
 - k-medoids returns actual instances as centers for each cluster
 - MMD-critic identifies both prototypes and criticisms
 - see book for details
- Identify globally or per class

DISCUSSION: PROTOTYPES AND CRITICISMS

- Easy to inspect data, useful for debugging outliers
 - Generalizes to different kinds of data and problems
 - Easy to implement algorithm
-
- Need to choose number of prototypes and criticism upfront
 - Uses all features, not just features important for prediction

EMERGING RESEARCH: INHERENTLY-INTERPRETABLE MODELS BASED ON PROTOTYPES



Chen, Chaofan, et al. "This looks like that: deep learning for interpretable image recognition." arXiv preprint arXiv:1806.10574 (2018).

INFLUENTIAL INSTANCES

Data debugging!

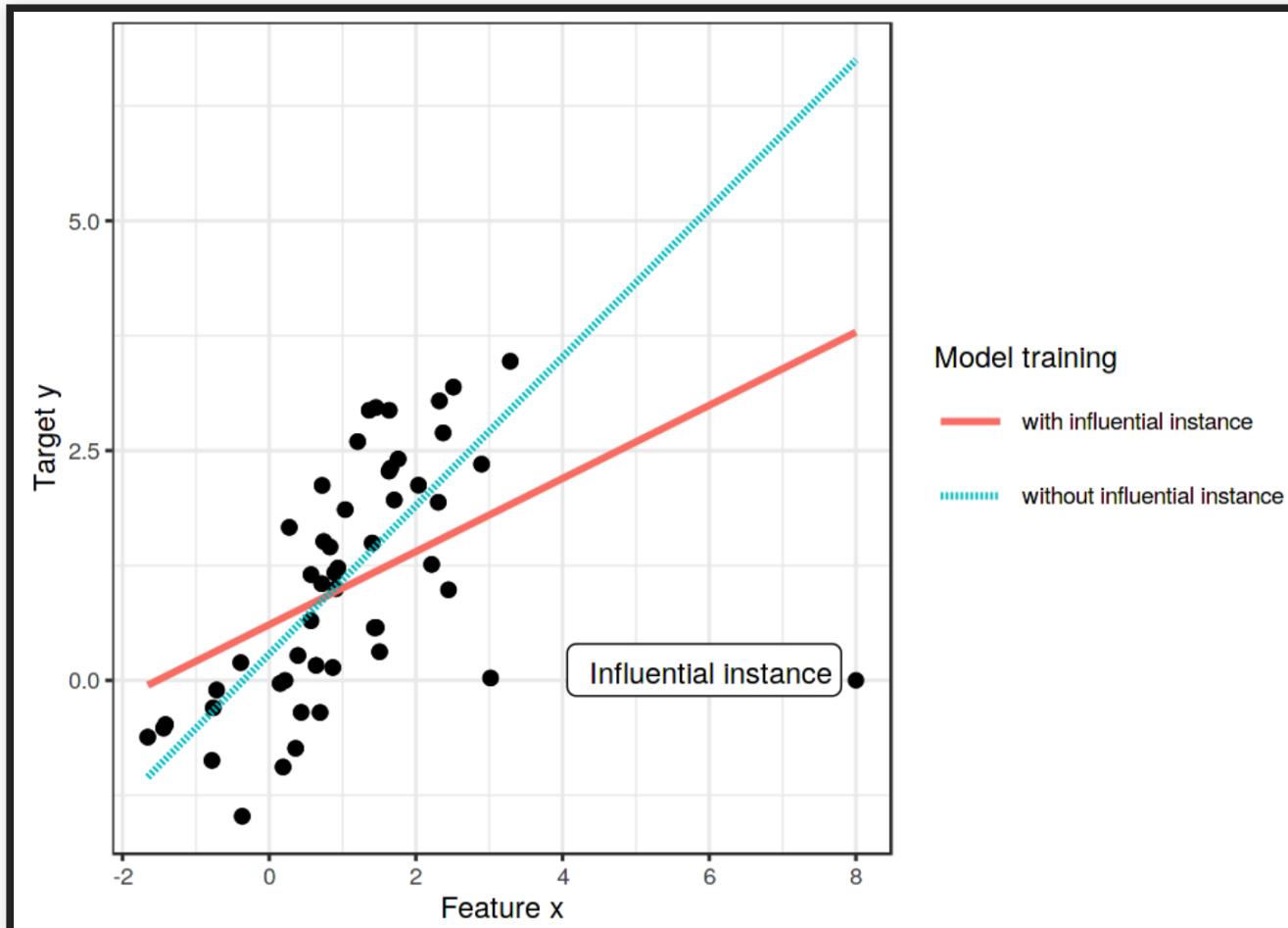
What data most influenced the training? Is the model skewed by few outliers?

- Training data with n instances
- Train model f with all n instances
- Train model g with $n - 1$ instances
- If f and g differ significantly, omitted instance was influential
 - Difference can be measured e.g. in accuracy or difference in parameters

Speaker notes

Instead of understanding a single model, comparing multiple models trained on different data

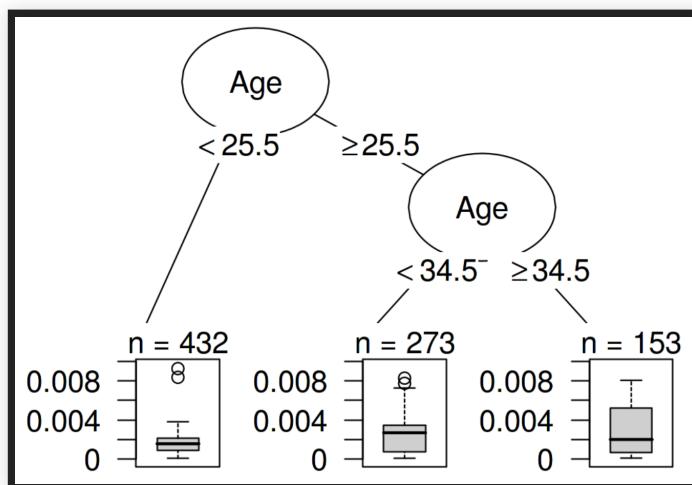
EXAMPLE: INFLUENTIAL INSTANCE



Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

WHAT DISTINGUISHES AN INFLUENTIAL INSTANCE FROM A NON-INFLUENTIAL INSTANCE?

Compute influence of every data point and create new model to explain influence in terms of feature values



(cancer prediction example)

Which features have a strong influence but little support in the training data?

Source: Christoph Molnar. "[Interpretable Machine Learning](#)." 2019

Speaker notes

Example from cancer prediction. The influence analysis tells us that the model becomes increasingly unstable when predicting cancer for higher ages. This means that errors in these instances can have a strong effect on the model.

DEBUGGING DRIFT WITH INFLUENTIAL INSTANCES

- Which data points on the training data influenced the model to work less on newer production data?
- Identify influential training instances on recent production misclassification
- Example: Cancer prediction model built in one hospital but works less well in other hospital
 - Is there training data that causes poor generalization? What are the characteristics of that data (e.g., different age groups)? Are differences due to concept or data drift?

SELECTIVELY CHECKING DATA QUALITY WITH INFLUENTIAL INSTANCES

- Labeled data comes in different qualities (see [data programming lecture](#))
- Double check labels of influential instances; lower quality labels may be sufficient for less influential instances

INFLUENTIAL INSTANCES DISCUSSION

- Retraining for every data point is simple but expensive
- For some class of models, influence of data points can be computed without retraining (e.g., logistic regression), see book for details
- Hard to generalize to taking out multiple instances together
- Useful model-agnostic debugging tool for models and data

Christoph Molnar. "[Interpretable Machine Learning: A Guide for Making Black Box Models Explainable](#)." 2019

WHAT MAKES GOOD EXPLANATIONS?



GOOD EXPLANATIONS ARE CONTRASTIVE

Counterfactuals. *Why this, rather than a different prediction?*

Your loan application has been declined. If your savings account had had more than \$100 your loan application would be accepted.

Partial explanations often sufficient in practice if contrastive

EXPLANATIONS ARE SELECTIVE

Often long or multiple explanations;
parts are often sufficient

*Your loan application has
been declined. If your savings
account had had more than
\$100 your loan application
would be accepted.*

*Your loan application has
been declined. If you lived in
Ohio your loan application
would be accepted.*



(Rashomon effect)

GOOD EXPLANATIONS ARE SOCIAL

Different audiences might benefit from different explanations

Accepted vs rejected loan applications?

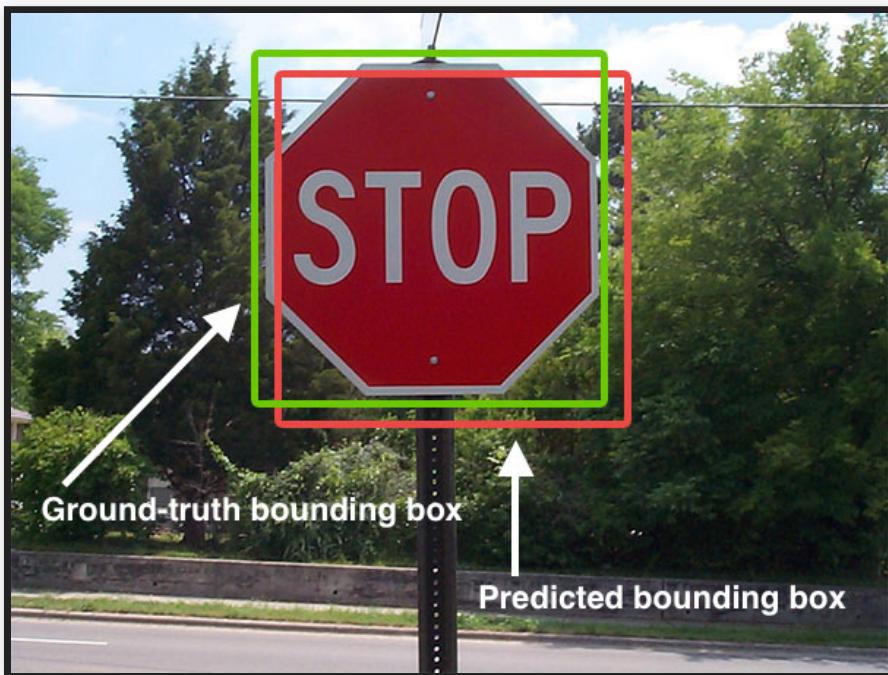
Explanation to customer or hotline support?

Consistent with prior belief of the explainee

EXERCISE: DEBUGGING A MODEL

Consider the following debugging challenges. In groups discuss which explainability tools may help and why. In 10 min report back to the group.

Algorithm bad at recognizing some signs in some conditions:



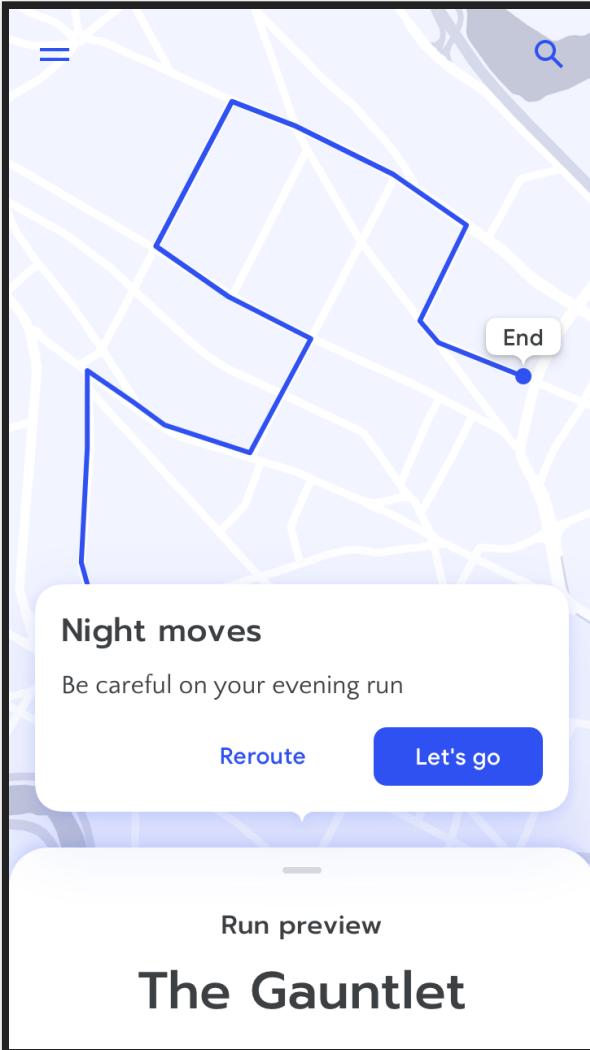
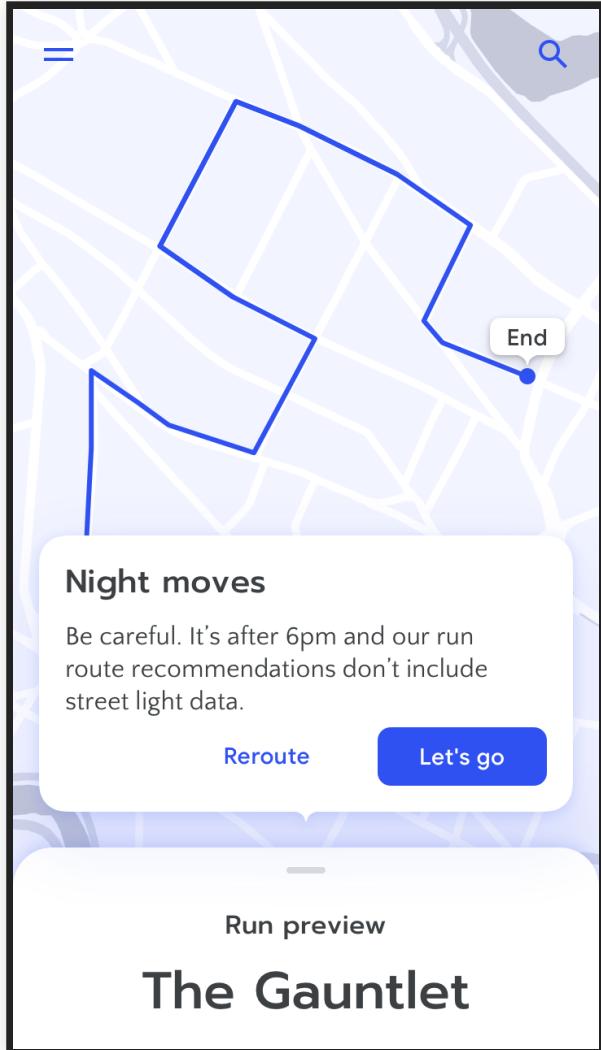
Graduate application system seems to rank applicants HBCUs lowly:



Left Image: CC BY-SA 4.0, Adrian Rosebrock

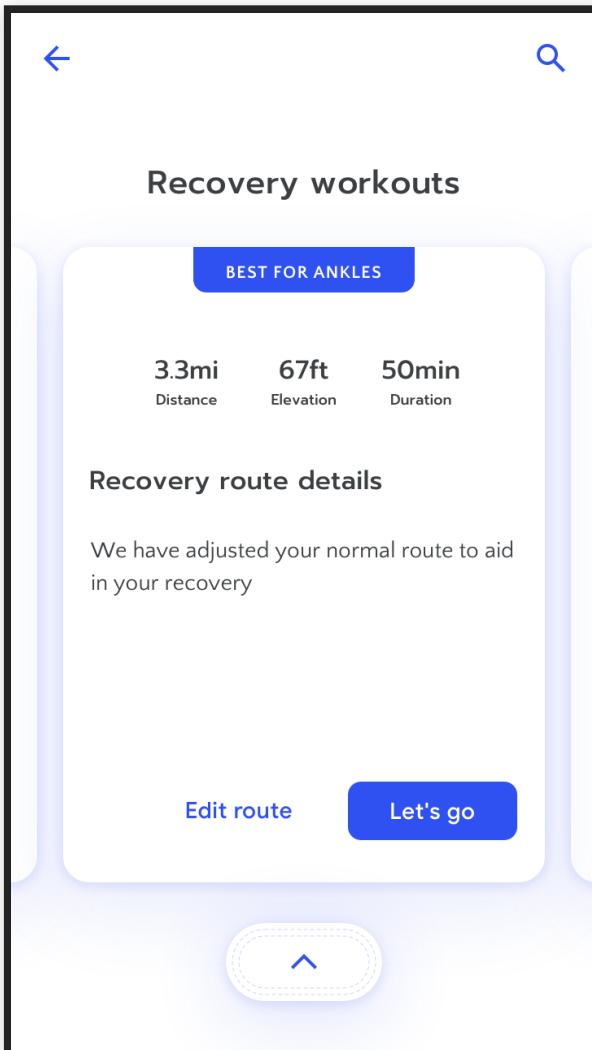
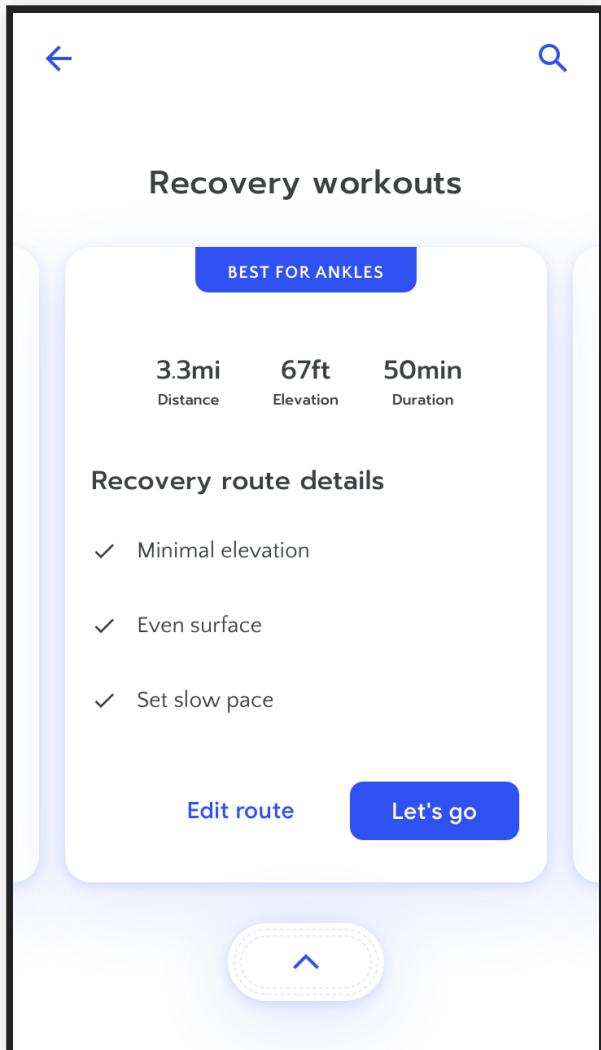
EXPLANATIONS AND USER INTERACTION DESIGN

[People + AI Guidebook](#), Google



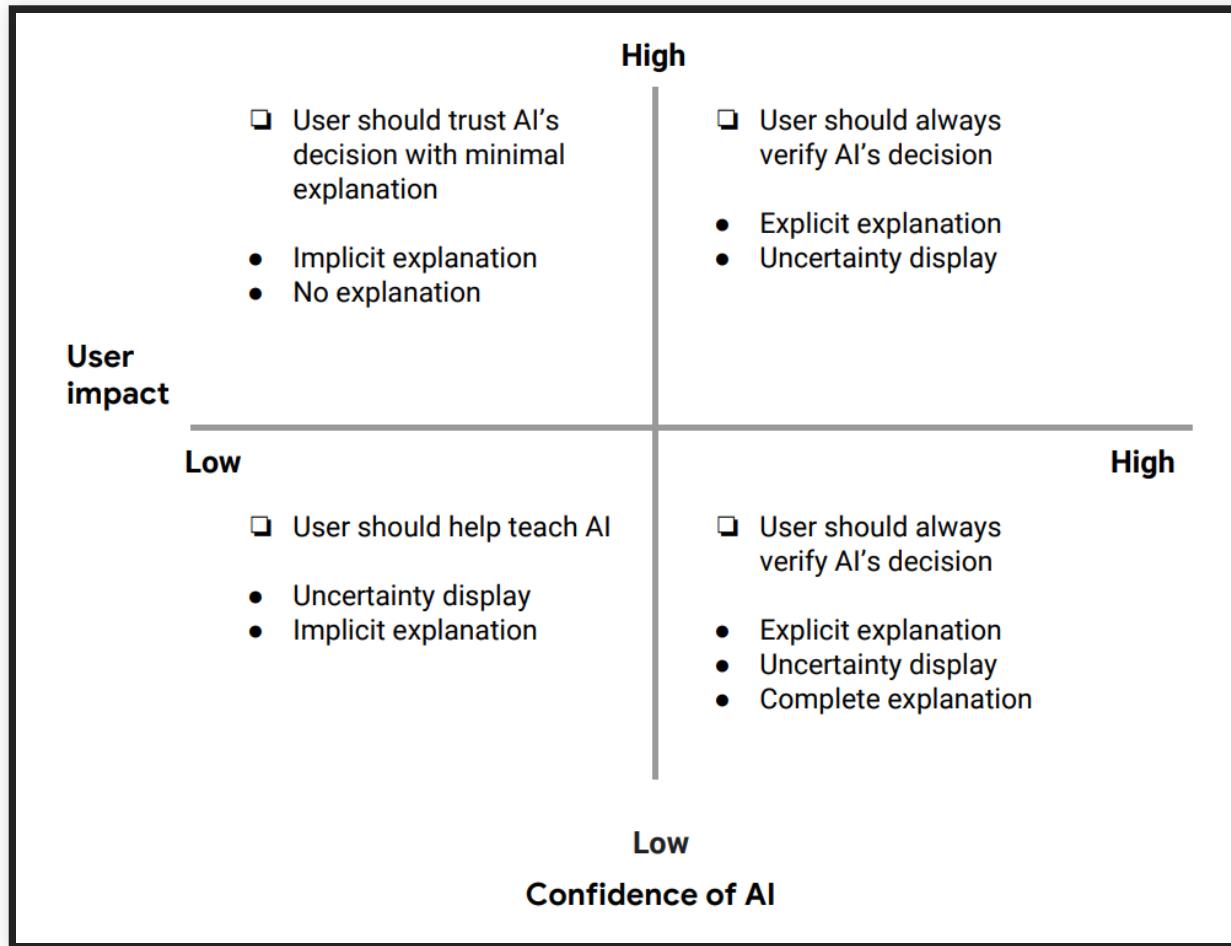
Tell the user when a lack of data might mean they'll need to use their own judgment. Don't be afraid to admit when a lack of data could affect the quality of the AI recommendations.

Source: [People + AI Guidebook](#), Google



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. Don't say "what" without saying "why" in a high stakes scenario.

Source: [People + AI Guidebook](#), Google



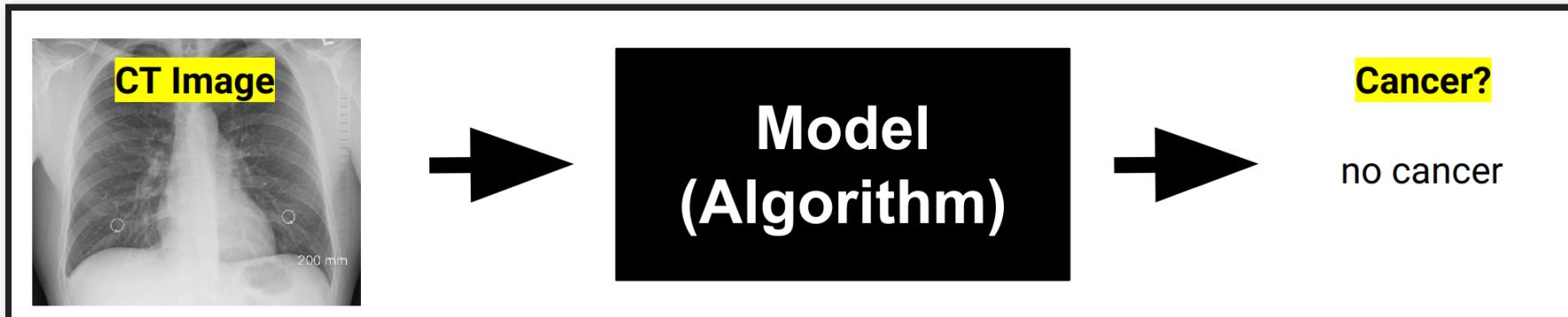
Example each?

Source: [People + AI Guidebook, Google](#)

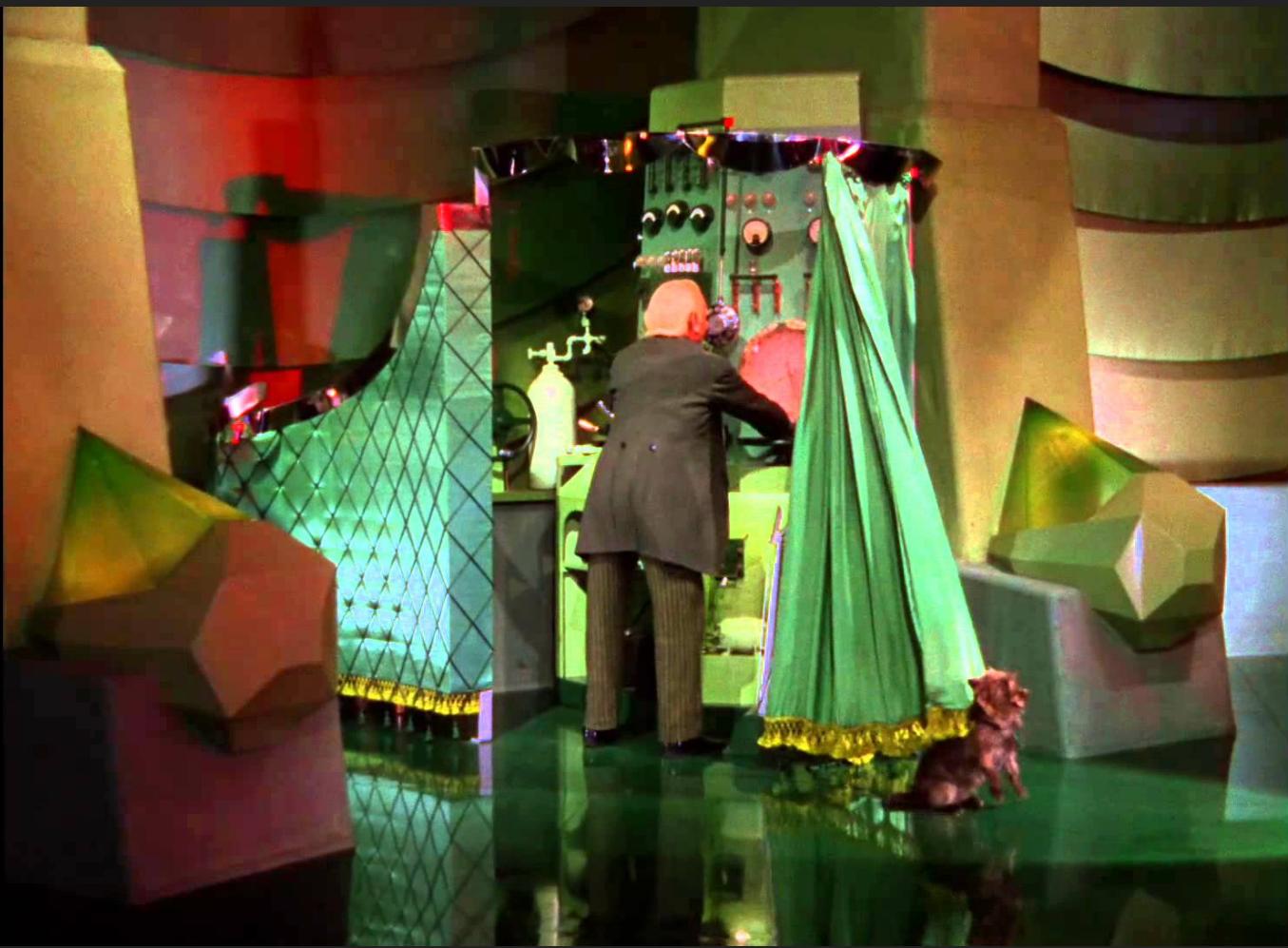
BEYOND "JUST" EXPLAINING THE MODEL

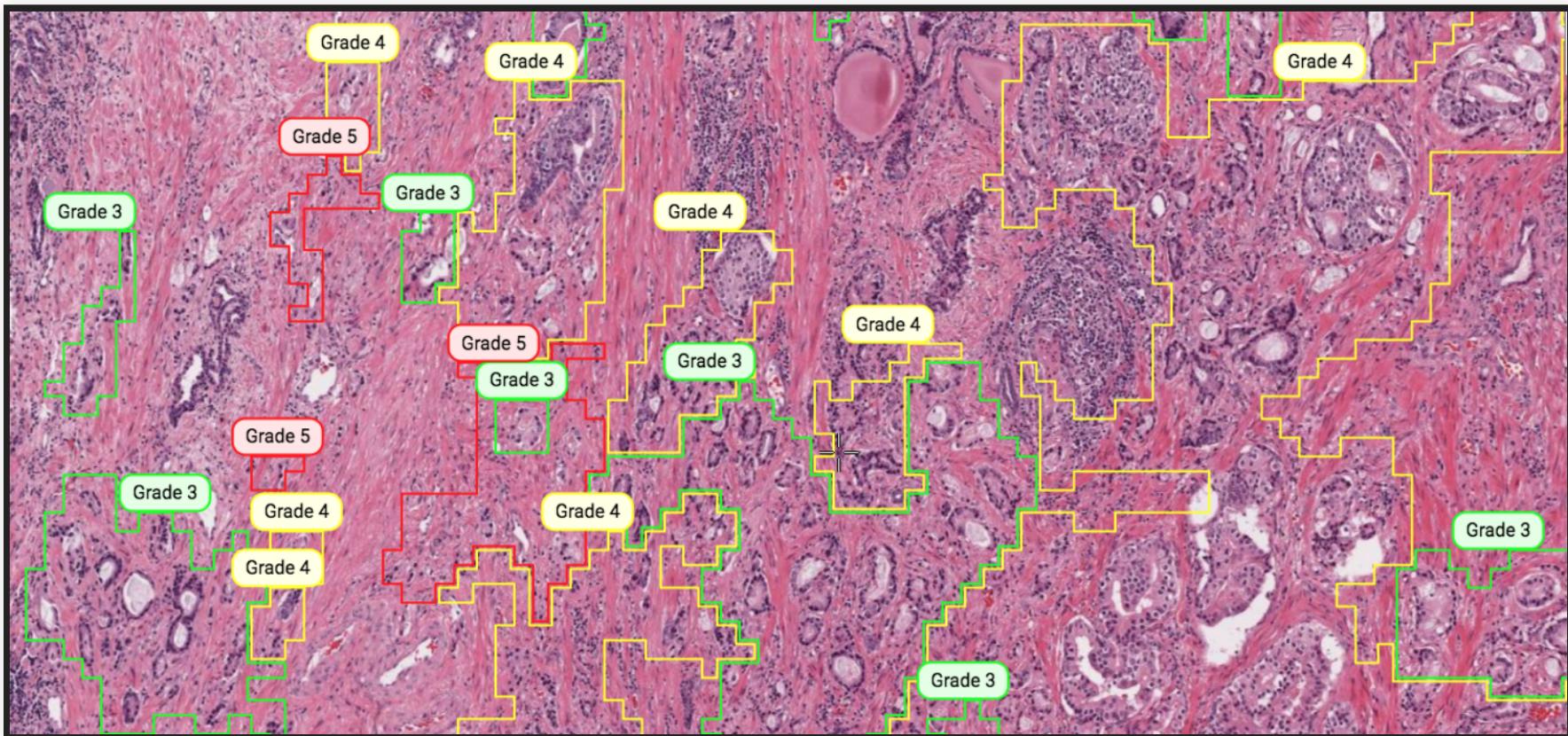
Cai, Carrie J., Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. ""Hello AI": Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making." Proceedings of the ACM on Human-computer Interaction 3, no. CSCW (2019): 1-24.

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 assistant have access to information that I don't have? Does it have access to any ancillary studies?" Is all used data shown in the user interface?
- 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

Paper, Tab 1

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.

TRANSPARENCY

CASE STUDY: FACEBOOK'S FEED CURATION

All Stories



Aaron Bird
"Happy Birthday, Clay! Much love!" on Clay Huston's timeline.

Saturday 20th September 7:29 AM.



Meem Malekushlugh
Meem Malekushlugh posted a video.



Saturday 20th September 12:30 PM.



Ankush Dharker
Chatted with Mark Cuban (from Shark Tank) on his Cyber Dust. Very thoughtful and useful app.
Give it a try and add me: +ankushdharker

Friday 19th September 2:41 PM.



Mohammad Sameki
WOW, I wish I was there:)



Saturday 20th September 12:27 PM.



Aaron Bird
Not sure I want to know when I'll die, but 83 sounds okay

Shown Stories



Meem Malekushlugh
Meem Malekushlugh posted a video.



Saturday 20th September 12:30 PM.



Mohammad Sameki
WOW, I wish I was there:)



Saturday 20th September 12:27 PM.



Aaron Bird
Not sure I want to know when I'll die, but 83 sounds okay



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.

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

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.

CASE STUDY: HR APPLICATION SCREENING

Tweet

THE DARK SIDE OF EXPLANATIONS

- Explanations can induce overconfidence in the model; people do not trust their own intuitions
- Users may feel influence and control, even with placebo controls
- Companies give vague generic explanations to appease regulators

Real ————— (a) News Feeds ————— Random

xoNecole @xonecole · Sep 13
Meet the 11-year-old who went from being bullied about her dark skin complexion, to debuting her line during #NYFW [xon.ec/1PYmnNT](#)

13 320 604

RI @hyori_sunie · Sep 13
Jessica after @marcjacobs show #NYFW
"She was amazingly beautiful. Thanks Jessica!"

376 238

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)

(b) Control Setting

Popularity

Less popular More popular

Vogue Magazine @voguemagazine · 3m
. @Rihanna stunned in a custom couture gown at her annual charity fundraiser Diamond Ball.

1

Monica Kim @monicamkim · 1 Nov 2016
See Seoul Fashion Week's famous street style in motion—now on [@voguemagazine: vogue.com/13497565/seoul...](#)

1 9

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)

- Stumpf, Simone, Adrian Bussone, and Dympna O'sullivan. "Explanations considered harmful? user interactions with machine learning systems." In Proc. CHI. 2016.
- Vaccaro, Kristen, Dylan Huang, Motahare Eslami, Christian Sandvig, Kevin Hamilton, and Karrie Karahalios. "The illusion of control: Placebo effects of control settings." In Proc CHI, 2018.

APPROPRIATE LEVEL OF ALGORITHMIC TRANSPARENCY

IP/Trade Secrets/Fairness/Perceptions/Ethics?

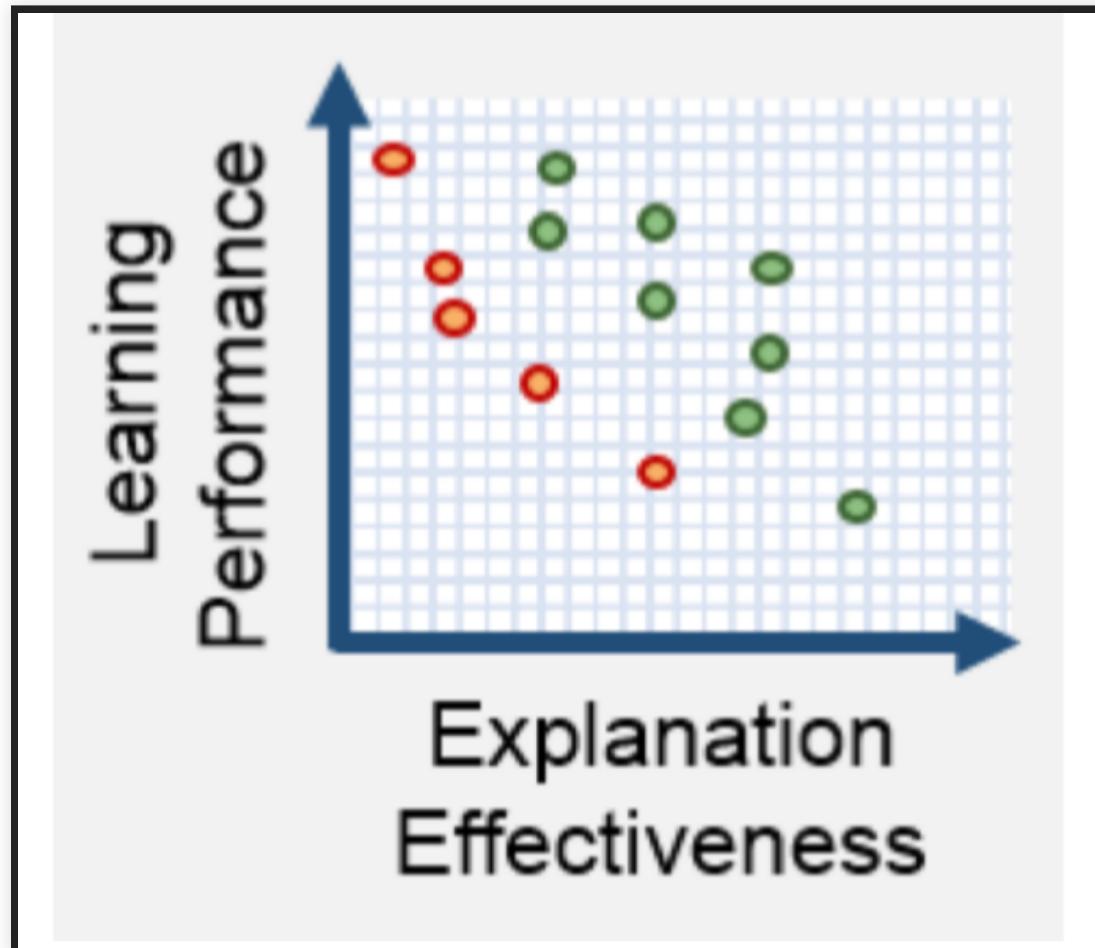
How to design? How much control to give?



**"STOP EXPLAINING BLACK
BOX MACHINE LEARNING
MODELS FOR HIGH STAKES
DECISIONS AND USE
INTERPRETABLE MODELS
INSTEAD."**

Cynthia Rudin (32min) or [Cynthia Rudin](#), Cynthia. "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead." *Nature Machine Intelligence* 1, no. 5 (2019): 206-215.

ACCURACY VS EXPLAINABILITY CONFLICT?



Graphic from the DARPA XAI BAA (Explainable Artificial Intelligence)

FAITHFULNESS OF EX-POST EXPLANATIONS



CORELS' MODEL FOR RECIDIVISM RISK PREDICTION

```
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 arrest  
ELSE  
IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Simple, interpretable model with comparable accuracy to proprietary COMPAS model

"STOP EXPLAINING BLACK BOX MACHINE LEARNING MODELS FOR HIGH STAKES DECISIONS AND USE INTERPRETABLE MODELS INSTEAD"

Hypotheses:

- It is a myth that there is necessarily a trade-off between accuracy and interpretability (when having meaningful features)
- Explainable ML methods provide explanations that are not faithful to what the original model computes
- Explanations often do not make sense, or do not provide enough detail to understand what the black box is doing
- Black box models are often not compatible with situations where information outside the database needs to be combined with a risk assessment
- Black box models with explanations can lead to an overly complicated decision pathway that is ripe for human error

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](#))

INTERPRETABLE MODELS VS POST-HOC EXPLANATIONS

- High-stakes decisions
 - interpretable models provide faithful explanations
 - post-hoc explanations may provide limited insights or illusion of understanding
 - interpretable models can be audited
- In many cases similar accuracy
- Larger focus on feature engineering, but insights into when and *why* the model works
 - exploratory data analysis, plots, association rule mining
 - more effort for building interpretable models (especially beyond well structured tabular data)
- Less research on interpretable models and some methods computationally expensive
 - additional constraints on model form for interpretability limit degrees of freedom: sparseness, parameters with easy to read weights, ...

PROPUBLICA CONTROVERSY



Bernard Parker, left, was rated high risk; Dylan Fugett was rated low risk. (Josh Ritchie for ProPublica)

Machine Bias

There's software used across the country to predict future criminals. And it's biased against blacks.

Speaker notes

"ProPublica's linear model was not truly an "explanation" for COMPAS, and they should not have concluded that their explanation model uses the same important features as the black box it was approximating."

PROPUBLICA CONTROVERSY

```
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 arrest  
ELSE  
IF more than three priors THEN predict arrest  
ELSE predict no arrest
```

Rudin, Cynthia. "[Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead.](#)" Nature Machine Intelligence 1, no. 5 (2019): 206-215.

DRAWBACKS OF INTERPRETABLE MODELS

- Intellectual property protection harder
 - may need to sell model, not license as service
 - who owns the models and who is responsible for their mistakes?
- Gaming possible; "security by obscurity" not a defense
- Expensive to build (feature engineering effort, debugging, computational costs)
- Limited to fewer factors, may discover fewer patterns, lower accuracy

CALL FOR TRANSPARENT AND AUDITED MODELS

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

- High-stakes decisions with government involvement (recidivism, policing, city planning, ...)
- High-stakes decisions in medicine
- High-stakes decisions with discrimination concerns (hiring, loans, housing, ...)
- Decisions that influence society and discourse? (content curation on Facebook, targeted advertisement, ...)

Regulate possible conflict: Intellectual property vs public health/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](#))

(SELF-)REGULATION AND POLICY

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?



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."

- 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.*"

JAN 13 2020 DRAFT RULES FOR PRIVATE SECTOR AI

- *Public Trust in AI*: Overarching theme: reliable, robust, trustworthy AI
- *Public participation*: public oversight in AI regulation
- *Scientific Integrity and Information Quality*: science-backed regulation
- *Risk Assessment and Management*: risk-based regulation
- *Benefits and Costs*: regulation costs may not outweigh benefits
- *Flexibility*: accommodate rapid growth and change
- *Disclosure and Transparency*: context-based transparency regulation
- *Safety and Security*: private sector resilience

Draft: Guidance for Regulation of Artificial Intelligence Applications

OTHER REGULATIONS

- *China*: policy ensures state control of Chinese companies and over valuable data, including storage of data on Chinese users within the country and mandatory national standards for AI
- *EU*: Ethics Guidelines for Trustworthy Artificial Intelligence; Policy and investment recommendations for trustworthy Artificial Intelligence; draft regulatory framework for high-risk AI applications, including procedures for testing, record-keeping, certification, ...
- *UK*: Guidance on responsible design and implementation of AI systems and data ethics

Source: https://en.wikipedia.org/wiki/Regulation_of_artificial_intelligence

CRITICISM: ETHICS WASHING, ETHICS BASHING, REGULATORY CAPTURE



SUMMARY

- Interpretability useful for many scenarios: user feedback, debugging, fairness audits, science, ...
- Defining and measuring interpretability
- Inherently interpretable models: sparse regressions, shallow decision trees
- Providing ex-post explanations of blackbox models
 - global and local surrogates
 - dependence plots and feature importance
 - invariants (anchors)
 - counter-factual explanations
- Data debugging with prototypes, criticisms, and influential instances
- Consider implications on user interface design
- Considerations for high-stakes decisions
- Regulations may be coming

