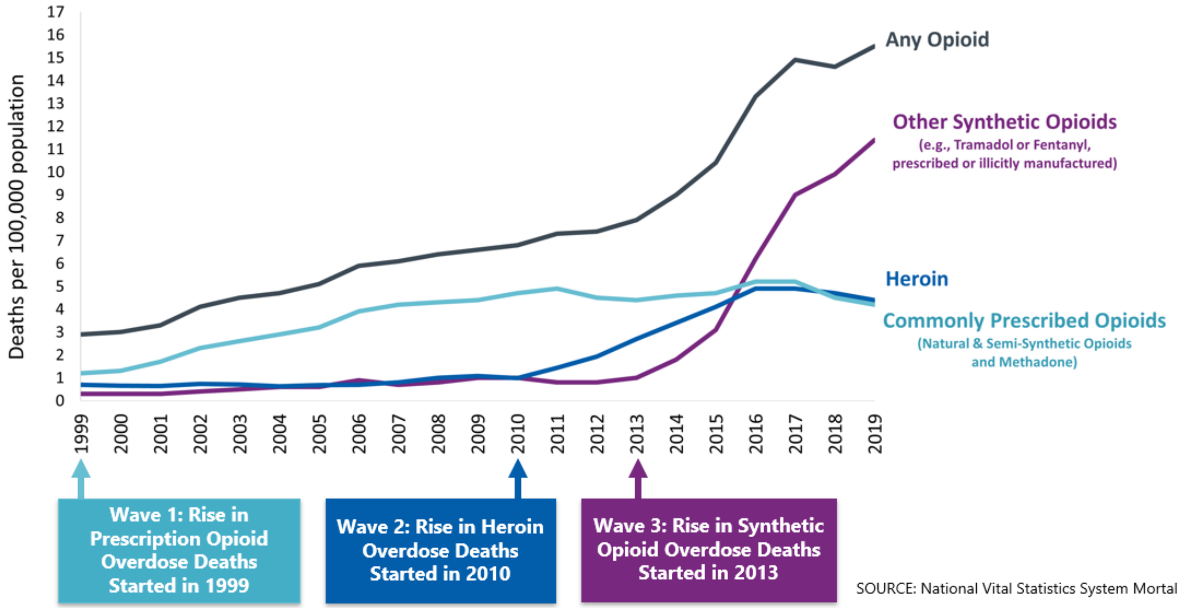
AI Ethics: Explainability of Machine Learning

CS229: Machine Learning

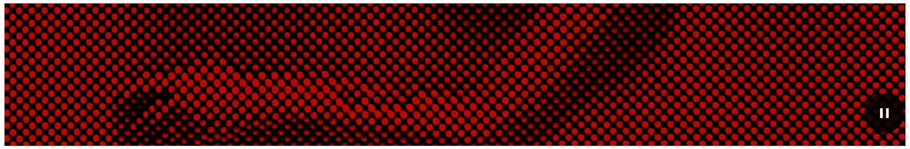
Carlos Guestrin
Stanford University

Three Waves of the Rise in Opioid Overdose Deaths



SOURCE: National Vital Statistics System Mortality File.

WIRED BACKCHANNEL BUSINESS CULTURE GEAR IDEAS SCIENCE SECURITY SIGN IN SUBSCRIBE



VIDEO: SAM CANNON

MAIA SZALAVITZ BACKCHANNEL AUG 11, 2021 6:00 AM

The Pain Was Unbearable. So Why Did Doctors Turn Her Away?

A sweeping drug addiction risk algorithm has become central to how the US handles the opioid crisis. It may only be making the crisis worse.

The AI Database →

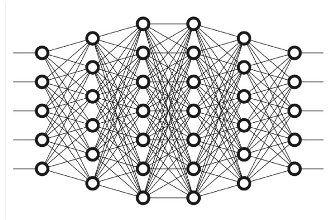
APPLICATION: ETHICS, PREDICTION, REGULATION

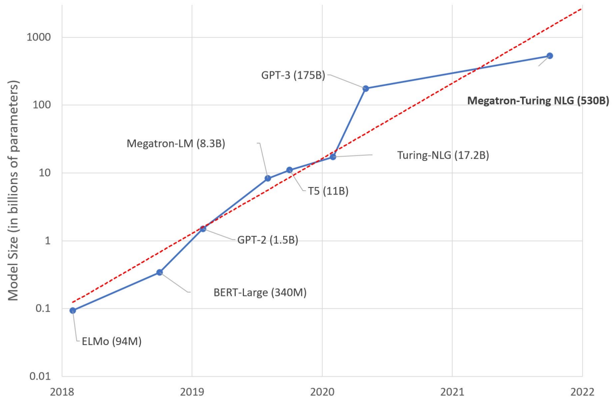
SECTOR: HEALTH CARE, PUBLIC SAFETY

ONE EVENING IN July of 2020, a woman named Kathryn went to the hospital in excruciating pain.

A 32-year-old psychology grad student in Michigan, Kathryn lived with endometriosis, an agonizing condition that causes uterine-like cells to abnormally develop in the wrong

ML Models More and More Complex





When is a model ready to deploy?
Hard to understand when models are working (for the right reasons) and not working!!

Isn’t test accuracy enough?

A User Study on Test Accuracy

“Why should I trust you?”: Explaining the Predictions of Any Classifier. Ribeiro, Singh & G. KDD 16

Train a neural network to predict wolf v. husky

Husky

Wolf

Slate

VIDEO SLATE IN MOTION. OCT. 14 2016 3:18 PM

The Man Who Accidentally Adopted a Wolf Pup

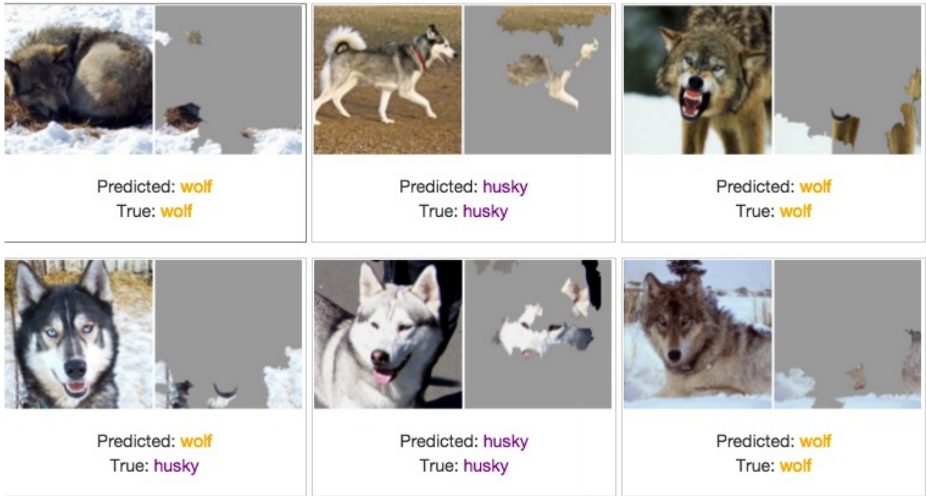
It did not go well.

By A.J. McCarthy

10k 547 6

Train a neural network to predict wolf v. husky

Explanations for neural network prediction



Test accuracy may not capture critical issues

- Bad data
- Biases
- Poor performance in critical cases
- ...

Examining Models

Debugging is One Reason to Examine Models

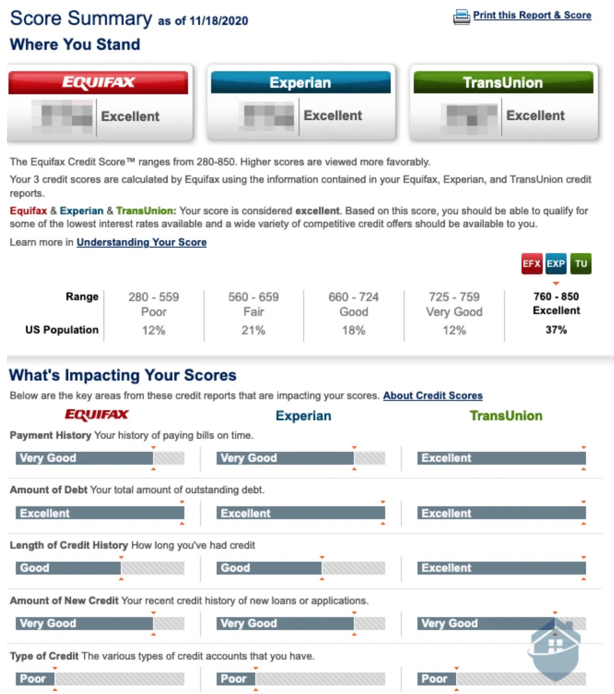
- Examining models:
  - Why a model makes particular predictions
  - What alternative predictions are possible
  - How robust/stable are predictions
  - What data supports predictions
- Examining models for debugging: discover bad, unexpected or unstable behavior
  - Typically not discovered by accuracy in train/test data

Examining Models to Detect Algorithmic Bias

- Evaluate multiple fairness criteria
- Verify how/if decisions depend on sensitive features
- Discover what groups are privileged/disadvantaged by predictions

Examine Models for Recourse

- In opioid overdose risk case, patient deemed risky had no way to discover why
  - Or how to fix bad data
- Understanding why could enable individuals to:
  - Address data issues
  - Change their actions to change outcomes

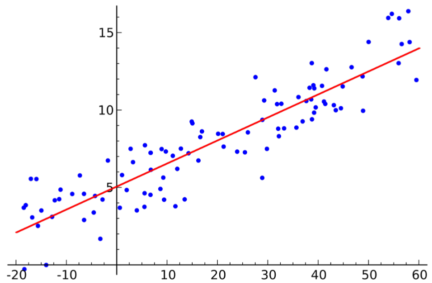


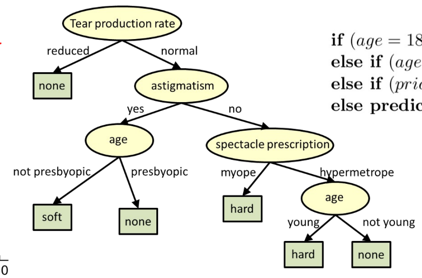
Interpretable Models vs Post-hoc Explanations

Interpretability in ML

*Giving humans a **mental model** of the machine's model behavior*

Learning Interpretable Models (c.f., Lethan & Rudin 2015)

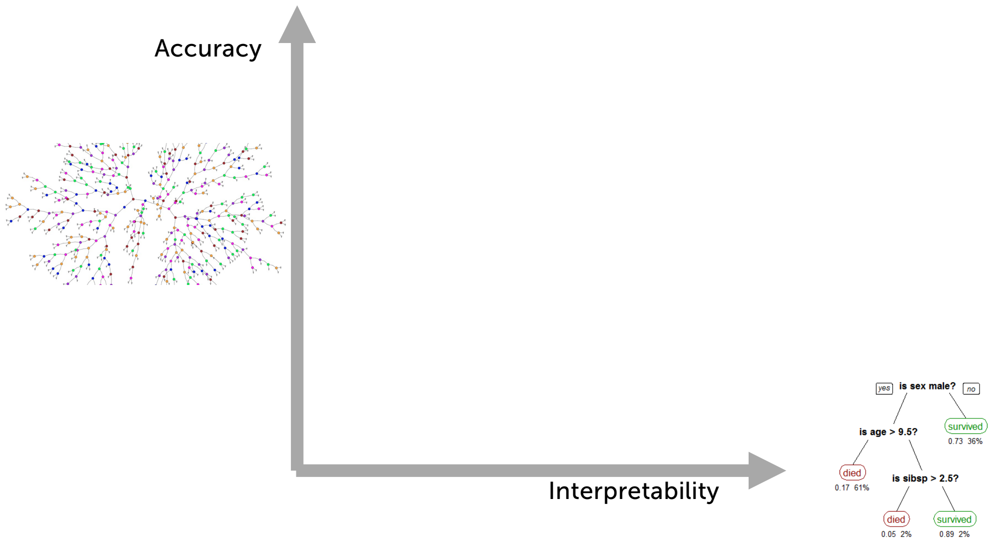




if $(age = 18 - 20)$ **and** $(sex = male)$ **then predict** yes
else if $(age = 21 - 23)$ **and** $(priors = 2 - 3)$ **then predict** yes
else if $(priors > 3)$ **then predict** yes
else predict no

Image credit: Lakkaraju, Adebayo, Singh NeurIPS 2020 Tutorial

Accuracy vs Interpretability



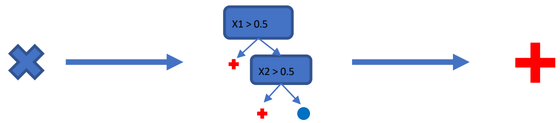
Post-hoc Explanations

- Given a (huge, complex) model, provide human explanations for predictions

LIME: Local, Interpretable Model-Agnostic Explanations

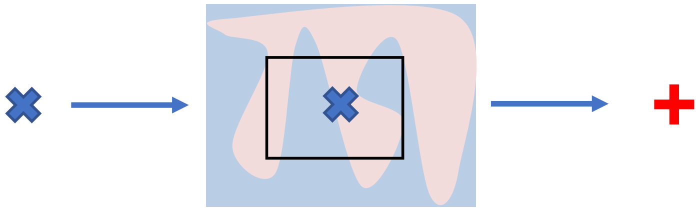
“Why should I trust you?”: Explaining the Predictions of Any Classifier. Ribeiro, Singh & G. KDD 16

Model agnostic → Ignore any internal structure



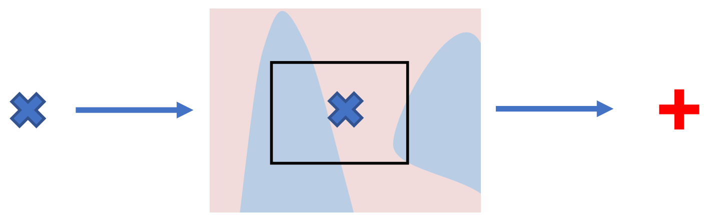
Explaining predictions

Global decision may be very complicat



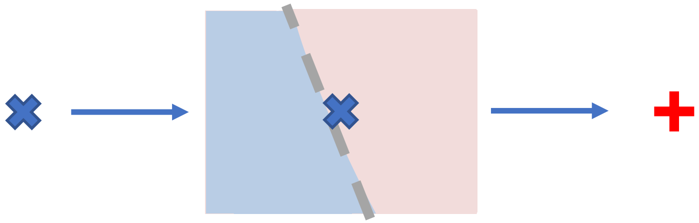
Explaining predictions

Locally, decision looks simpler…



Explaining predictions

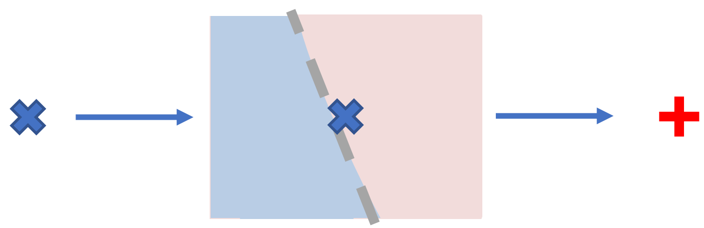
Very locally, decision looks linear



“Why should I trust you?”: Explaining the Predictions of Any Classifier. Ribeiro, Singh & G. KDD 16

Explaining predictions Very locally, decision looks linear

LIME: Learn locally sparse linear model around each prediction

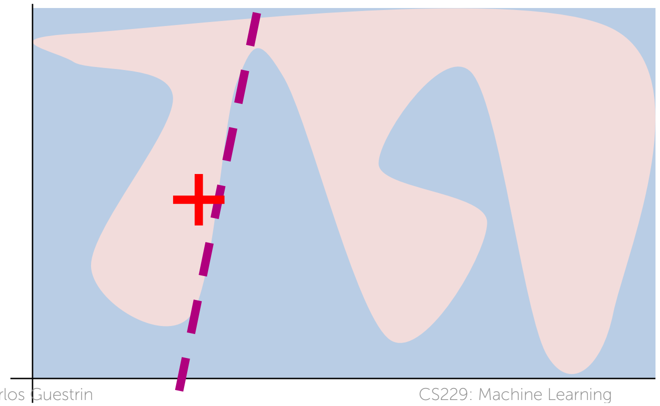


"Why should I trust you?": Explaining the Predictions of Any Classifier. Ribeiro, Singh & G. KDD 16

LIME – Key Ideas

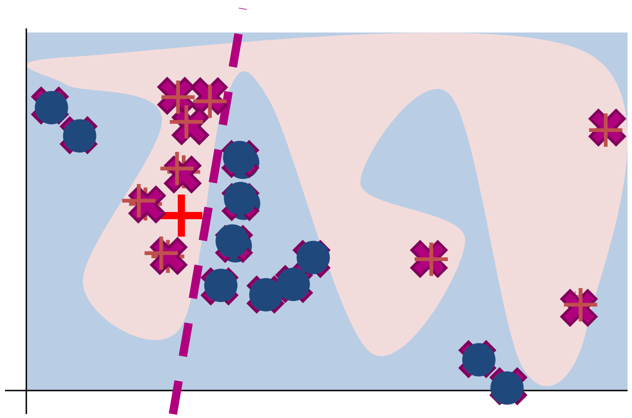
1. Pick a model class interpretable by humans

2. Locally approximate global (blackbox) model
   – Simple model globally bad, but locally good



Sparse linear Explanations

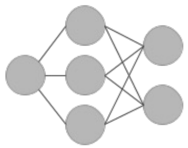
1. Sample points around x_i
2. Use complex model to predict labels for each sample
3. Weigh samples according to distance to x_i
4. Learn new simple model on weighted samples
5. Use simple model to explain



Interpretable representations

x (embeddings)

0.5	0.3	1.3	4.4	1.1	…



Model

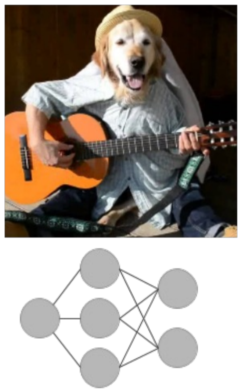
x' (words)

This is a horrible movie.

Human

Interpretable representation: images

x (3 color channels / pixel)

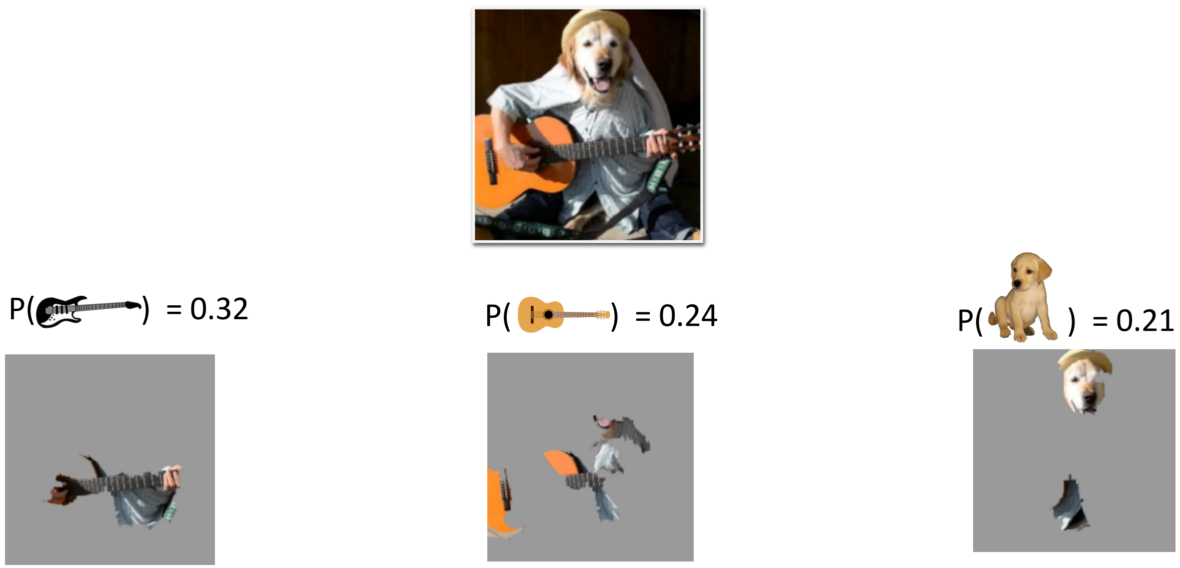


Model

x' (contiguous superpixels)

Human

Explaining prediction of Inception Neural Network



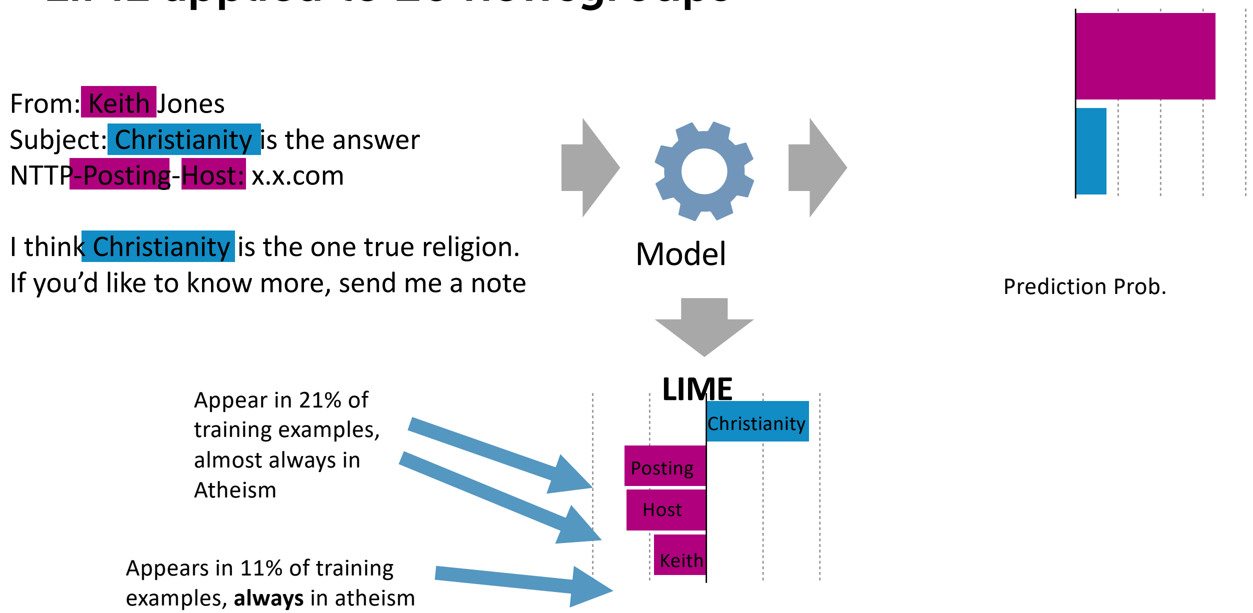
Achieving target metric may not be enough

Atheism vs Christianity posts
(Newsgroups data, circa 1995)

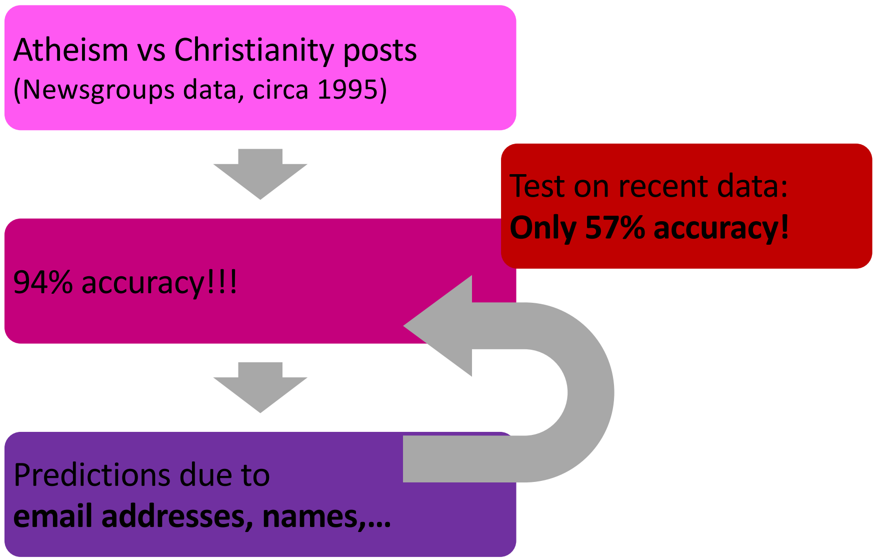
↓

94% accuracy!!!

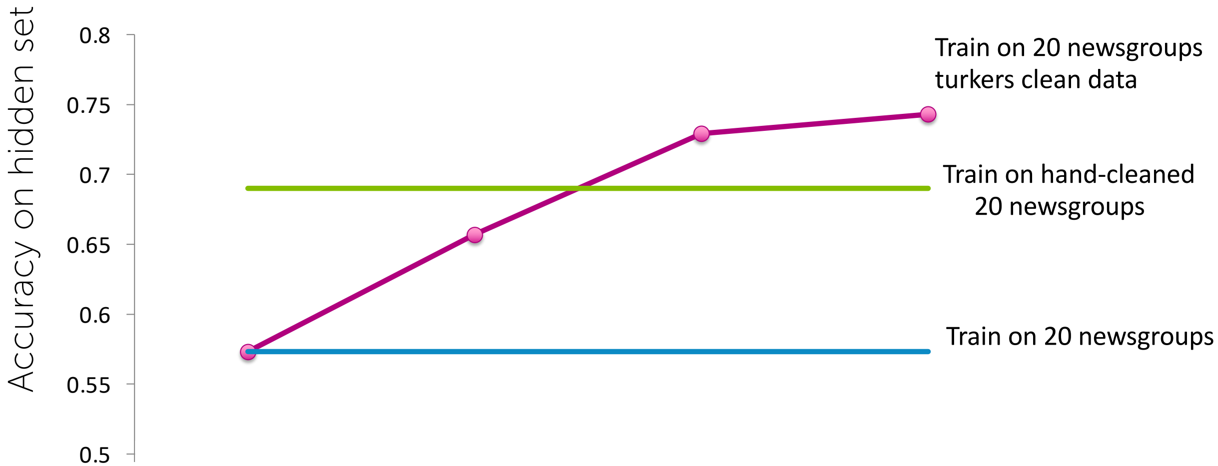
LIME applied to 20 newsgroups

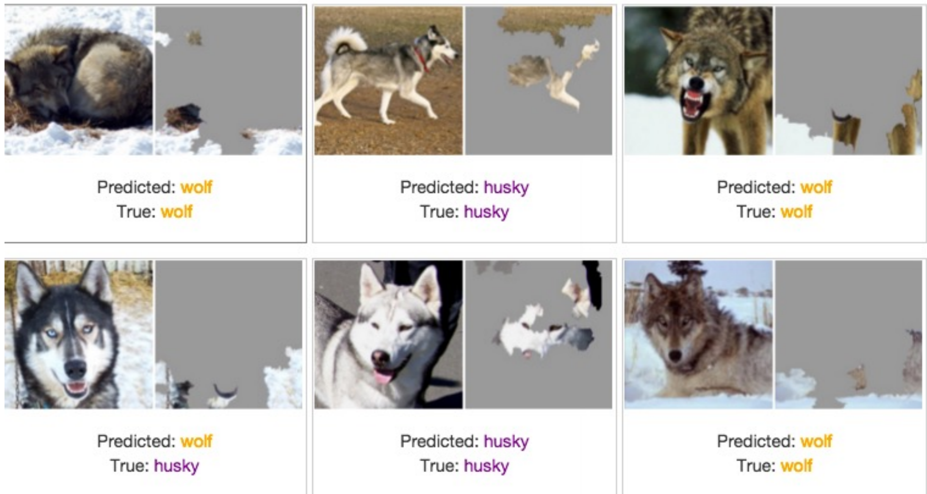


Achieving target metric may not be enough

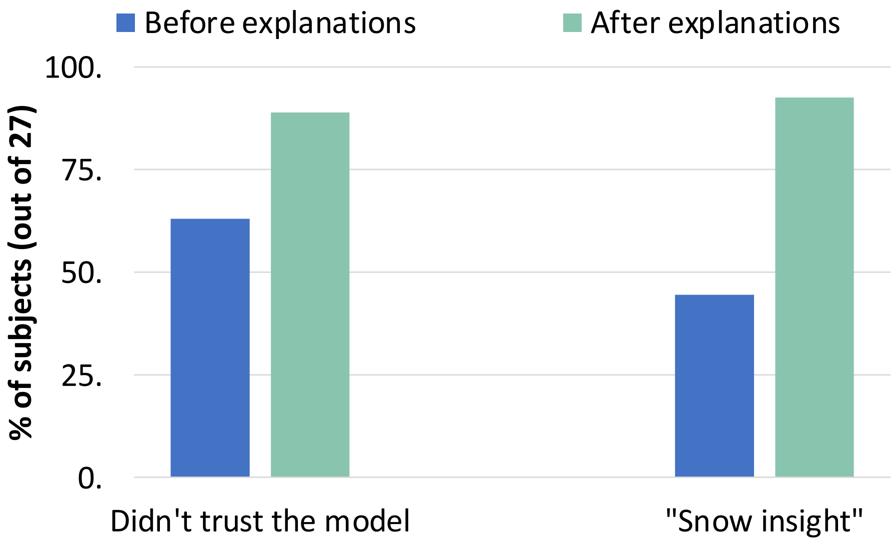


Fixing bad classifiers



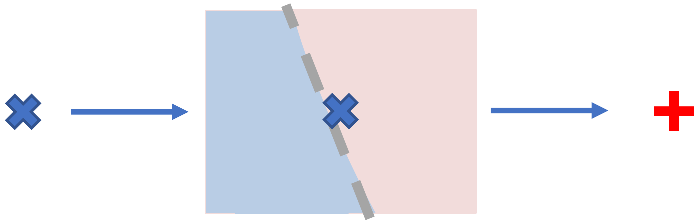

Predicted: wolf
True: wolf
Predicted: husky
True: husky
Predicted: wolf
True: wolf
Predicted: wolf
True: husky
Predicted: husky
True: husky
Predicted: wolf
True: wolf

Did explanations help with wolf problem?



More Examples

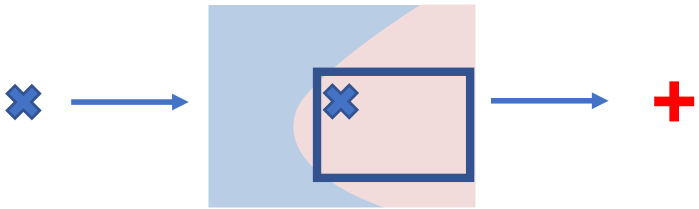
LIME: Learn locally sparse linear model around each prediction



“Why should I trust you?”: Explaining the Predictions of Any Classifier. Ribeiro, Singh & G. KDD 16

Anchors: Sufficient Conditions

Conditions under which classifier makes same prediction



Anchors: High-Precision Model-Agnostic Explanations. Ribeiro, Singh & G. AAAI 18

Salary Prediction

Feature	Value
Age	$37 < \text{Age} \leq 48$
Workclass	Private
Education	$\leq$ High School
Marital Status	Married
Occupation	Craft-repair
Relationship	Husband
Race	Black
Sex	Male
Capital Gain	0
Capital Loss	0
Hours per week	≤ 40
Country	United States

Salary Prediction: LIME vs Anchors

Feature	Value
Age	$37 < \text{Age} \leq 48$
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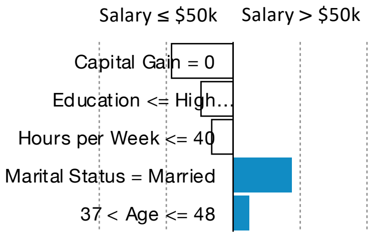
Model

Salary ≤ $50K

LIME



Anchor

IF Education ≤ High School
Then
P(prediction = ≤ 50K) > 0.95

Anchors for Images: Classification

Prediction: Beagle

Anchor for Beagle

Anchors for Visual Question Answering

What is the mustache made of?	*Banana*

How many bananas are in the picture?	*2*

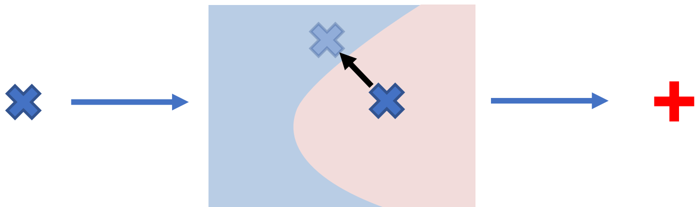
Anchors for Visual Question Answering

What is the mustache made of?	*Banana*
What is the ground made of?	*Banana*
What is the hair made of?	*Banana*
What is the picture of?	*Banana*
What was the head of the US?	*Banana*

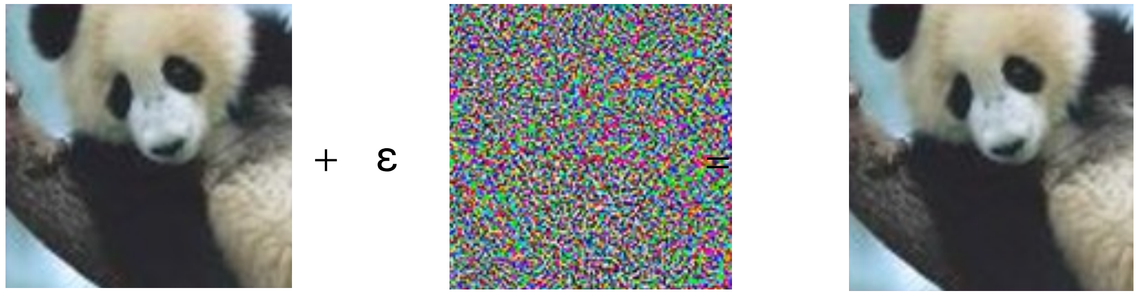
How **many** bananas are in the picture?	*2*
How **many** are in the picture?	*2*
How **many** people in the picture?	*2*
Are there **many** animals in the picture?	*2*
How **many** is too many?	*2*

Adversarial Bug Discovery

Find closest input with different prediction



Oversensitivity in image classification



"Panda" "Gibbon"

Adversary not distinguishable by human
→ Unlikely to be a real-world issue (except for attacks)

Explaining and Harnessing Adversarial Examples. Goodfellow, Shlens & Szegedy 2015

What type of road sign is shown?

STOP

The biggest city on the river Rhine is Cologne, Germany with a population of more than 1,050,000 people. It is the second-longest river in Central and Western Europe, at about 1,230 km.

How long is the Rhine?

1,230 km

What type of road sign is shown?

STOP

Which type of road sign is shown?

Do not enter

The biggest city on the river Rhine is Cologne, Germany with a population of more than 1,050,000 people. It is the second-longest river in Central and Western Europe, at about 1,230 km.

How long is the Rhine?

1,230 km

How long is the Rhine??

More than 1,050,000

Goal: Find semantically-equivalent adversarial examples

Semantically Equivalent Adversarial Rules for Debugging NLP Models. Ribeiro, Singh & G. ACL 18

Semantically-equivalent

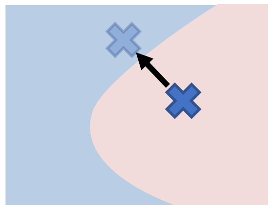
Use paraphrasing model
[Lapata et al. 2017]

+

Adversarial

Changes correct
model prediction

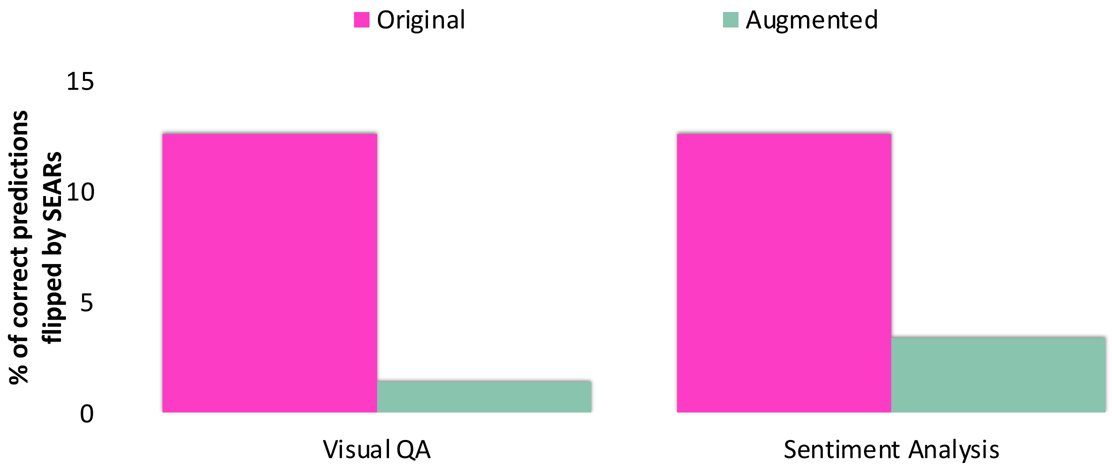
What color is the tray?	*Pink*
What **colour** is the tray?	*Green*
Which color is the tray?	*Green*
What color is **it**?	*Green*
What color is ~~the~~ tray?	*Pink*
How color is ~~the~~ tray?	*Green*



Semantically Equivalent Adversarial Rules for Debugging NLP Models. Ribeiro, Singh & G. ACL 18

Closing the Loop with Simple Data Augmentation

Augment by applying validated SEARs to training data



Typical challenges with explainability methods

- Explanations to simplistic
- Not focused on information needs for task
- Unstable
- Not causal
- …