THE WEB CONFERENCE | TAIPEI 2020

Explainable AI in Industry

WWW 2020 Tutorial

Krishna Gade, Sahin Cem Geyik,
Krishnaram Kenthapadi, Varun Mithal,
Ankur Taly

https://sites.google.com/view/www20-explainable-ai-tutorial

Agenda

- Part I: Introduction and Motivation
  - Motivation and Need for Explainable AI
  - Challenges for Explainable AI @ Scale
- Part II: Explainable Machine Learning
  - Overview of Explainable AI Techniques
- Part III: Case Studies from Industry
  - Applications, Key Challenges, and Lessons Learned
- Part IV: Open Problems, Research Challenges, and Conclusion

Introduction and Motivation

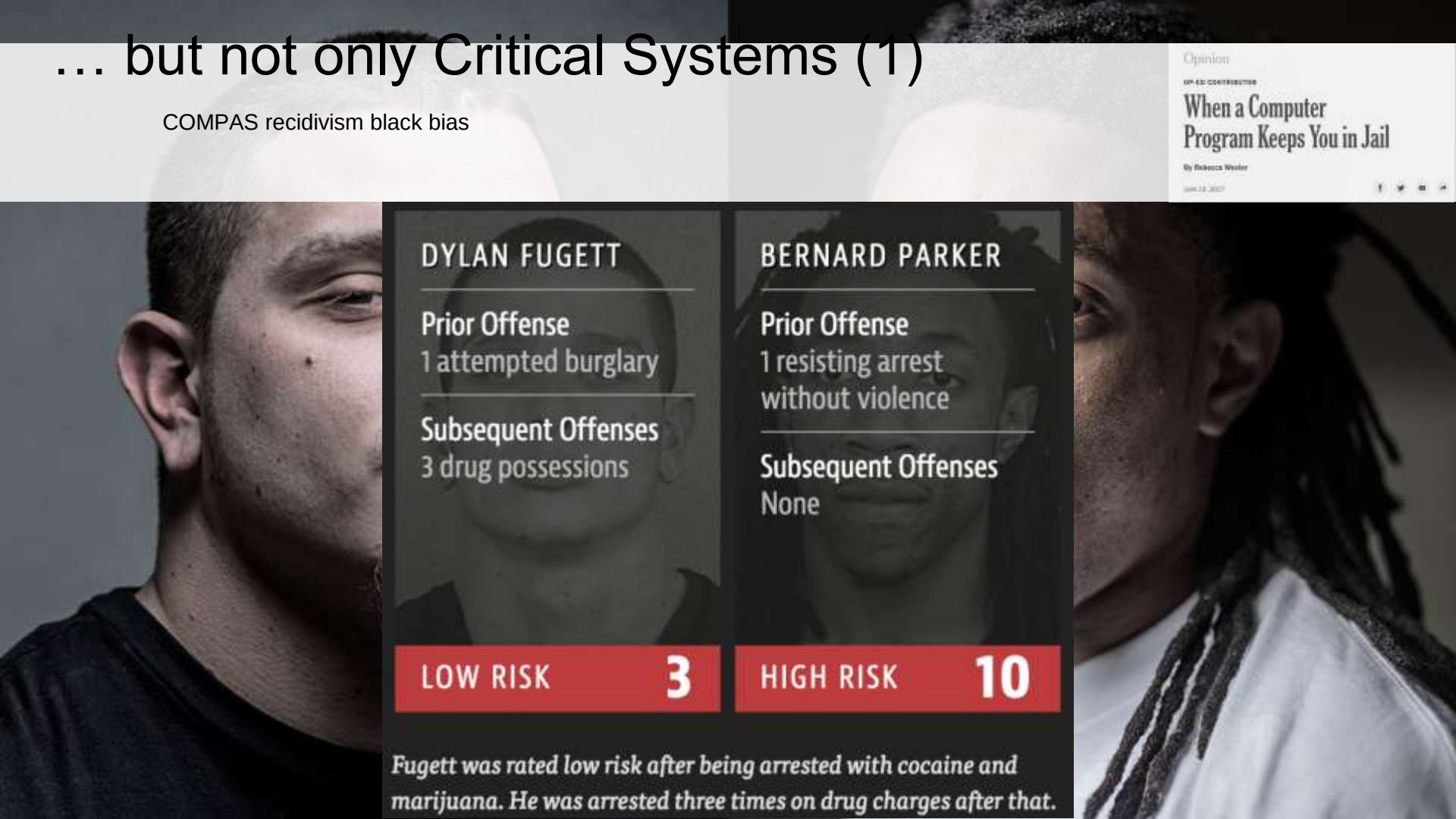
Explanation - From a Business Perspective

Critical Systems (1)

Critical Systems (2)

… but not only Critical Systems (1)

COMPAS recidivism black bias



… but not only Critical Systems (2)

Finance:

- Credit scoring, loan approval
- Insurance quotes

community.fico.com/s/explainable-machine-learning-challenge

https://www.ft.com/content/e07cee0c-3949-11e7-821a-6027b8a20f23

… but not only Critical Systems (3)

Healthcare

- Applying ML methods in medical care is problematic.
- AI as 3rd-party actor in physician-patient relationship
- Responsibility, confidentiality?
- Learning must be done with available data.

  Cannot randomize cares given to patients!
- Must validate models before use.

Patricia Hannon ,https://med.stanford.edu/news/all-news/2018/03/researchers-say-use-of-ai-in-medicine-raises-ethical-questions.html

Rich Caruana, Yin Lou, Johannes Gehrke, Paul Koch, Marc Sturm, Noemie Elhadad: Intelligible Models for HealthCare: Predicting Pneumonia Risk and Hospital 30-day Readmission. KDD 2015: 1721-1730

Black-box AI creates business risk for Industry

Bloomberg Businessweek

Apple Card's Gender-Bias Claims Look Familiar to Old-School Banks

Updated on November 12, 2019, 4:23 AM

MIT News

Study finds gender and skin-type bias in commercial AI systems

Feb 12, 2018

BBC NEWS

Tay: Microsoft issues apology over racist chatbot fiasco

Sep 22, 2017

Missouri S&T News and Research

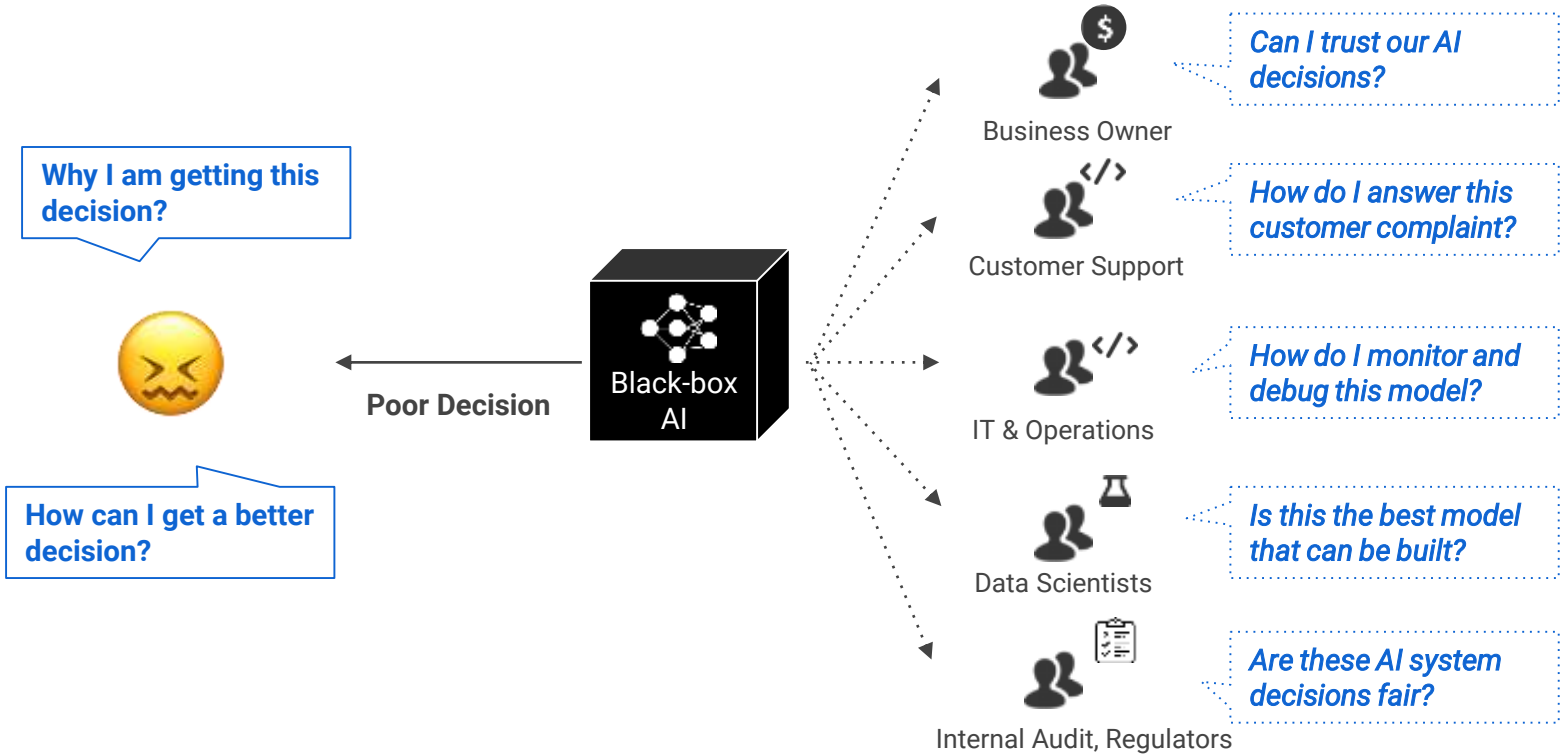
After Uber, Tesla incidents, can artificial intelligence be trusted?

Apr 10, 2018

Guilty! AI Is Found to Perpetuate Biases in Jailing

1 day ago

Black-box AI creates confusion and doubt



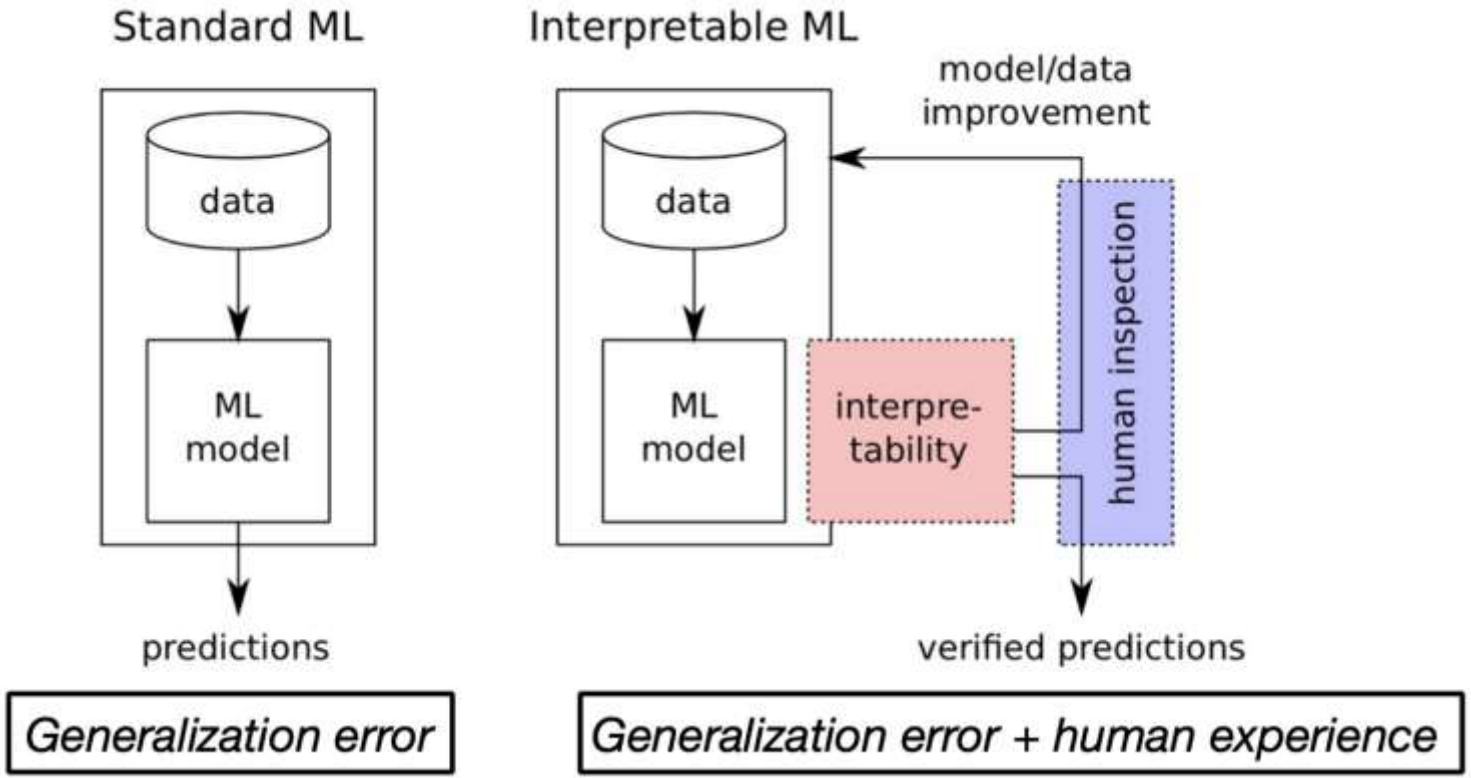
Explanation - From a Model Perspective

Why Explainability: Debug (Mis-)Predictions

Top label: **“clog”**

Why did the network label this image as **“clog”**?

Why Explainability: Improve ML Model



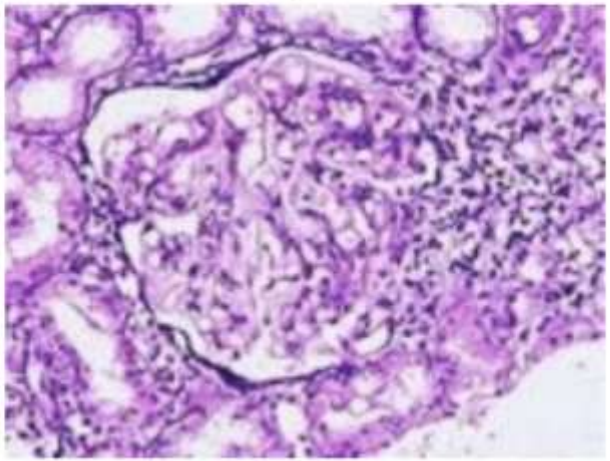
Credit: Samek, Binder, Tutorial on Interpretable ML, MICCAI'18

Why Explainability: Verify the ML Model / System

Wrong decisions can be costly and dangerous

"Autonomous car crashes, because it wrongly recognizes …"

"AI medical diagnosis system misclassifies patient's disease …"

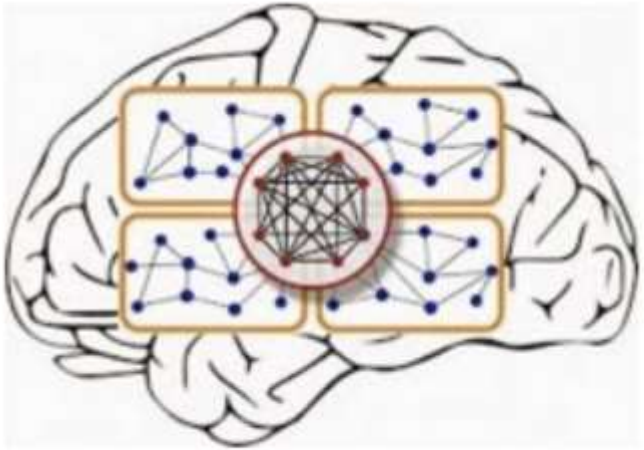


Credit: Samek, Binder, Tutorial on Interpretable ML, MICCAI'18

Why Explainability: Learn New Insights

"It's not a human move. I've never seen a human play this move." (Fan Hui)

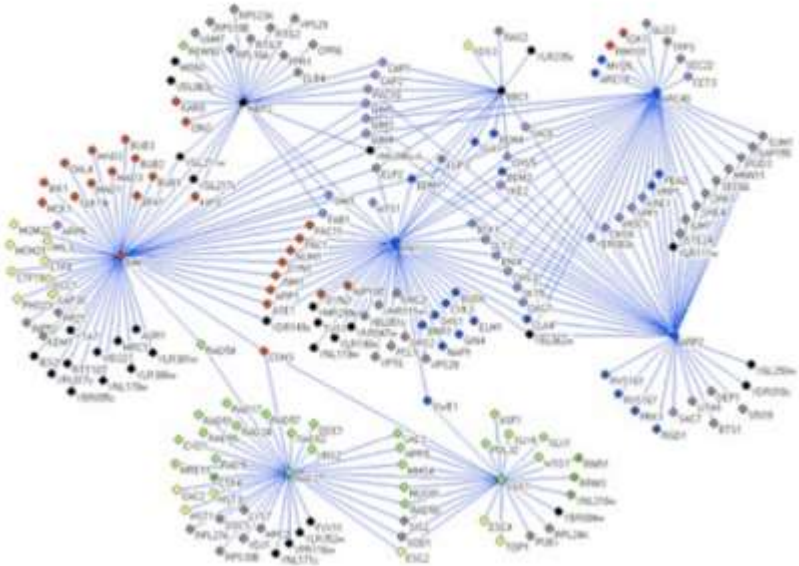
Old promise:
"Learn about the human brain."

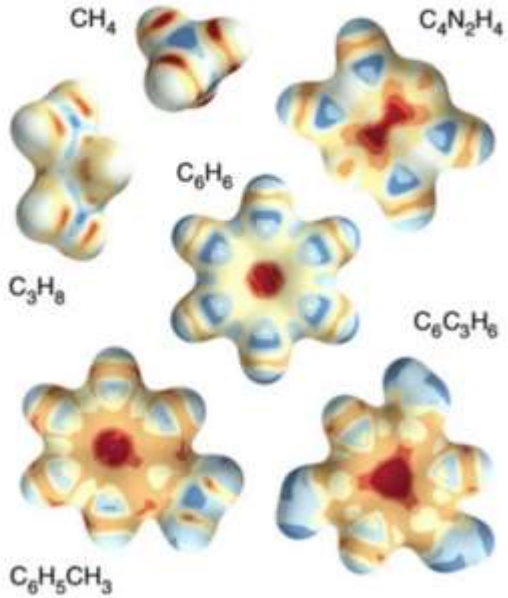


Credit: Samek, Binder, Tutorial on Interpretable ML, MICCAI'18

Why Explainability: Learn Insights in the Sciences

Learn about the physical / biological / chemical mechanisms.
(e.g. find genes linked to cancer, identify binding sites …)





Credit: Samek, Binder, Tutorial on Interpretable ML, MICCAI'18

Explanation - From a Regulatory Perspective

Why Explainability: Laws against Discrimination

Citizenship

Immigration Reform and Control Act

Sex

Equal Pay Act of 1963;
Civil Rights Act of 1964

Age

Age Discrimination in Employment Act of 1967

Race

Civil Rights Act of 1964

Disability status

Rehabilitation Act of 1973;
Americans with Disabilities Act of 1990

And more...

SR 11-7: Guidance on Model Risk Management

BOARD OF GOVERNORS
OF THE FEDERAL RESERVE SYSTEM
WASHINGTON, D.C. 20551

Fairness

Privacy

Transparency

Explainability

GDPR Concerns Around Lack of Explainability in AI

“

Companies should commit to ensuring systems that could fall under GDPR, including AI, will be compliant. The threat of ***sizeable fines of €20 million or 4% of global turnover*** *provides a sharp incentive.*

Article 22 of GDPR empowers individuals with the ***right to demand an explanation of how an AI system made a decision that affects them.***

”

- European Commision

VP, European Commision

Article 22. Automated individual decision making, including profiling

1. The data subject shall have the right not to be subject to a decision based solely on automated processing, including profiling, which produces legal effects concerning him or her or similarly significantly affects him or her.
2. Paragraph 1 shall not apply if the decision:
   (a) is necessary for entering into, or performance of, a contract between the data subject and a data controller;
   (b) is authorised by Union or Member State law to which the controller is subject and which also lays down suitable measures to safeguard the data subject's rights and freedoms and legitimate interests; or
   (c) is based on the data subject's explicit consent.
3. In the cases referred to in points (a) and (c) of paragraph 2, the data controller shall implement suitable measures to safeguard the data subject's rights and freedoms and legitimate interests, at least the right to obtain human intervention on the part of the controller, to express his or her point of view and to contest the decision.
4. Decisions referred to in paragraph 2 shall not be based on special categories of personal data referred to in Article 9(1), unless point (a) or (g) of Article 9(2) apply and suitable measures to safeguard the data subject's rights and freedoms and legitimate interests are in place.

Recital 71

Profiling*

Fai

cy

[1] The data subject should have the right not to be subject to a decision, which may include a measure, evaluating personal aspects relating to him or her which is based solely on automated processing and which produces legal effects concerning him or her or similarly significantly affects him or her, such as automatic refusal of an online credit application or e-recruiting practices without any human intervention. [2] Such processing includes 'profiling' that consists of any form of automated processing of personal data evaluating the personal aspects relating to a natural person, in particular to analyse or predict aspects concerning the data subject's performance at work, economic situation, health, personal preferences or interests, reliability or behaviour, location or movements, where it produces legal effects concerning him or her or similarly significantly affects him or her. [3] However, decision-making based on such processing,

Transparency

Explainability

Why Explainability: Growing Global AI Regulation

- GDPR: Article 22 empowers individuals with the right to demand an explanation of how an automated system made a decision that affects them.
- Algorithmic Accountability Act 2019: Requires companies to **provide an assessment of the risks** posed by the automated decision system to the **privacy** or **security** and the risks that contribute to **inaccurate, unfair, biased, or discriminatory decisions** impacting consumers
- California Consumer Privacy Act: Requires companies to rethink their approach to capturing, storing, and sharing personal data to align with the new requirements by January 1, 2020.
- Washington Bill 1655: Establishes guidelines for the use of automated decision systems to protect consumers, improve transparency, and create more market predictability.
- Massachusetts Bill H.2701: Establishes a commission on automated decision-making, transparency, fairness, and individual rights.
- Illinois House Bill 3415: States predictive data analytics determining creditworthiness or hiring decisions may not include information that correlates with the applicant race or zip code.

SR 11-7 and OCC regulations for Financial Institutions

SR 11-7: Guidance on Model Risk Management

BOARD OF GOVERNORS
OF THE FEDERAL RESERVE SYSTEM
WASHINGTON, D.C. 20551

What's driving Stress Testing and Model Risk Management efforts?

Regulatory efforts

SR 11-7 says "Banks benefit from **conducting model stress testing** to check performance over a wide range of inputs and parameter values, including extreme values, **to verify that the model is robust**"

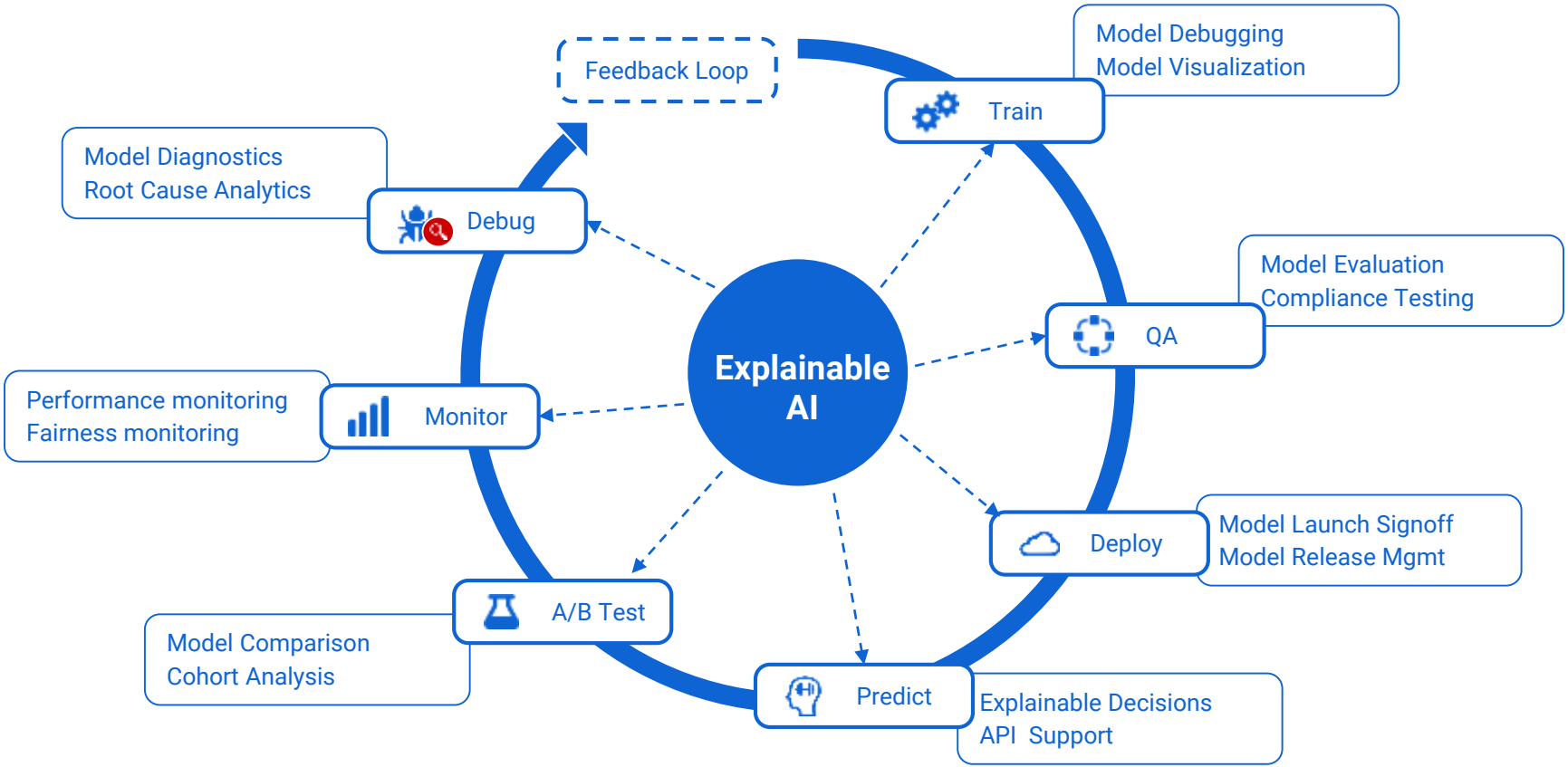
In fact, **SR14-03** explicitly calls for **all models used for Dodd-Frank Act Company-Run Stress Tests must fall under the purview of Model Risk Management**.

In addition **SR12-07** calls for **incorporating validation or other type of independent review of the stress testing framework to ensure the integrity of stress testing processes and results.**

JOHN HILL
GLOBAL HEAD OF MODEL RISK GOVERNANCE, CREDIT SUISSE

"In the current regulatory environment, model validation policies must be fully compliant with the requirements of SR11-7. While SR11-7 officially applies to US conforming bank and non-US banks doing business in the US, many European financial firms have adopted SR11-7 as their standard as well."

“Explainability by Design” for AI products



AI @ Scale - Challenges for Explainable AI

LinkedIn operates the largest professional network on the Internet

645M+ members

35K+
skills listed

30M+
companies are represented on LinkedIn

20M+
open jobs on LinkedIn Jobs

90K+
schools listed (high school & college)

280B
Feed updates

The AWS ML Stack

Broadest and most complete set of Machine Learning capabilities

AI SERVICES

VISION	SPEECH		TEXT			SEARCH NEW	CHATBOTS	PERSONALIZATION	FORECASTING	FRAUD NEW	DEVELOPMENT NEW	CONTACT CENTERS NEW
Amazon Rekognition	Amazon Polly	Amazon Transcribe NEW *+Medical*	Amazon Comprehend *+Medical*	Amazon Translate	Amazon Textract	Amazon Kendra	Amazon Lex	Amazon Personalize	Amazon Forecast	Amazon Fraud Detector	Amazon CodeGuru	Contact Lens *For Amazon Connect*

ML SERVICES

Amazon SageMaker

Ground Truth | Augmented AI

SageMaker Studio IDE NEW

Built-in algorithms | SageMaker Notebooks NEW | SageMaker Experiments NEW | Model tuning | SageMaker Debugger NEW | SageMaker Autopilot NEW | Model hosting | SageMaker Model Monitor NEW

SageMaker Neo

ML FRAMEWORKS & INFRASTRUCTURE

TensorFlow NEW | mxnet NEW | PYTORCH NEW

GLUON | Keras

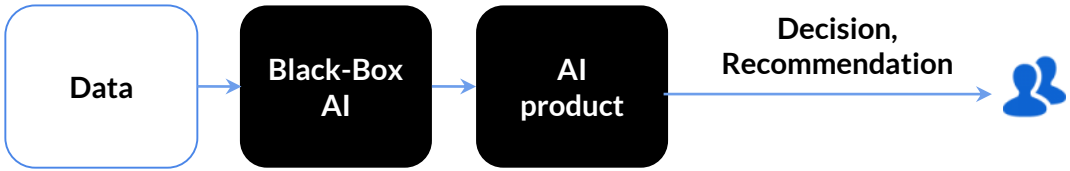
Deep Learning AMIs & Containers | GPUs & CPUs | Elastic Inference | Inferentia | FPGA

aws machine learning

Explanation - In a Nutshell

What is Explainable AI?

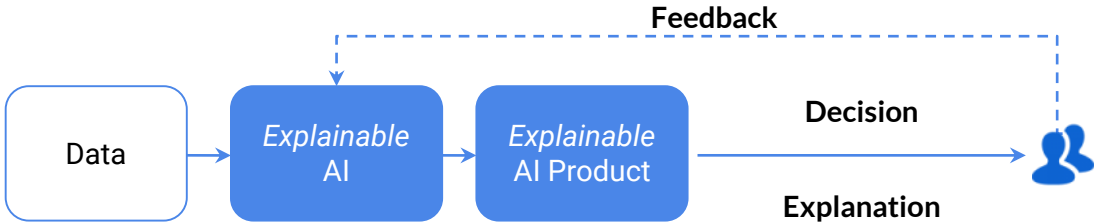
Black Box AI



Confusion with Today's AI Black Box

- Why did you do that?
- Why did you not do that?
- When do you succeed or fail?
- How do I correct an error?

Explainable AI

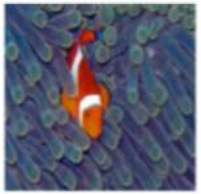


Clear & Transparent Predictions

- I understand why
- I understand why not
- I know why you succeed or fail
- I understand, so I trust you

Example of an End-to-End XAI System

1



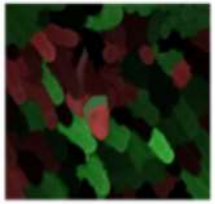
ML Classifier

C: I predict FISH

2

H: Why?

C: See below:



Green regions argue for FISH, while RED pushes towards DOG. There's more green.

3

H: (Hmm. Seems like it might be just recognizing anemone texture!) Which training examples are most influential to the prediction?

C: These ones:

4

H: What happens if the background anemones are removed? E.g.,

C: I still predict FISH, because of these green superpixels:

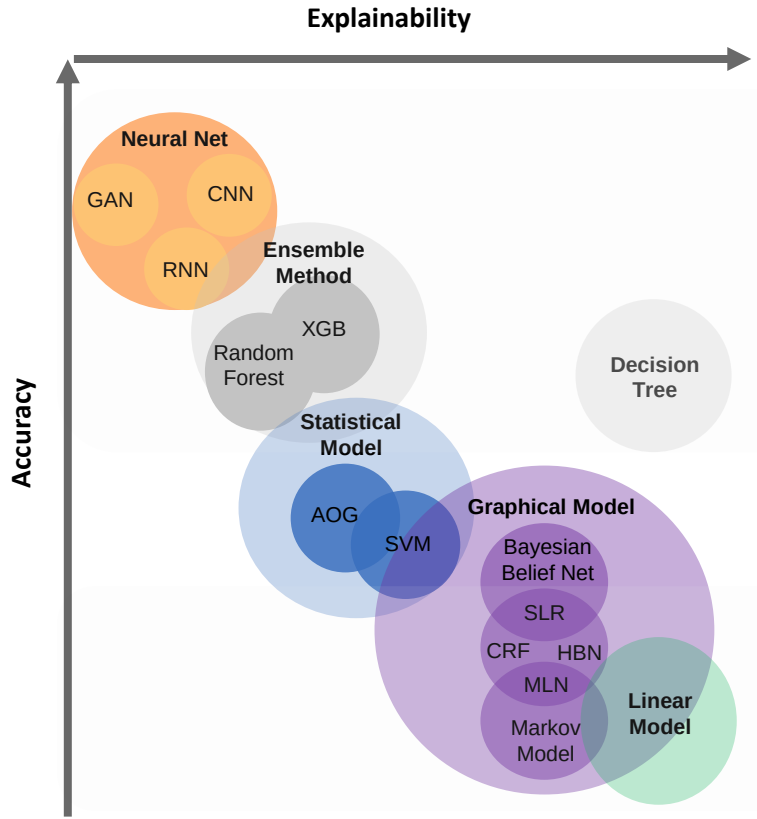
- Humans may have follow-up questions
- Explanations cannot answer all users' concerns

Weld, D., and Gagan Bansal. "The challenge of crafting intelligible intelligence." Communications of ACM (2018).

How to Explain? Accuracy vs. Explainability

Learning

- Challenges:
  - Supervised
  - Unsupervised learning
- Approach:
  - Representation Learning
  - Stochastic selection
- Output:
  - **Correlation**
  - **No causation**



Interpretability

- Non-Linear functions
- Polynomial functions
- Quasi-Linear functions

XAI Definitions - Explanation vs. Interpretation

Oxford Dictionary of English

explanation | ɛksplə'neɪʃ(ə)n |

noun

a statement or account that makes something clear: *the birth rate is central to any explanation of population trends.*

interpret | ɪn'tə:prɪt |

verb **(interprets, interpreting, interpreted)** *[with object]*

1 explain the meaning of (information or actions): *the evidence is difficult to interpret.*

On the Role of Data in XAI

Table of baby-name data
(baby-2010.csv)

name	rank	gender	year
Jacob	1	boy	2010
Isabella	1	girl	2010
Ethan	2	boy	2010
Sophia	2	girl	2010
Michael	3	boy	2010

Field names

One row (4 fields)

2000 rows all told

Tabular

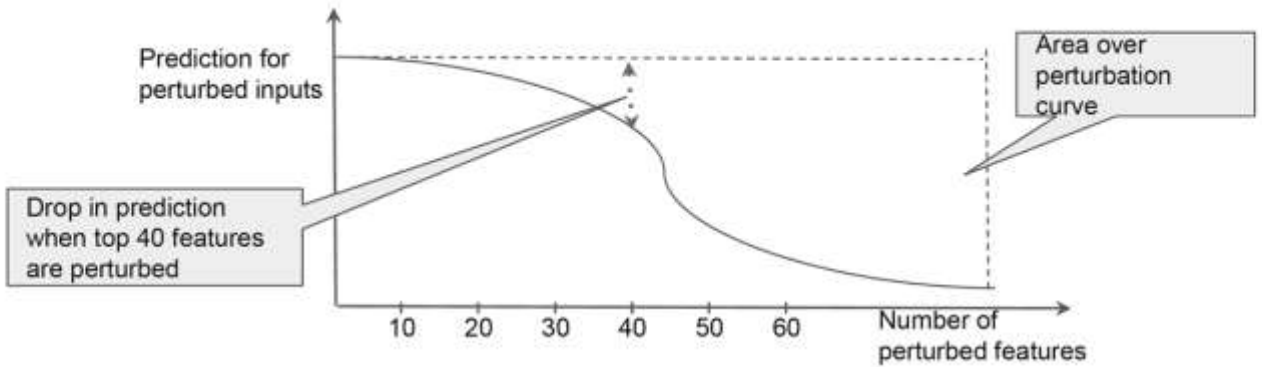
Images

Text

Evaluation (1) - Perturbation-based Approaches

Perturb top-k features by attribution and observe change in prediction

- Higher the change, better the method
- Perturbation may amount to replacing the feature with a random value
- Samek et al. formalize this using a metric: **Area over perturbation curve**
  - Plot the prediction for input with top-k features perturbed as a function of k
  - Take the area over this curve



Evaluation (2) - Human (Role)-based Evaluation is Essential… but too often based on size!

Evaluation criteria for Explanations [Miller, 2017]

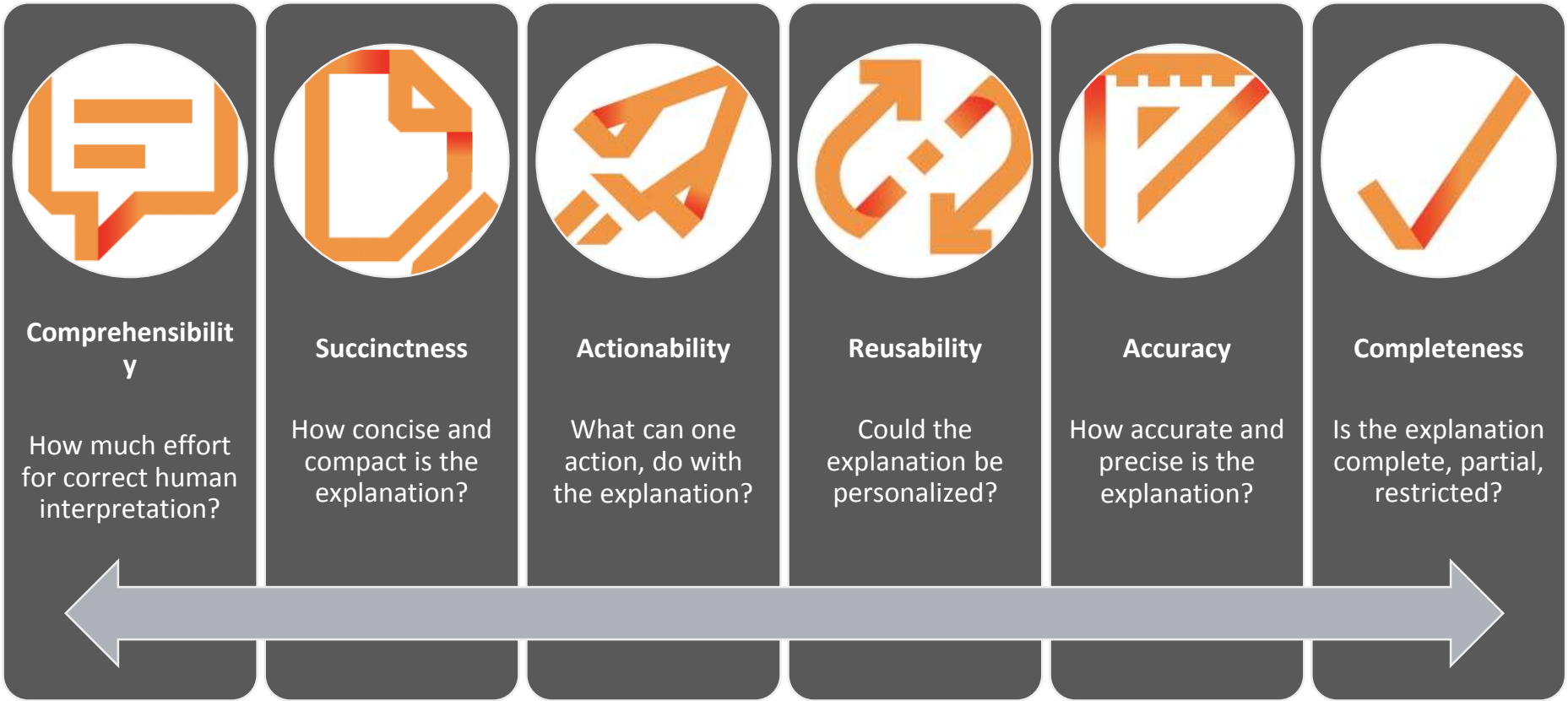
- Truth & probability
- Usefulness, relevance
- Coherence with prior belief
- Generalization

Cognitive chunks = basic explanation units (for different explanation needs)

- Which basic units for explanations?
- How many?
- How to compose them?
- Uncertainty & end users?

[Doshi-Velez and Kim 2017, Poursabzi-Sangdeh 18]

Evaluation (3) - XAI: One Objective, Many Metrics



Source: Accenture Point of View. Understanding Machines: Explainable AI. Freddy Lecue, Dadong Wan

Explainable AI

(from a Machine Learning Perspective)

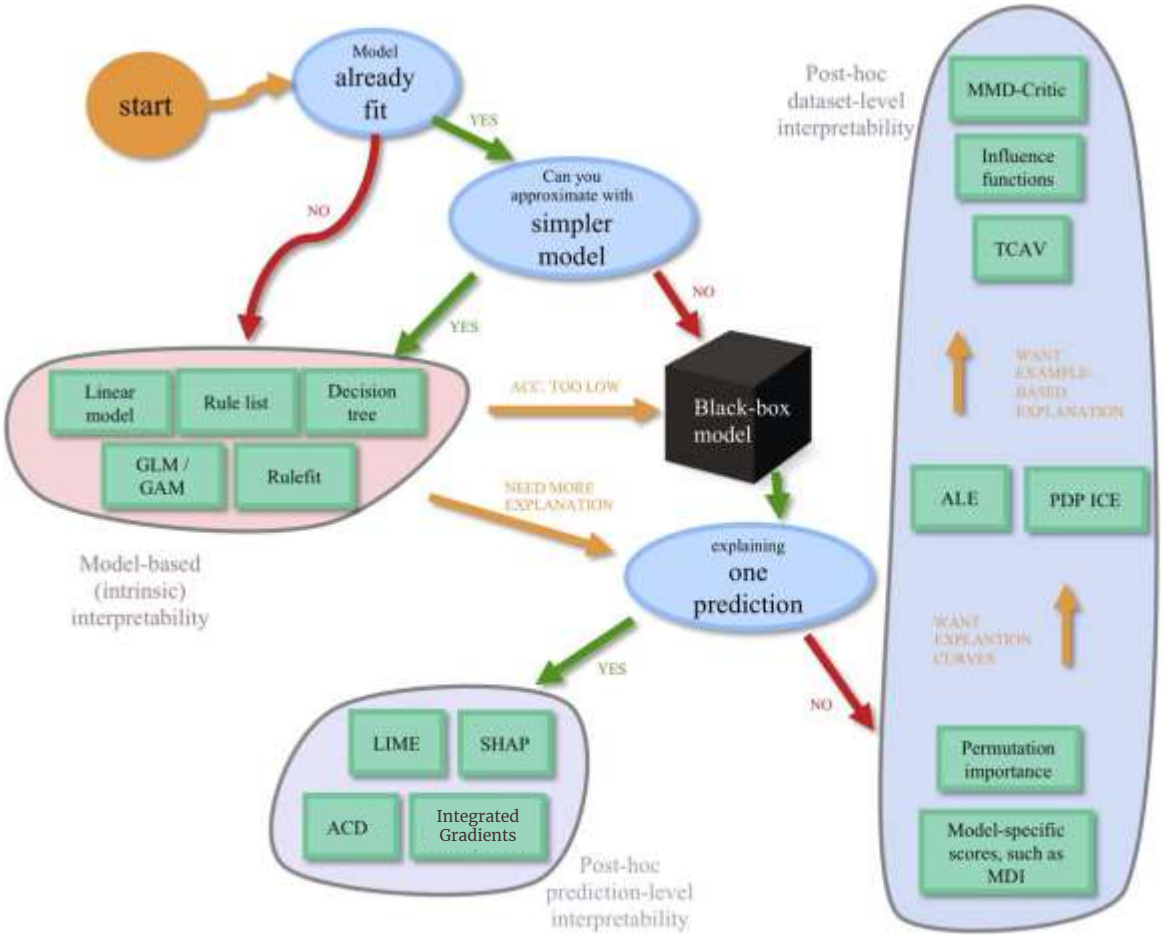
Achieving Explainable AI

Approach 1: **Post-hoc explain a given AI model**

- **Individual prediction explanations** in terms of input features, influential examples, concepts, local decision rules
- **Global prediction explanations** in terms of entire model in terms of partial dependence plots, global feature importance, global decision rules

Approach 2: **Build an interpretable model**

- Logistic regression, Decision trees, Decision lists and sets, Generalized Additive Models (GAMs)



interpretability cheat-sheet

View on github

Based on this interpretability review and the sklearn cheat-sheet.
More in this book + these slides.

Summaries and links to code

RuleFit – automatically add features extracted from a small tree to a linear model

LIME – linearly approximate a model at a point

SHAP – find relative contributions of features to a prediction

ACD – hierarchical feature importances for a DNN prediction

Text – DNN generates text to explain a DNN's prediction (sometimes not faithful)

Permutation importance – permute a feature and see how it affects the model

ALE – perturb feature value of nearby points and see how outputs change

PDP ICE – vary feature value of all points and see how outputs change

TCAV – see if representations of certain points learned by DNNs are linearly separable

Influence functions – find points which highly influence a learned model

MMD-CRITIC – find a few points which summarize classes

Slide credit: https://twitter.com/chandan_singh96/status/1138811752769101825

Achieving Explainable AI

Approach 1: **Post-hoc explain a given AI model**

- **Individual prediction explanations** in terms of input features, influential examples, concepts, local decision rules
- **Global prediction explanations** in terms of entire model in terms of partial dependence plots, global feature importance, global decision rules

Approach 2: **Build an interpretable model**

- Logistic regression, Decision trees, Decision lists and sets, Generalized Additive Models (GAMs)

Individual Prediction Explanations

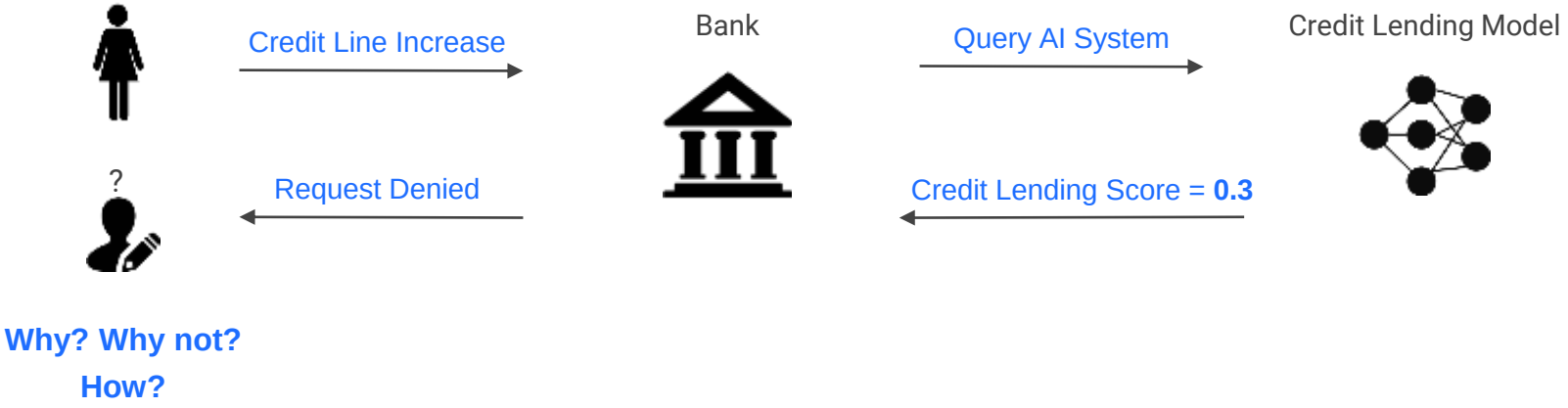
Top label: **“clog”**

Why did the network label this image as **“clog”**?

Top label: **“fireboat”**

Why did the network label this image as **“fireboat”**?

Credit Lending in a black-box ML world



Fair lending laws [ECOA, FCRA] require credit decisions to be explainable

The Attribution Problem

Attribute a model's prediction on an input to features of the input

Examples:

- Attribute an object recognition network's prediction to its pixels
- Attribute a text sentiment network's prediction to individual words
- Attribute a lending model's prediction to its features

A reductive formulation of "why this prediction" but surprisingly useful

Application of Attributions

- Debugging model predictions
  E.g., Attribution an image misclassification to the pixels responsible for it
- Generating an explanation for the end-user
  E.g., Expose attributions for a lending prediction to the end-user
- Analyzing model robustness
  E.g., Craft adversarial examples using weaknesses surfaced by attributions
- Extract rules from the model
  E.g., Combine attribution to craft rules (pharmacophores) capturing prediction logic of a drug screening network

Next few slides

We will cover the following **attribution methods****

- Ablations
- Gradient based methods (specific to differentiable models)
- Score Backpropagation based methods (specific to NNs)

We will also discuss game theory (Shapley value) in attributions

**Not a complete list!
See Ancona et al. [ICML 2019], Guidotti et al. [arxiv 2018] for a comprehensive survey

Ablations

Drop each feature and attribute the change in prediction to that feature

Pros:

- Simple and intuitive to interpret

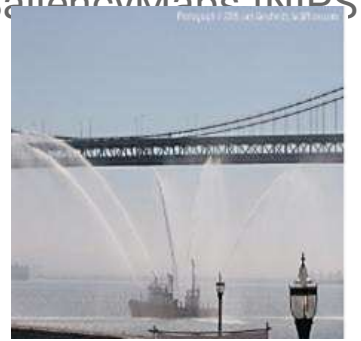
Cons:

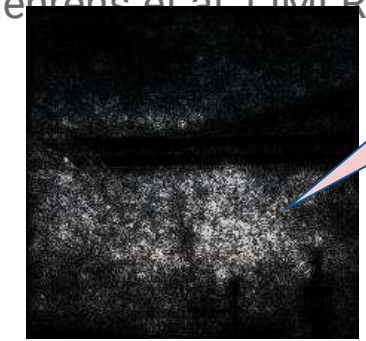
- Unrealistic inputs
- Improper accounting of interactive features
- Can be computationally expensive

Feature*Gradient

Attribution to a feature is feature value times gradient, i.e., $x_i * \partial y/\partial x_i$

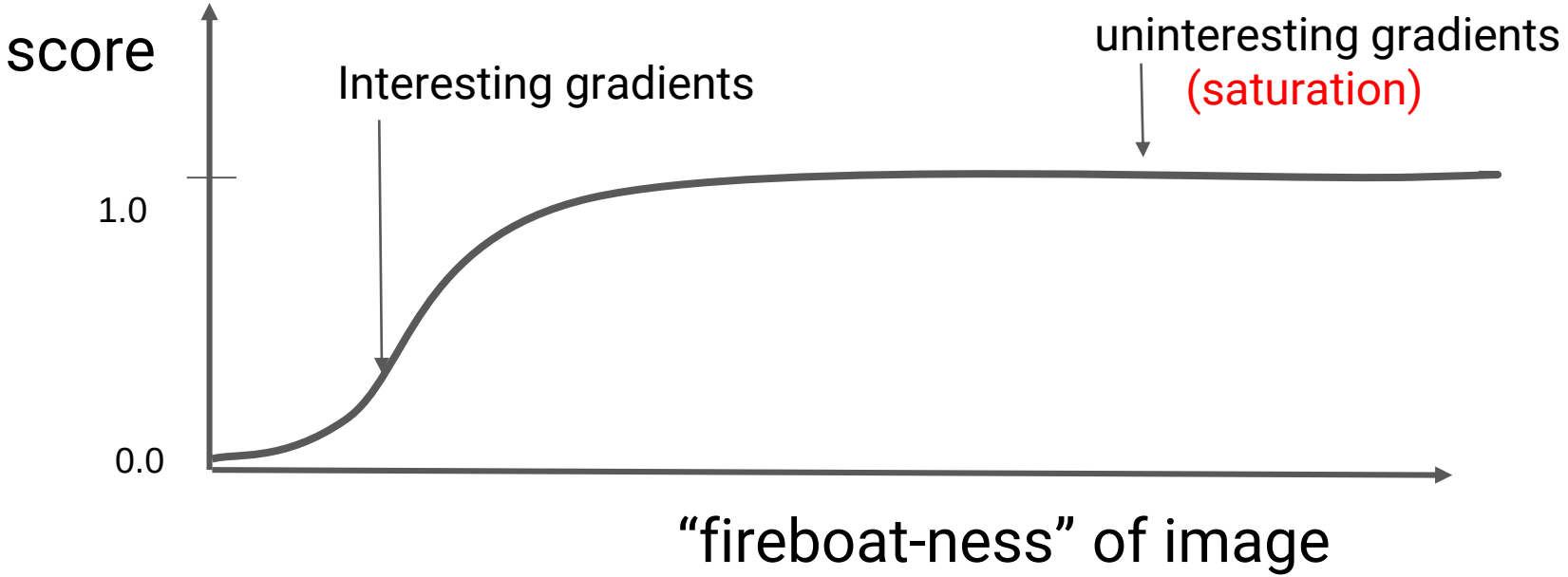
- Gradient captures sensitivity of output w.r.t. feature
- Equivalent to Feature*Coefficient for linear models
  - **First-order Taylor approximation** of non-linear models
- Popularized by SaliencyMaps [NIPS 2013], Baehrens et al. [JMLR 201





Gradients in the vicinity of the input seem like noise?

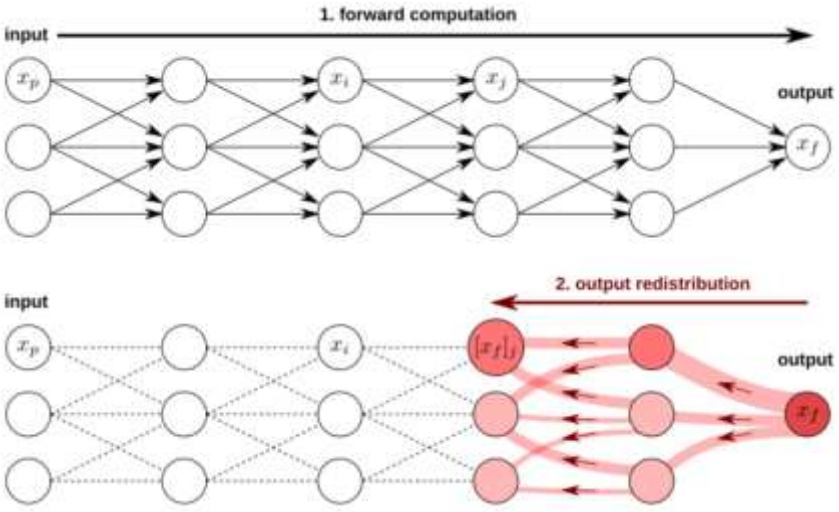
Local linear approximations can be too local



Score Back-Propagation based Methods

Re-distribute the prediction score through the neurons in the network

- LRP [JMLR 2017], DeepLift [ICML 2017], Guided BackProp [ICLR 2014]



Easy case: Output of a neuron is a linear function of previous neurons (i.e., $n_i = \sum w_{ij} * n_j$)
e.g., the logit neuron

- Re-distribute the contribution in proportion to the coefficients w_{ij}

Image credit heatmapping.org

Score Back-Propagation based Methods

Re-distribute the prediction score through the neurons in the network

- LRP [JMLR 2017], DeepLift [ICML 2017], Guided BackProp [ICLR 2014]

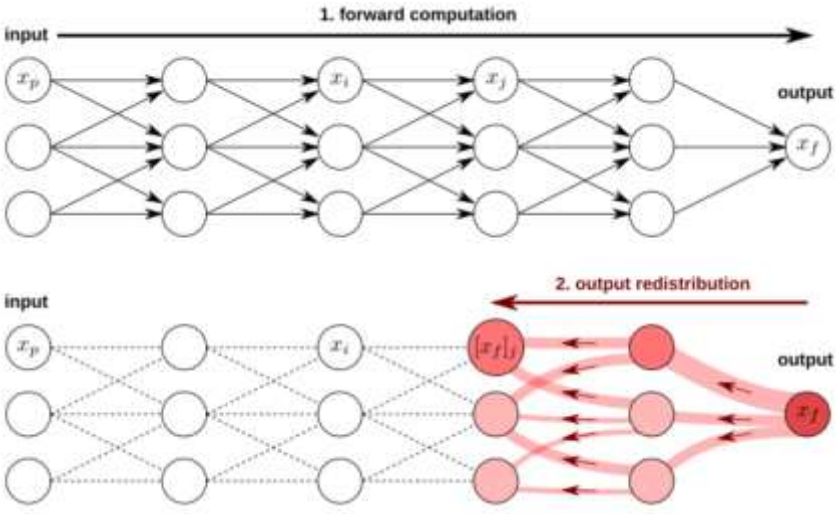


Image credit heatmapping.org

Tricky case: Output of a neuron is a **non-linear** function, e.g., ReLU, Sigmoid, etc.

- **Guided BackProp**: Only consider ReLUs that are on (linear regime), and which contribute positively
- **LRP**: Use first-order Taylor decomposition to linearize activation function
- **DeepLift**: Distribute activation difference relative a reference point in proportion to edge weights

Score Back-Propagation based Methods

Re-distribute the prediction score through the neurons in the network

- LRP [JMLR 2017], DeepLift [ICML 2017], Guided BackProp [ICLR 2014]

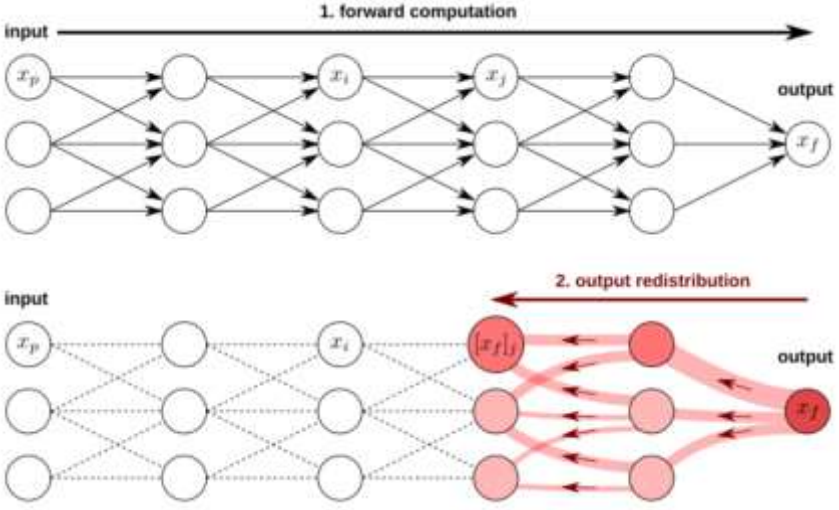


Image credit heatmapping.org

Pros:

- Conceptually simple
- Methods have been empirically validated to yield sensible result

Cons:

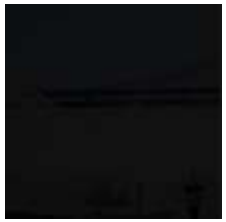
- Hard to implement, requires instrumenting the model
- **Often breaks implementation invariance**
  Think: F(x, y, z) = x * y *z and
  G(x, y, z) = x * (y * z)

Baselines and additivity

- When we decompose the score via backpropagation, we imply a normative alternative called a **baseline**
  - “Why Pr(fireboat) = 0.91 [instead of 0.00]”
- Common choice is an **informationless input for the model**
  - E.g., Black image for image models
  - E.g., Empty text or zero embedding vector for text models
- ***Additive*** attributions explain **F(input) - F(baseline)** in terms of input features

Another approach: gradients at many points

Baseline



… scaled inputs ...

Input

… gradients of scaled inputs ….

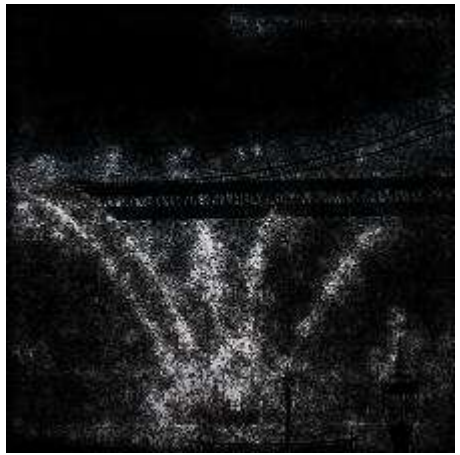
Integrated Gradients [ICML 2017]

Integrate the gradients along a **straight-line path from baseline to input**

$$IG(input, base) ::= (input - base) * \int_{0}^{1} \nabla F(\alpha * input + (1-\alpha) * base)\, d\alpha$$

Original image

Integrated Gradients



Integrated Gradients in action

Why is this image labeled as “clog”?

Original image

“Clog”

Why is this image labeled as “clog”?

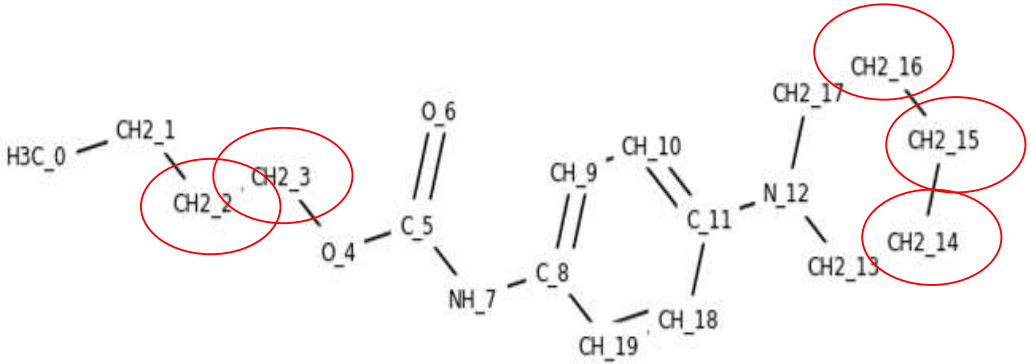
Original image

Integrated Gradients
(for label “clog”)

“Clog”

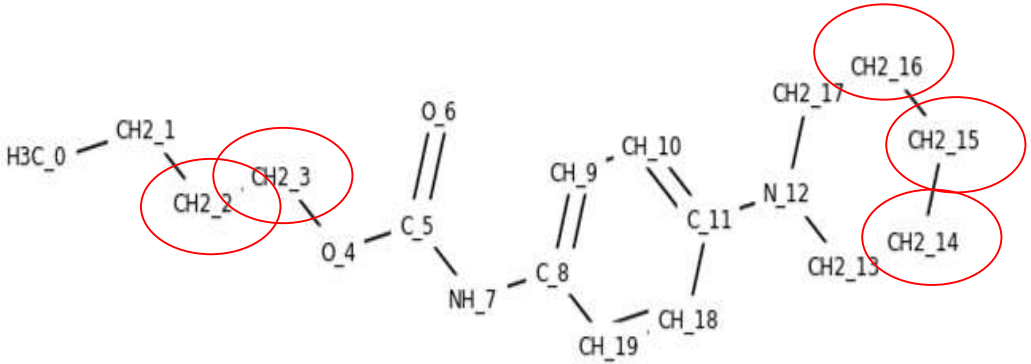
Detecting an architecture bug

- Deep network [Kearns, 2016] predicts if a molecule binds to certain DNA site
- **Finding**: Some atoms had identical attributions despite different connectivity



Detecting an architecture bug

- Deep network [Kearns, 2016] predicts if a molecule binds to certain DNA site
- **Finding**: Some atoms had identical attributions despite different connectivity



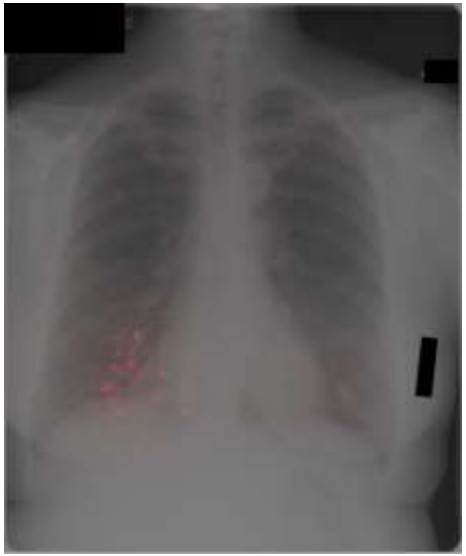
- **Bug**: The architecture had a bug due to which the convolved bond features did not affect the prediction!

Detecting a data issue

- Deep network predicts various diseases from chest x-rays

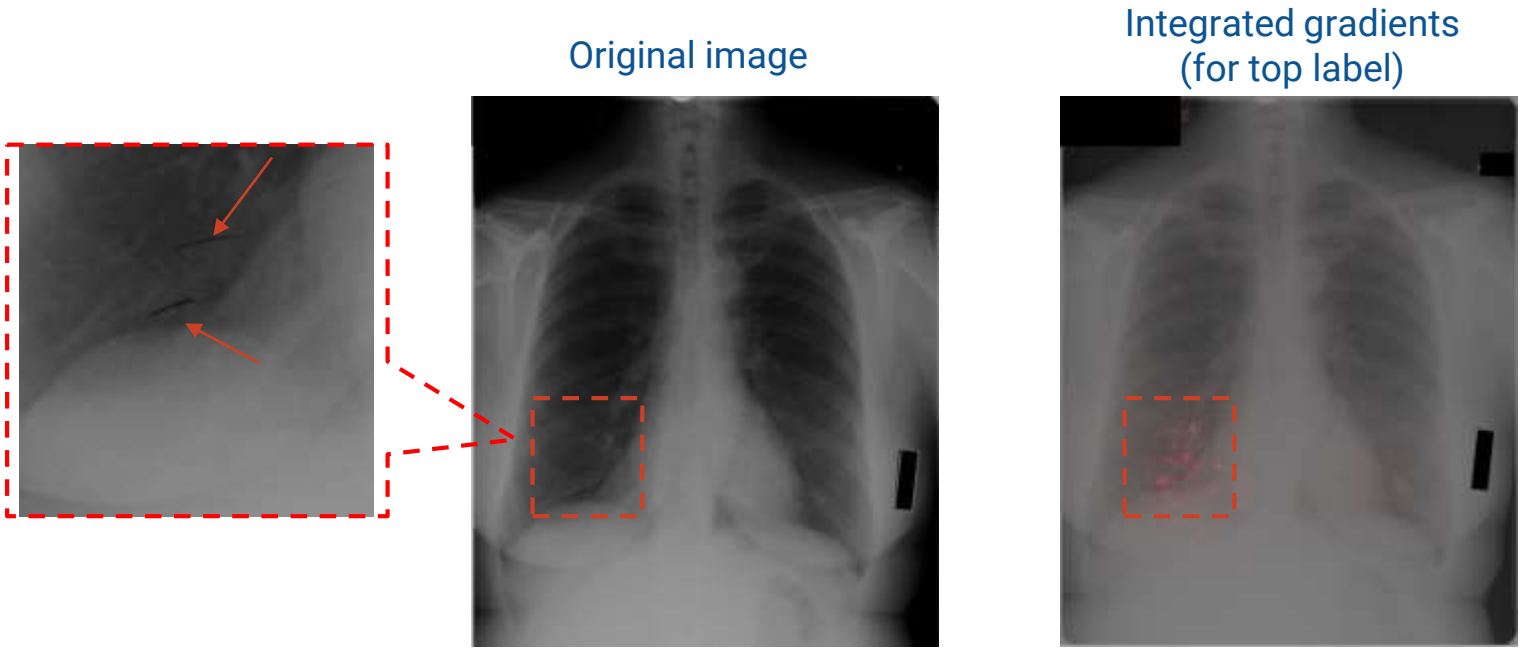
Original image

Integrated gradients
(for top label)



Detecting a data issue

- Deep network predicts various diseases from chest x-rays
- **Finding**: Attributions fell on radiologist's markings (rather than the pathology)



Cooperative game theory in attributions

Shapley Value [Annals of Mathematical studies,1953]

Classic result in game theory on distributing gain in a **coalition game**

- **Coalition Games**
  - Players collaborating to generate some **gain** (think: revenue)
  - Set function v(S) determining the gain for any subset S of players

Shapley Value [Annals of Mathematical studies, 1953]

Classic result in game theory on distributing gain in a **coalition game**

- **Coalition Games**
  - Players collaborating to generate some **gain** (think: revenue)
  - Set function v(S) determining the gain for any subset S of players
- **Shapley Values** are a fair way to attribute the total gain to the players based on their contributions
  - Concept: **Marginal contribution** of a player to a subset of other players (v(S U {i}) - v(S))
  - Shapley value for a player is a **specific weighted aggregation of its marginal** over all possible subsets of other players

$$\textbf{Shapley Value for player i} = \sum_{S \subseteq N} w(S) * (v(S \cup \{i\}) - v(S))$$

(where $w(S) = N! / |S|! (N - |S| - 1)!$)

Shapley Value Justification

Shapley values are unique under four simple axioms

- **Dummy:** If a player never contributes to the game then it must receive zero attribution
- **Efficiency:** Attributions must add to the total gain
- **Symmetry:** Symmetric players must receive equal attribution
- **Linearity:** Attribution for the (weighted) sum of two games must be the same as the (weighted) sum of the attributions for each of the games

Shapley Values for Explaining ML models

SHAP [NeurIPS 2018], QII [S&P 2016], Strumbelj & Konenko [JMLR 2009]

- Define a coalition game for each model input X
  - **Players are the features in the input**
  - **Gain is the model prediction** (output), i.e., gain = F(X)
- Feature attributions are the Shapley values of this game

Shapley Values for Explaining ML models

SHAP [NeurIPS 2018], QII [S&P 2016], Strumbelj & Konenko [JMLR 2009]

- Define a coalition game for each model input X
  - **Players are the features in the input**
  - **Gain is the model prediction** (output), i.e., gain = F(X)
- Feature attributions are the Shapley values of this game

Challenge: Shapley values require the gain to be defined for all subsets of players

- What is the prediction when **some players (features) are absent**?

  i.e., what is **F(x_1, <absent>, x_3, …, <absent>)**?

Modeling Feature Absence

Key Idea: Take the expected prediction when the (absent) feature is sampled from a certain distribution.

Different approaches choose different distributions

- [SHAP, NIPS 2018] Use conditional distribution w.r.t. the present features
- [QII, S&P 2016] Use marginal distribution
- [Strumbelj et al., JMLR 2009] Use uniform distribution

Preprint: The Explanation Game: Explaining Machine Learning Models with Cooperative Game Theory

Computing Shapley Values

Exact Shapley value computation is exponential in the number of features

- Shapley values can be expressed as an expectation of marginals

$$\phi(i) = E_{S \sim \mathcal{D}}\ [\text{marginal}(S, i)]$$

  - Sampling-based methods can be used to approximate the expectation
  - See: “Computational Aspects of Cooperative Game Theory”, Chalkiadakis et al. 2011
- The method is still computationally infeasible for models with hundreds of features, e.g., image models

Non-atomic Games: Aumann-Shapley Values and IG

- *Values of Non-Atomic Games* (1974): Aumann and Shapley extend their method → players can contribute fractionally
- Aumann-Shapley values calculated by integrating along a straight-line path… **same as Integrated Gradients!**
- IG through a game theory lens: continuous game, feature absence is modeled by replacement with a baseline value
- Axiomatically justified as a result:
    - Integrated Gradients is the unique path-integral method satisfying: **Sensitivity**, **Insensitivity**, **Linearity preservation**, **Implementation invariance**, **Completeness**, and **Symmetry**

Lesson learned: baselines are important

Baselines (or Norms) are essential to explanations [Kahneman-Miller 86]

- E.g., A man suffers from indigestion. Doctor blames it to a stomach ulcer. Wife blames it on eating turnips. Both are correct relative to their baselines.
- The baseline may also be an important analysis knob.

Attributions are **contrastive,** whether we think about it or not.

Some limitations and caveats for attributions

Attributions don’t explain everything

Some things that are missing:

- Feature interactions (ignored or averaged out)
- What training examples influenced the prediction (training agnostic)
- Global properties of the model (prediction-specific)

An instance where attributions are useless:

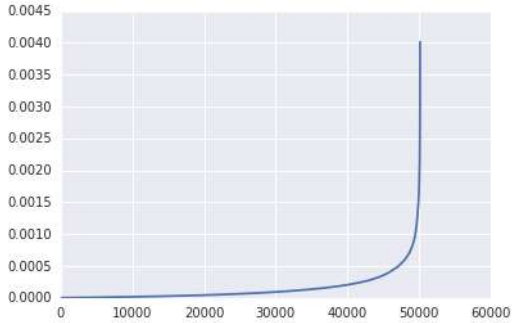
- A model that predicts TRUE when there are **even number** of black pixels and FALSE otherwise

Attributions are for human consumption

- **Humans** interpret attributions and generate insights
  - Doctor maps attributions for x-rays to pathologies
- **Visualization** matters as much as the attribution technique

Naive scaling of attributions from 0 to 255

Attributions have a **large range** and **long tail** across pixels



After clipping attributions at 99% to reduce range

Other individual prediction explanation methods

Local Interpretable Model-agnostic Explanations
(Ribeiro et al. KDD 2016)

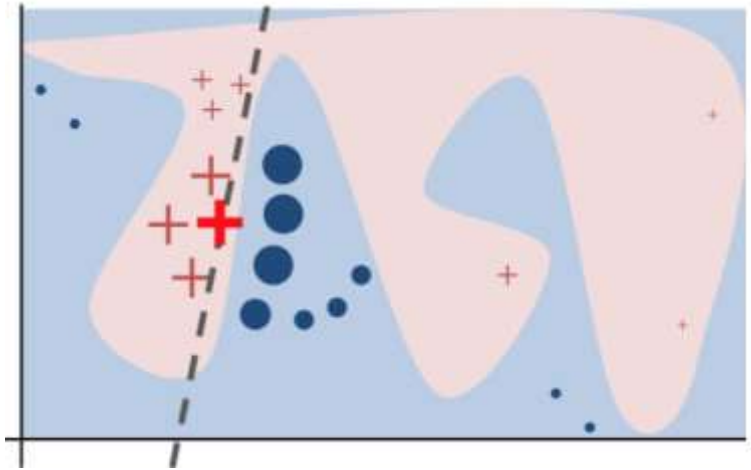


Figure credit: Ribeiro et al. KDD 2016

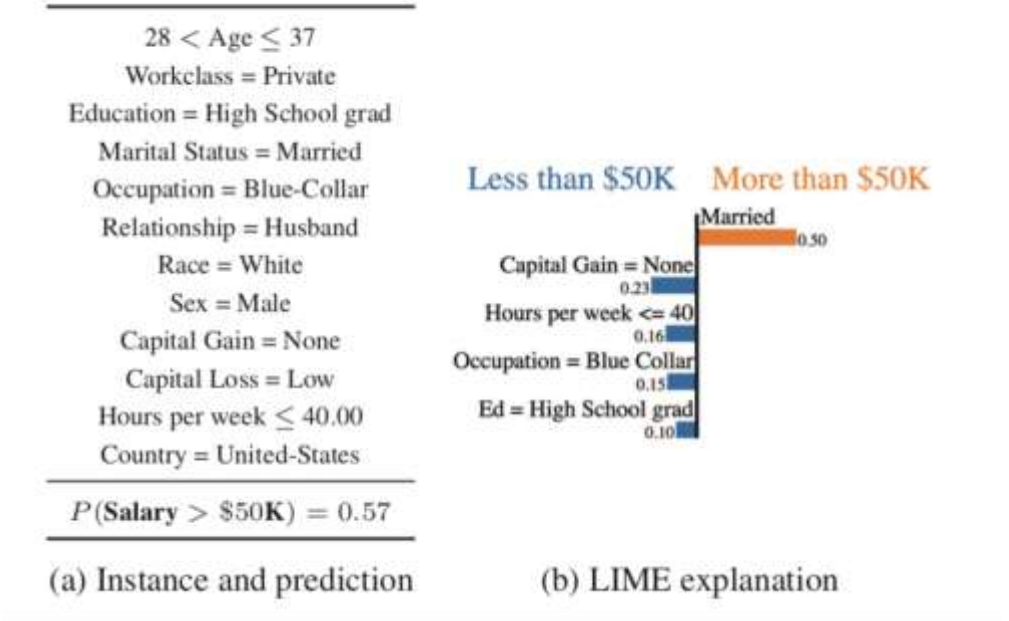
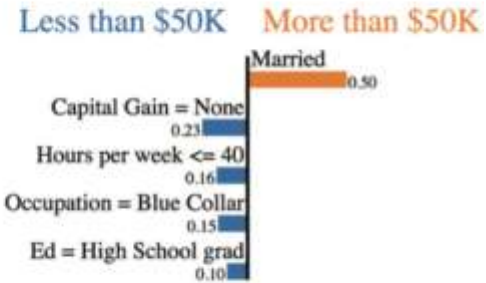


Figure credit: Anchors: High-Precision Model-Agnostic Explanations. Ribeiro et al. AAAI 2018

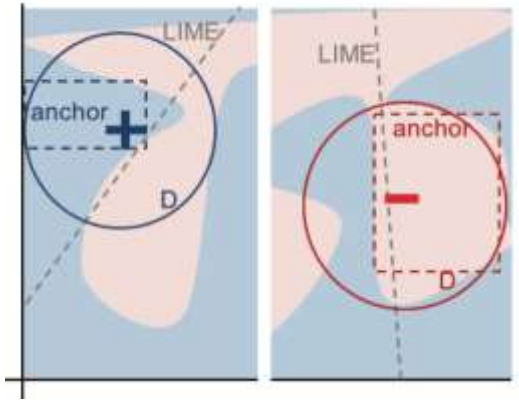
Anchors

$28 < \text{Age} \leq 37$
Workclass = Private
Education = High School grad
Marital Status = Married
Occupation = Blue-Collar
Relationship = Husband
Race = White
Sex = Male
Capital Gain = None
Capital Loss = Low
Hours per week ≤ 40.00
Country = United-States
$P(\textbf{Salary} > \$50\textbf{K}) = 0.57$

(a) Instance and prediction



(b) LIME explanation



IF Country = United-States **AND** Capital Loss = Low
AND Race = White **AND** Relationship = Husband
AND Married **AND** $28 < \text{Age} \leq 37$
AND Sex = Male **AND** High School grad
AND Occupation = Blue-Collar
THEN PREDICT Salary $> \$50\text{K}$

(c) An *anchor* explanation

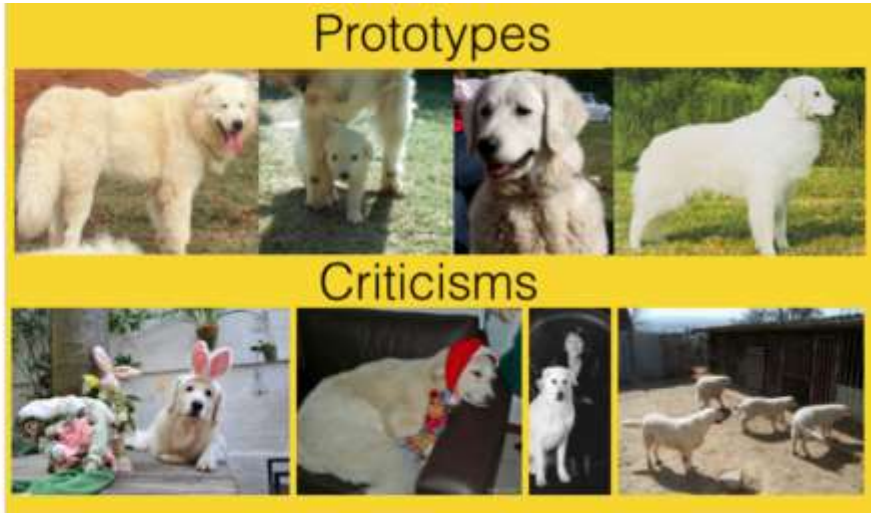
Figure credit: Anchors: High-Precision Model-Agnostic Explanations. Ribeiro et al. AAAI 2018

Influence functions

- Trace a model’s prediction through the learning algorithm and back to its training data
- Training points “responsible” for a given prediction

Figure credit: Understanding Black-box Predictions via Influence Functions. Koh and Liang. ICML 2017

Example based Explanations



Learned prototypes and criticisms from Imagenet dataset (two types of dog breeds)

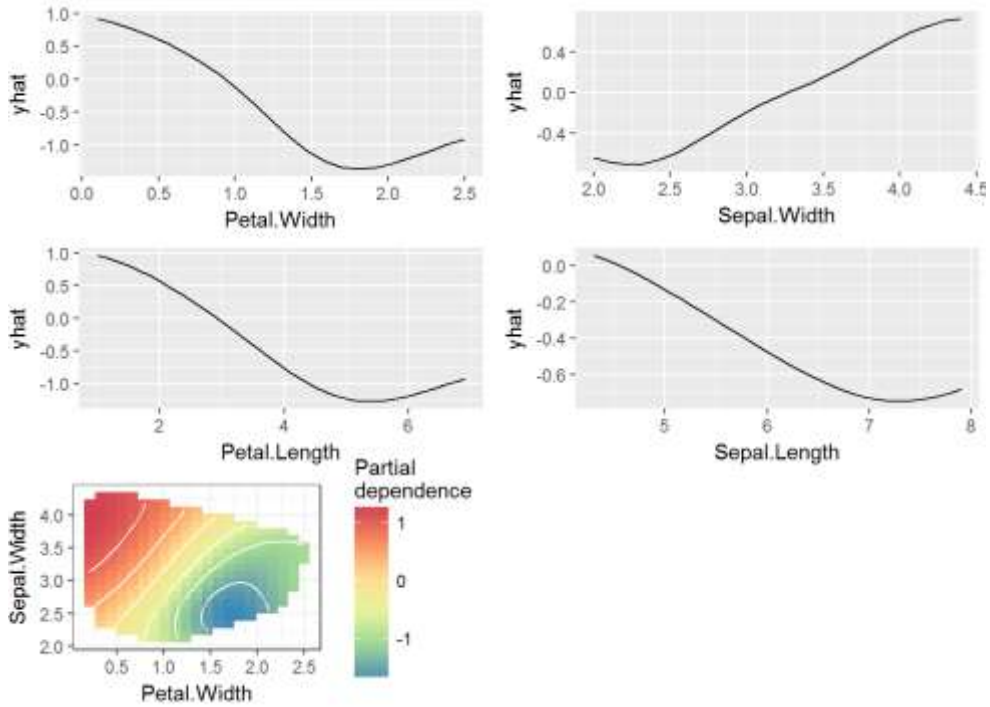
- Prototypes: Representative of all the training data.
- Criticisms: Data instance that is not well represented by the set of prototypes.

Figure credit: Examples are not Enough, Learn to Criticize! Criticism for Interpretability. Kim, Khanna and Koyejo. NIPS 2016

Global Explanations

Global Explanations Methods

- Partial Dependence Plot:
  Shows the marginal effect one or two features have on the predicted outcome of a machine learning model



Global Explanations Methods

- Permutations: The importance of a feature is the increase in the prediction error of the model after we permuted the feature's values, which breaks the relationship between the feature and the true outcome.

	RD Spend	Administration	Marketing Spend	Profit	state_California
1	165349.2	136897.8	471784.1	192261.83	0
2	162597.7	151377.59	443898.53	191792.06	1
3	153441.51	101145.55	407934.54	191050.39	1
...	...	...	...	...	...
48	0	135426.92	0	42559.73	1
49	542.05	51743.15	0	35673.41	0
50	0	116983.8	45173.06	14681.4	1

Random Shuffle of the first feature

Achieving Explainable AI

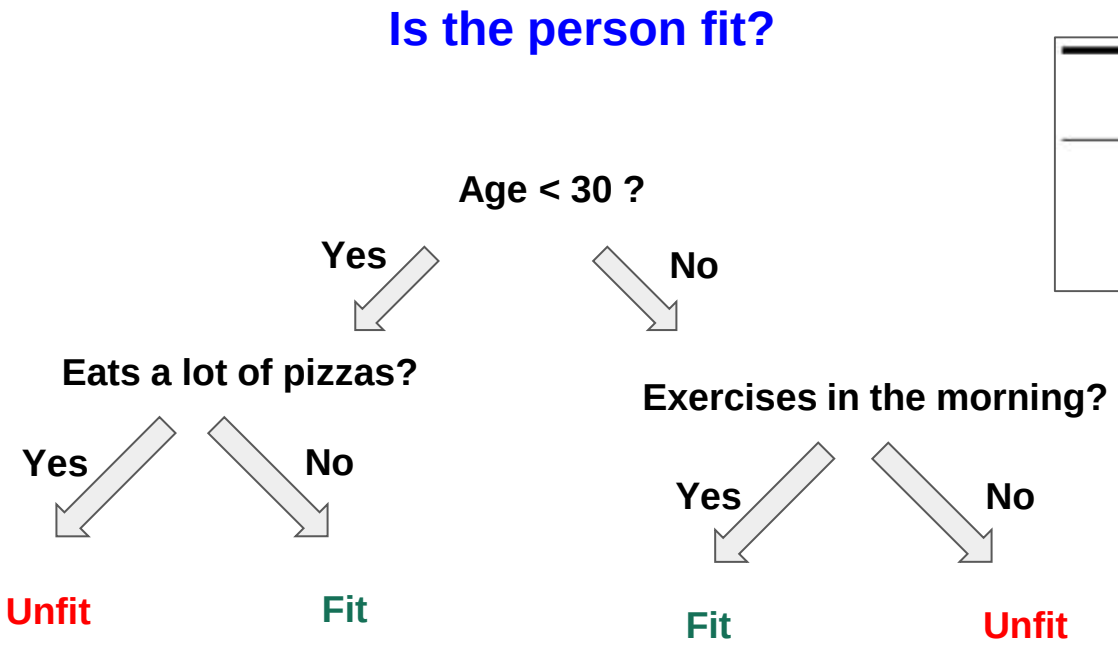
Approach 1: **Post-hoc explain a given AI model**

- **Individual prediction explanations** in terms of input features, influential examples, concepts, local decision rules
- **Global prediction explanations** in terms of entire model in terms of partial dependence plots, global feature importance, global decision rules

Approach 2: **Build an interpretable model**

- Logistic regression, Decision trees, Decision lists and sets, Generalized Additive Models (GAMs)

Decision Trees



Optimal Sparse Decision Trees

Xiyang Hu[1], Cynthia Rudin[2], Margo Seltzer[3]*
[1]Carnegie Mellon University, xiyanghu@cmu.edu
[2]Duke University, cynthia@cs.duke.edu
[3]The University of British Columbia, mseltzer@cs.ubc.ca

Decision Set

If Allergies =Yes **and** Smoker =Yes **and** Irregular-Heartbeat =Yes, **then** Asthma

If Allergies =Yes **and** Past-Respiratory-Illness =Yes **and** Avg-Body-Temperature $\geq$ 0.1, **then** Asthma

If Smoker =Yes **and** BMI $\geq$ 0.2 **and** Age $\geq$ 60, **then** Diabetes

If Family-Risk-Diabetes =Yes **and** BMI $\geq$ 0.4 =Frequency-Infections $\geq$ 0.2, **then** Diabetes

If Frequency-Doctor-Visits $\geq$ 0.4 **and** Childhood-Obesity =Yes **and** Past-Respiratory-Illness =Yes, **then** Diabetes

If Family-Risk-Depression =Yes **and** Past-Depression =Yes **and** Gender =Female, **then** Depression

If BMI $\geq$ 0.3 **and** Insurance-Coverage =None **and** Avg-Blood-Pressure $\geq$ 0.2, **then** Depression

If Past-Respiratory-Illness =Yes **and** Age $\geq$ 50 **and** Smoker =Yes, **then** Lung Cancer

If Family-Risk-LungCancer =Yes **and** Allergies =Yes **and** Avg-Blood-Pressure $\geq$ 0.3, **then** Lung Cancer

If Disposition-Tiredness =Yes **and** Past-Anemia =Yes **and** BMI $\geq$ 0.3 **and** Rapid-Weight-Loss =Yes, **then** Leukemia

If Family-Risk-Leukemia =Yes **and** Past-Blood-Clotting =Yes **and** Frequency-Doctor-Visits $\geq$ 0.3, **then** Leukemia

If Disposition-Tiredness =Yes **and** Irregular-Heartbeat =Yes **and** Short-Breath-Symptoms =Yes **and** Abdomen-Pains =Yes, **then** Myelofibrosis

Figure credit: Interpretable Decision Sets: A Joint Framework for Description and Prediction, Lakkaraju, Bach, Leskovec

Decision Set

A Bayesian Framework for Learning Rule Sets for Interpretable Classification

Tong Wang TONG-WANG@UIOWA.EDU *University of Iowa*

Cynthia Rudin CYNTHIA@CS.DUKE.EDU *Duke University*

Finale Doshi-Velez FINALE@SEAS.HARVARD.EDU *Harvard University*

Yimin Liu LIUYIMIN2000@GMAIL.COM *Edward Jones*

Erica Klampfl EKLAMPFL@FORD.COM *Ford Motor Company*

Perry MacNeille PMACNEIL@FORD.COM *Ford Motor Company*

Editor: Maya Gupta

Abstract

We present a machine learning algorithm for building classifiers that are comprised of a *small* number of *short* rules. These are restricted disjunctive normal form models. An example of a classifier of this form is as follows: *If* X satisfies (condition A AND condition B) OR (condition C) OR $\cdots$, *then* $Y = 1$. Models of this form have the advantage of being interpretable to human experts since they produce a set of rules that concisely describe a specific class. We present two probabilistic models with prior parameters that the user can set to encourage the model to have a desired size and shape, to conform with a domain-specific definition of interpretability. We provide a scalable MAP inference approach and develop theoretical bounds to reduce computation by iteratively pruning the search space. We apply our method (Bayesian Rule Sets – *BRS*) to characterize and predict user behavior with respect to in-vehicle context-aware personalized recommender systems. Our method has a major advantage over classical associative classification methods and decision trees in that it does not greedily grow the model.

Decision List

If Past-Respiratory-Illness $=$Yes **and** Smoker $=$Yes **and** Age $\geq$ 50, **then** Lung Cancer

Else if Allergies $=$Yes **and** Past-Respiratory-Illness $=$Yes, **then** Asthma

Else if Family-Risk-Respiratory $=$Yes, **then** Asthma

Else if Family-Risk-Depression $=$Yes, **then** Depression

Else if Gender $=$Female **and** Short-Breath-Symptoms $=$Yes, **then** Asthma

Else if BMI $\geq$ 0.2 **and** Age$\geq$ 60, **then** Diabetes

Else if Frequent-Headaches $=$Yes **and** Dizziness $=$Yes, **then** Depression

Else if Frequency-Doctor-Visits $\geq$ 0.3, **then** Diabetes

Else if Disposition-Tiredness $=$Yes, **then** Depression

Else if Chest-Pain $=$Yes **and** Nausea **and** Yes, **then** Diabetes

Else Diabetes

Figure credit: Interpretable Decision Sets: A Joint Framework for Description and Prediction, Lakkaraju, Bach, Leskovec

Falling Rule List

A falling rule list is an ordered list of if-then rules (falling rule lists are a type of decision list), such that the estimated probability of success decreases monotonically down the list. Thus, a falling rule list directly contains the decision-making process, whereby the most at-risk observations are classified first, then the second set, and so on.

	Conditions		Probability	Support
IF	IrregularShape AND Age $\geq$ 60	THEN malignancy risk is	85.22%	230
ELSE IF	SpiculatedMargin AND Age $\geq$ 45	THEN malignancy risk is	78.13%	64
ELSE IF	IllDefinedMargin AND Age $\geq$ 60	THEN malignancy risk is	69.23%	39
ELSE IF	IrregularShape	THEN malignancy risk is	63.40%	153
ELSE IF	LobularShape AND Density $\geq$ 2	THEN malignancy risk is	39.68%	63
ELSE IF	RoundShape AND Age $\geq$ 60	THEN malignancy risk is	26.09%	46
ELSE		THEN malignancy risk is	10.38%	366

Table 1: Falling rule list for mammographic mass dataset.

Box Drawings for Rare Classes

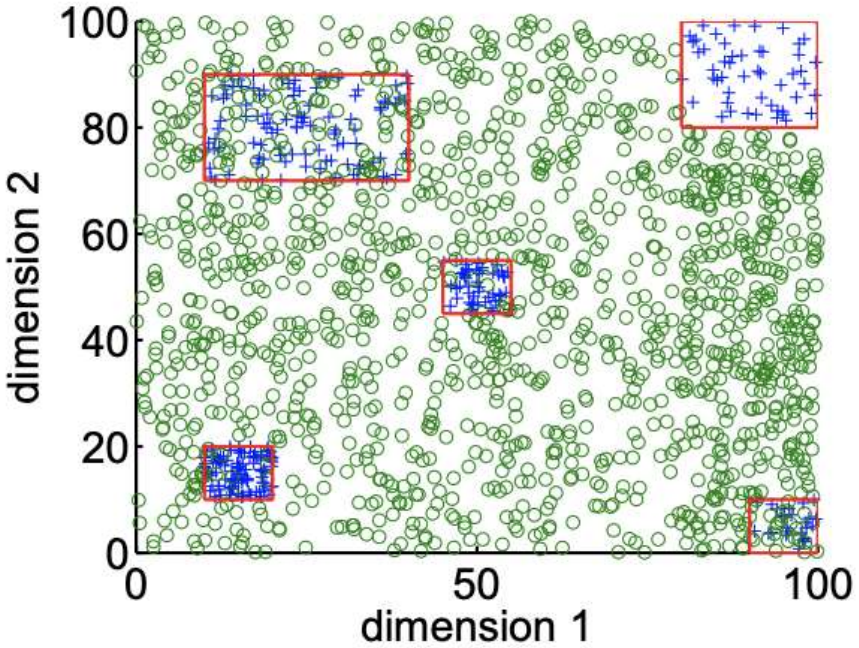


Figure credit: Box Drawings for Learning with Imbalanced. Data Siong Thye Goh and Cynthia Rudin

Supersparse Linear Integer Models for Optimized Medical Scoring Systems

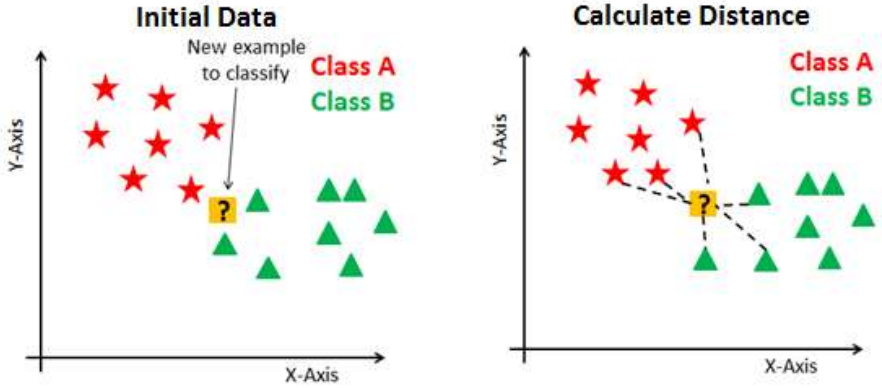
PREDICT PATIENT HAS OBSTRUCTIVE SLEEP APNEA IF SCORE > 1

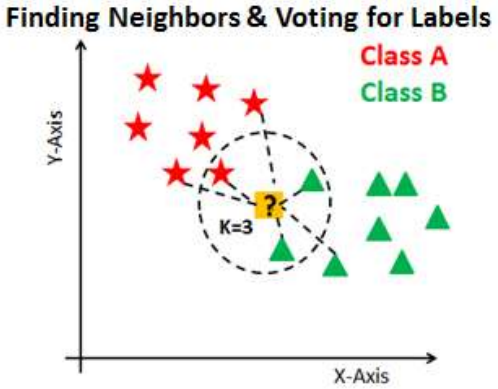
1.	*age* ≥ 60	4 points		.....
2.	*hypertension*	4 points	+	.....
3.	*body mass index* ≥ 30	2 points	+	.....
4.	*body mass index* ≥ 40	2 points	+	.....
5.	*female*	-6 points	+	.....
	ADD POINTS FROM ROWS 1 – 5	**SCORE**	=	.....

SLIM scoring system for sleep apnea screening. This model achieves a 10-CV mean test TPR/FPR of 61.4/20.9%, obeys all operational constraints, and was trained without parameter tuning. It also generalizes well due to the simplicity of the hypothesis space: here the training TPR/FPR of the final model is 62.0/19.6%.

Figure credit: Supersparse Linear Integer Models for Optimized Medical Scoring Systems. Berk Ustun and Cynthia Rudin

K- Nearest Neighbors





Explanation in terms of nearest training data points responsible for the decision

GLMs and GAMs

Model	Form	Intelligibility	Accuracy
Linear Model	$y = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n$	+++	+
Generalized Linear Model	$g(y) = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n$	+++	+
Additive Model	$y = f_1(x_1) + ... + f_n(x_n)$	++	++
Generalized Additive Model	$g(y) = f_1(x_1) + ... + f_n(x_n)$	++	++
Full Complexity Model	$y = f(x_1, ..., x_n)$	+	+++

Intelligible Models for Classification and Regression. Lou, Caruana and Gehrke KDD 2012

Accurate Intelligible Models with Pairwise Interactions. Lou, Caruana, Gehrke and Hooker. KDD 2013

XAI Case Studies in Industry:

Applications, Lessons Learned, and Research Challenges

Case Study:

Talent Platform

"Diversity Insights and Fairness-Aware Ranking"

Sahin Cem Geyik, Krishnaram Kenthapadi


Guiding Principle:
“Diversity by Design”

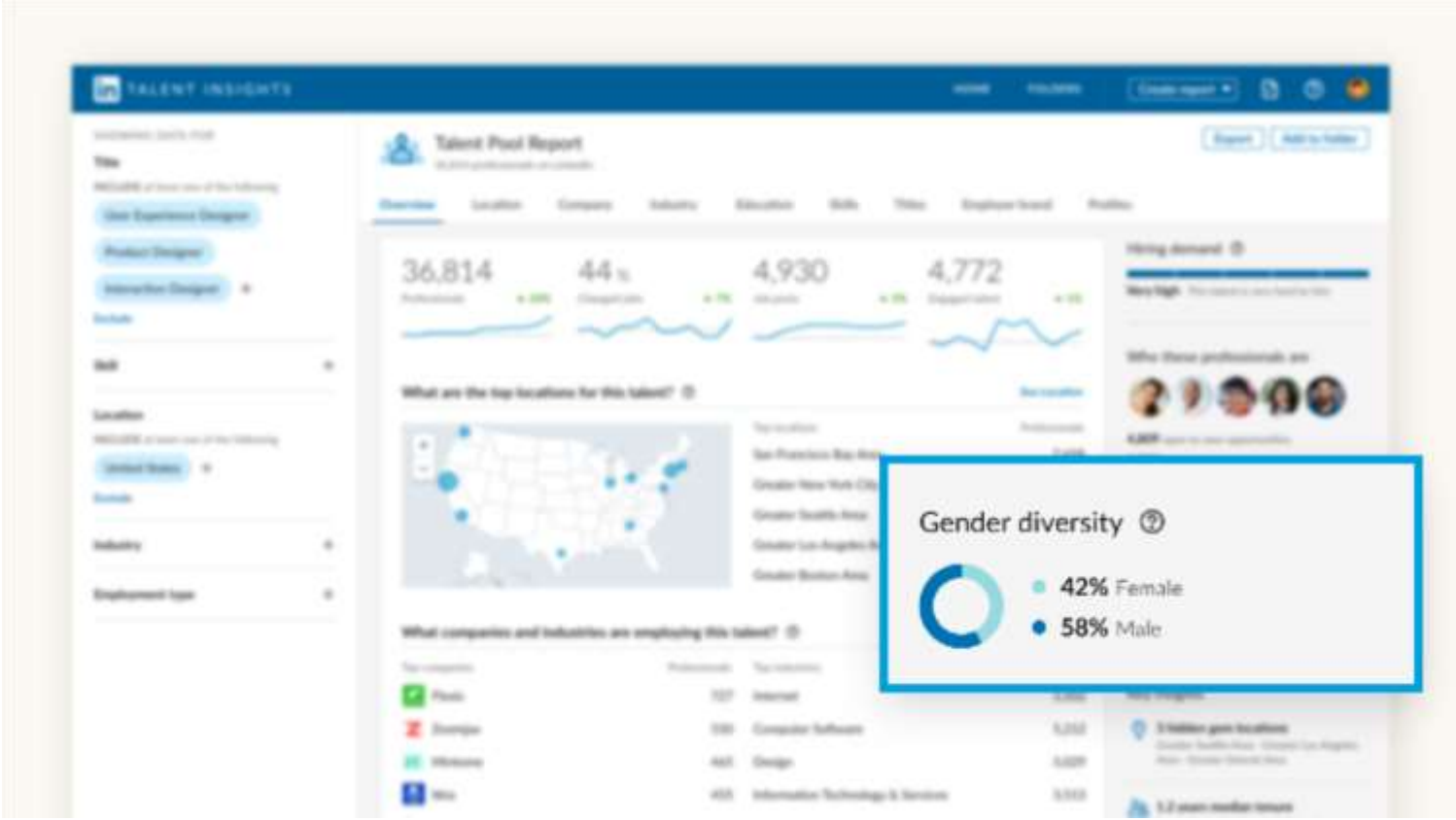
“Diversity by Design” in LinkedIn’s Talent Solutions

Insights to Identify Diverse Talent Pools

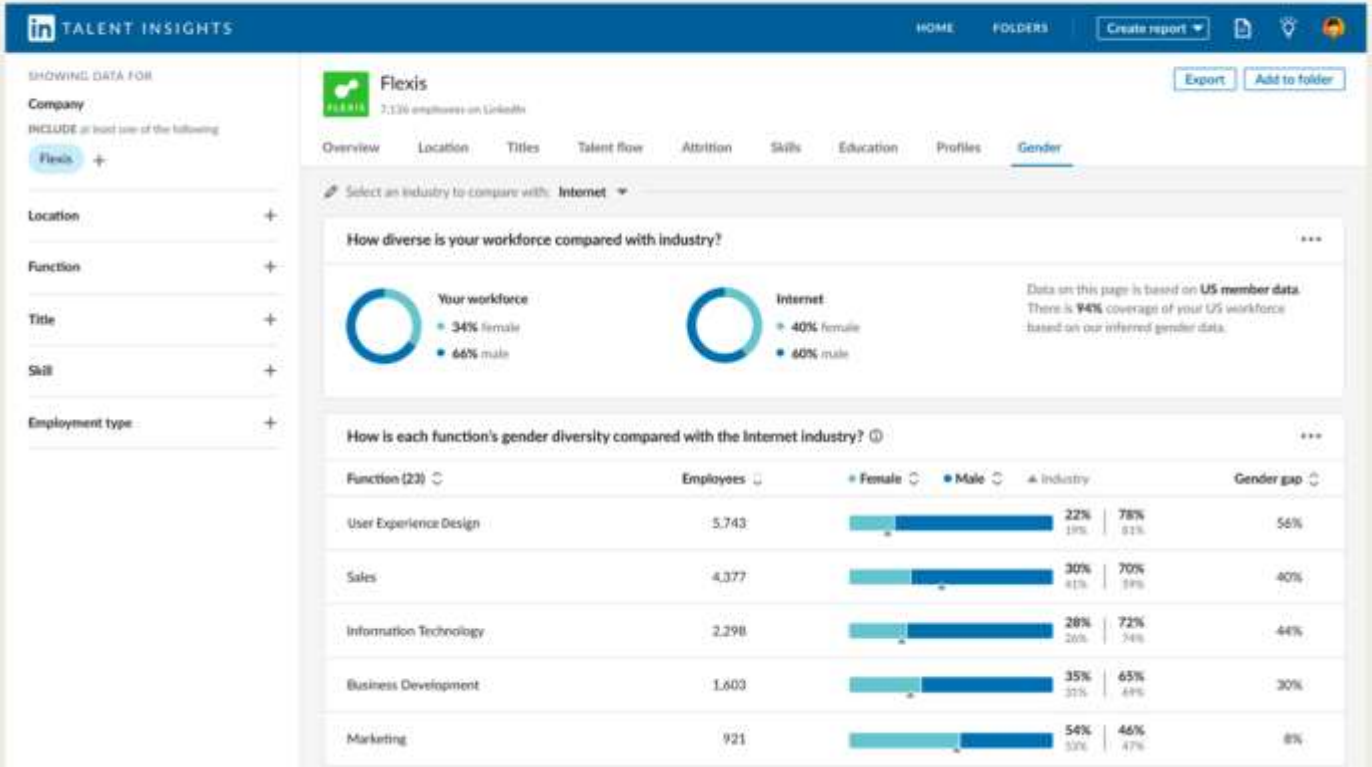
Representative Talent Search Results

Diversity Learning Curriculum

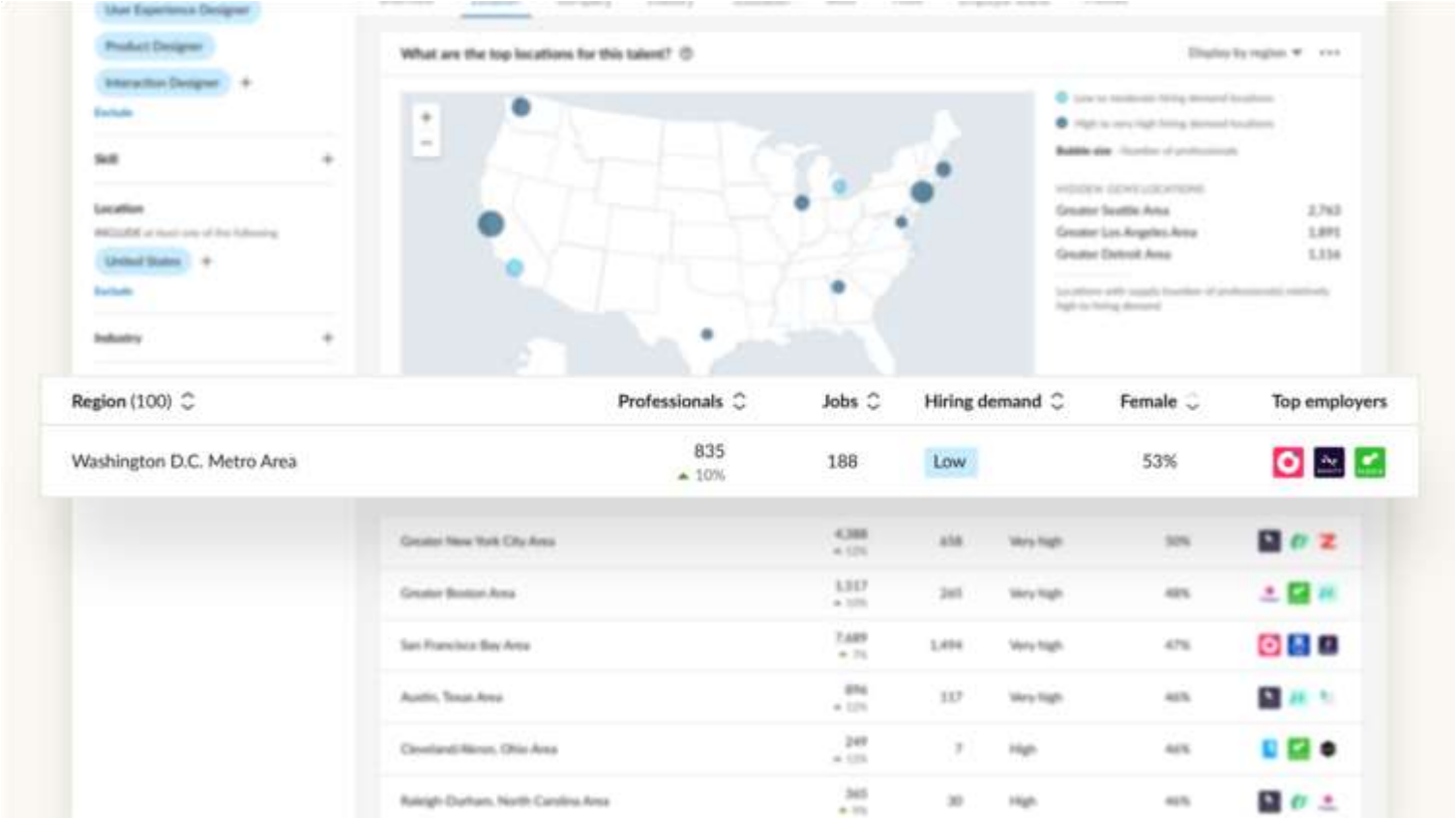
Plan for Diversity



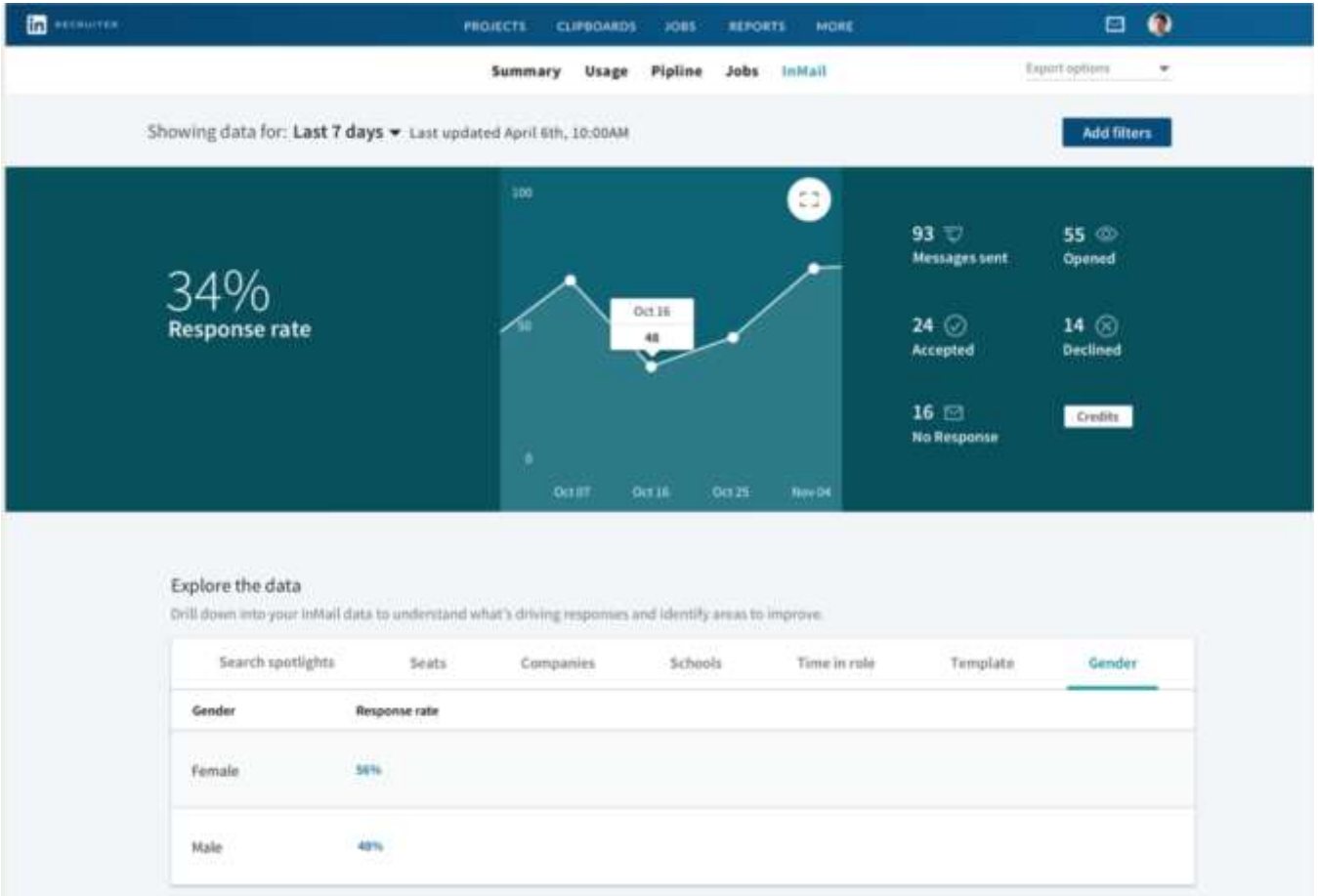
Plan for Diversity



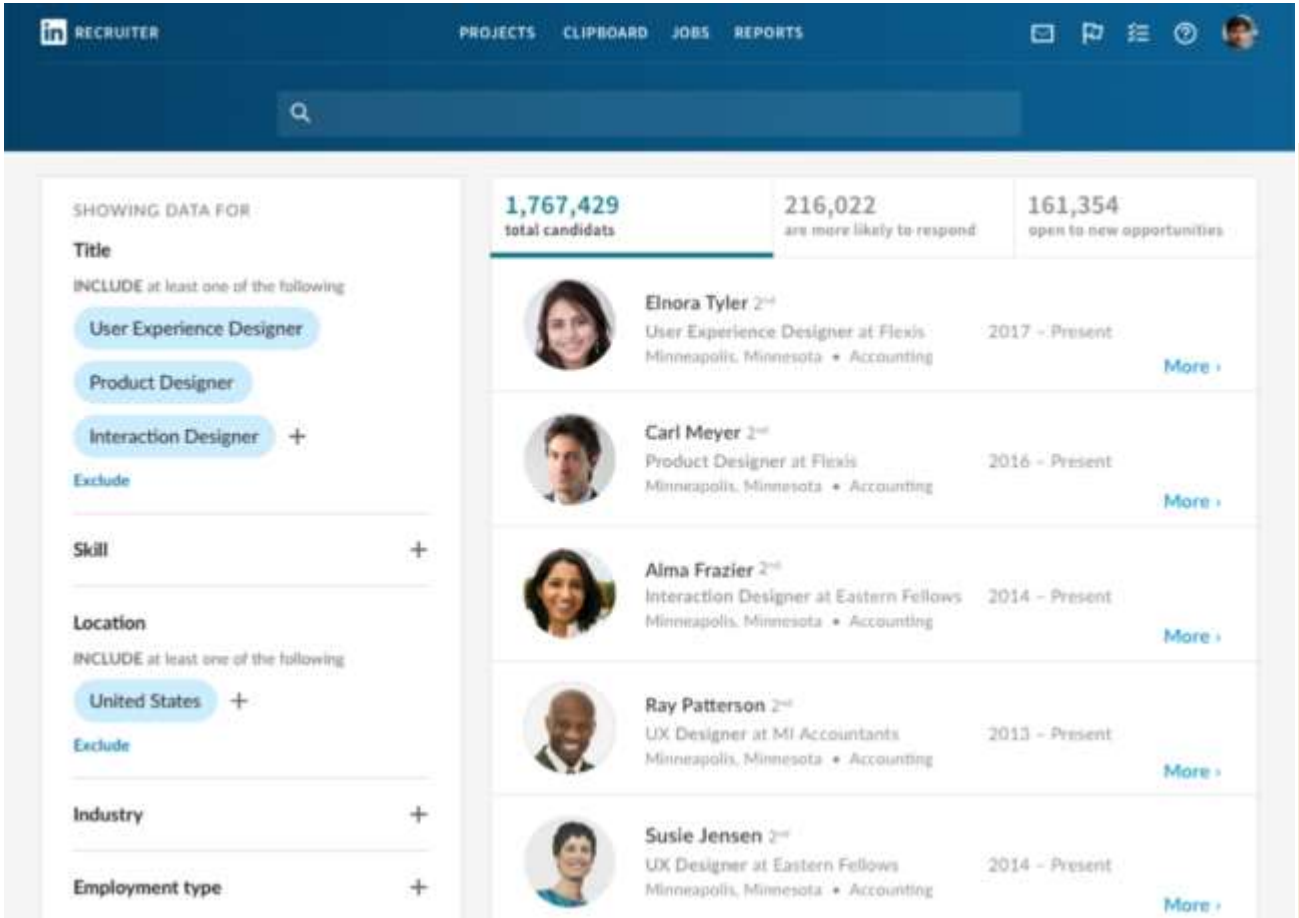
Identify Diverse Talent Pools



Inclusive Job Descriptions / Recruiter Outreach



Representative Ranking for Talent Search



S. C. Geyik, S. Ambler, K. Kenthapadi, Fairness-Aware Ranking in Search & Recommendation Systems with Application to LinkedIn Talent Search, KDD'19.

[Microsoft's AI/ML conference (MLADS'18). **Distinguished Contribution Award**]

Building Representative Talent Search at LinkedIn (LinkedIn engineering blog)

Intuition for Measuring and Achieving Representativeness

- Ideal: Top ranked results should follow a desired distribution on gender/age/…
  - E.g., same distribution as the underlying talent pool
- Inspired by “Equal Opportunity” definition [Hardt et al, NIPS’16]
- Defined measures (skew, divergence) based on this intuition

Desired Proportions within the Attribute of Interest

Compute the proportions of the values of the attribute (e.g., gender, gender-age combination) amongst the set of qualified candidates

- “Qualified candidates” = Set of candidates that match the search query criteria
- Retrieved by LinkedIn’s Galene search engine

Desired proportions could also be obtained based on legal mandate / voluntary commitment

Fairness-aware Reranking Algorithm (Simplified)

Partition the set of potential candidates into different buckets for each attribute value

Rank the candidates in each bucket according to the scores assigned by the machine-learned model

Merge the ranked lists, balancing the representation requirements and the selection of highest scored candidates

- Representation requirement: Desired distribution on gender/age/…
- Algorithmic variants based on how we achieve this balance

Validating Our Approach

Gender Representativeness

- Over 95% of all searches are representative compared to the qualified population of the search

Business Metrics

- A/B test over LinkedIn Recruiter users for two weeks
- No significant change in business metrics (e.g., # InMails sent or accepted)

Ramped to 100% of LinkedIn Recruiter users worldwide

Lessons learned

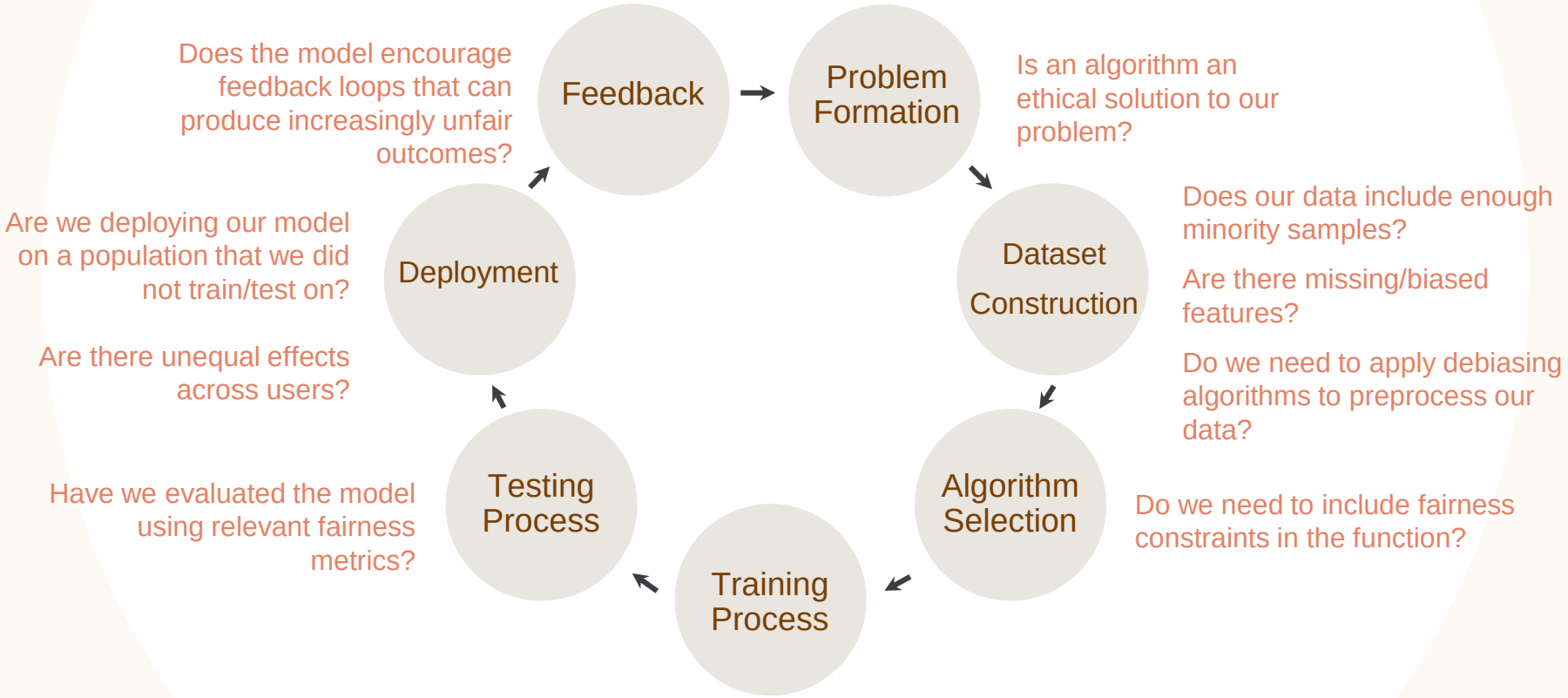
- Post-processing approach desirable
  - Model agnostic
    - Scalable across different model choices for our application
  - Acts as a “fail-safe”
    - Robust to application-specific business logic
  - Easier to incorporate as part of existing systems
    - Build a stand-alone service or component for post-processing
    - No significant modifications to the existing components
  - Complementary to efforts to reduce bias from training data & during model training
- Collaboration/consensus across key stakeholders

Acknowledgements

LinkedIn Talent Solutions Diversity team, Hire & Careers AI team, Anti-abuse AI team, Data Science Applied Research team

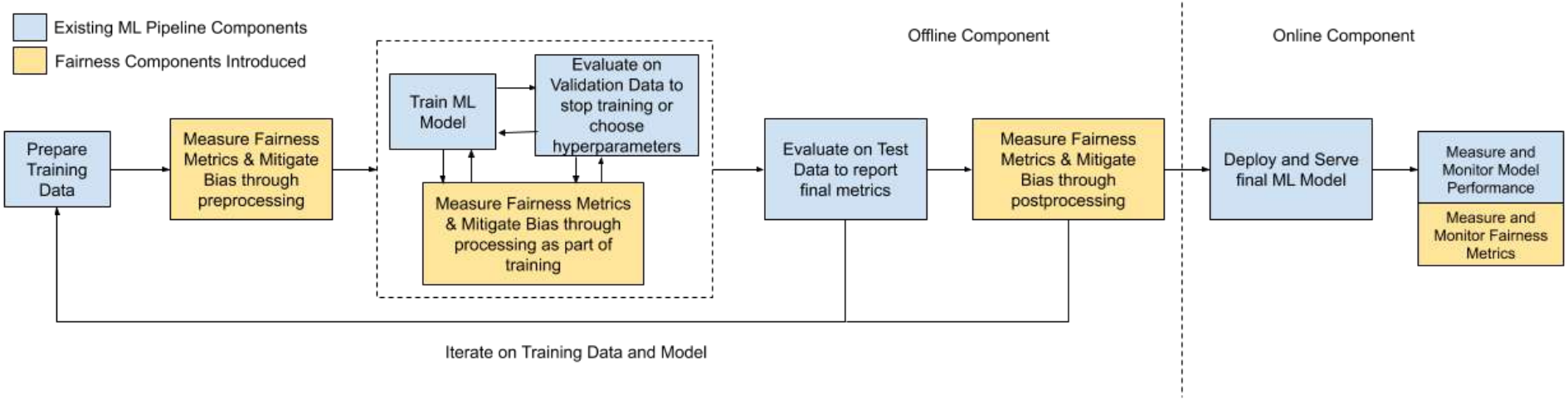
Special thanks to Deepak Agarwal, Parvez Ahammad, Stuart Ambler, Kinjal Basu, Jenelle Bray, Erik Buchanan, Bee-Chung Chen, Patrick Cheung, Gil Cottle, Cyrus DiCiccio, Patrick Driscoll, Carlos Faham, Nadia Fawaz, Priyanka Gariba, Meg Garlinghouse, Gurwinder Gulati, Rob Hallman, Sara Harrington, Joshua Hartman, Daniel Hewlett, Nicolas Kim, Rachel Kumar, Nicole Li, Heloise Logan, Stephen Lynch, Divyakumar Menghani, Varun Mithal, Arashpreet Singh Mor, Tanvi Motwani, Preetam Nandy, Lei Ni, Nitin Panjwani, Igor Perisic, Hema Raghavan, Romer Rosales, Guillaume Saint-Jacques, Badrul Sarwar, Amir Sepehri, Arun Swami, Ram Swaminathan, Grace Tang, Ketan Thakkar, Sriram Vasudevan, Janardhanan Vembunarayanan, James Verbus, Xin Wang, Hinkmond Wong, Ya Xu, Lin Yang, Yang Yang, Chenhui Zhai, Liang Zhang, Yani Zhang

Engineering for Fairness in AI Lifecycle



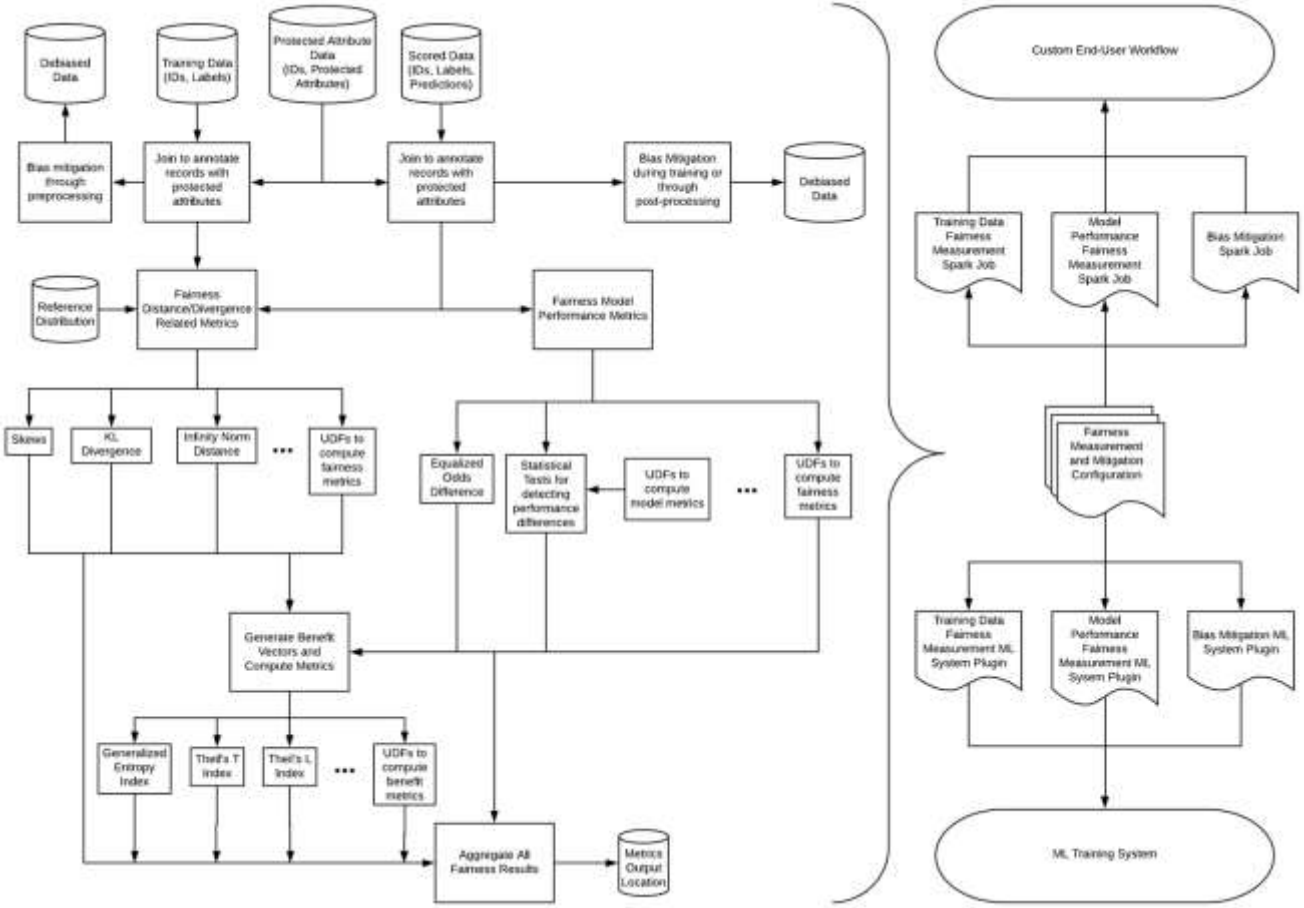
Credit: K. Browne & J. Draper

Engineering for Fairness in AI Lifecycle



S.Vasudevan, K. Kenthapadi,
FairScale: A Scalable Framework for Measuring Fairness in AI Applications, 2019

FairScale System Architecture [Vasudevan & Kenthapadi, 2019]



- Flexibility of Use (Platform agnostic)
  - Ad-hoc exploratory analyses
  - Deployment in offline workflows
  - Integration with ML Frameworks
- Scalability
- Diverse fairness metrics
  - Conventional fairness metrics
  - Benefit metrics
  - Statistical tests

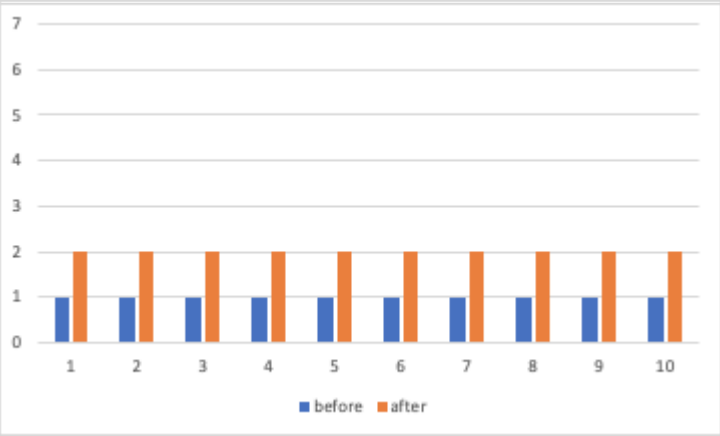
Fairness-aware experimentation

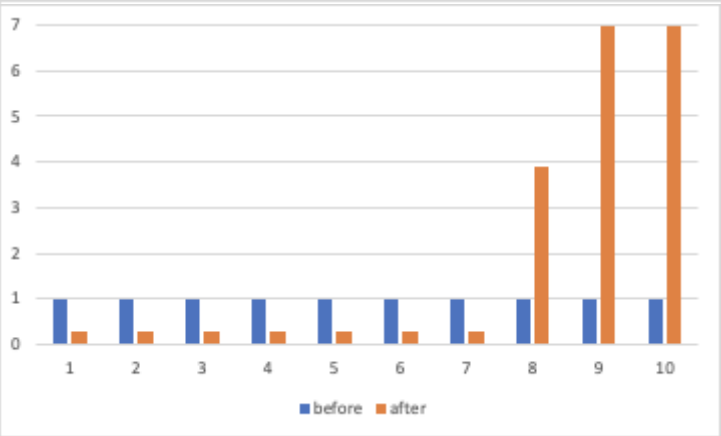
[Saint-Jacques and Sepehri, KDD'19 Social Impact Workshop]

Imagine LinkedIn has 10 members.

Each of them has 1 session a day.

A new product increases sessions by +1 session per member on average.





Both of these are +1 session / member on average!

One is much more unequal than the other. We want to catch that.

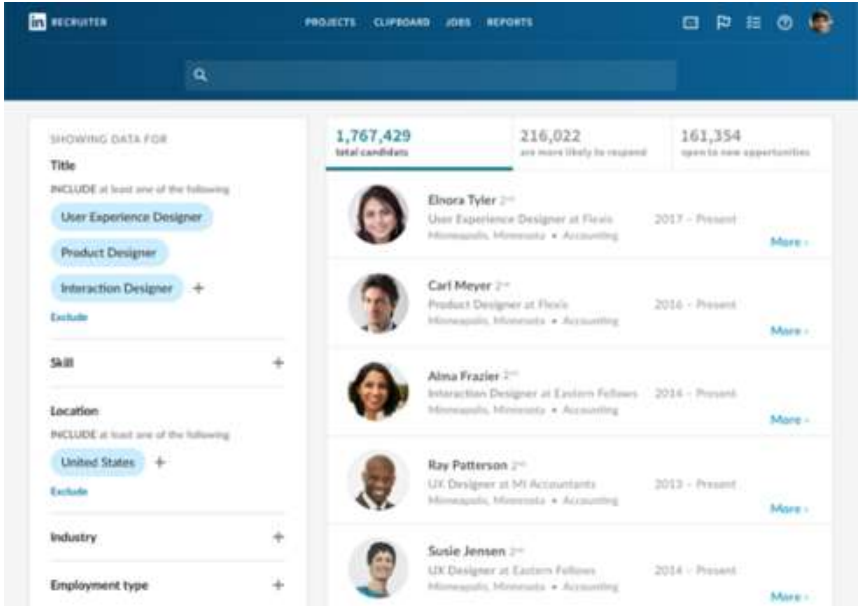
Case Study:

LinkedIn Talent Search

Varun Mithal, Girish Kathalagiri, Sahin Cem Geyik

LinkedIn Recruiter

- Recruiter Searches for Candidates
  - Standardized and free-text search criteria
- Retrieval and Ranking
  - Filter candidates using the criteria
  - Rank candidates in multiple levels using ML models

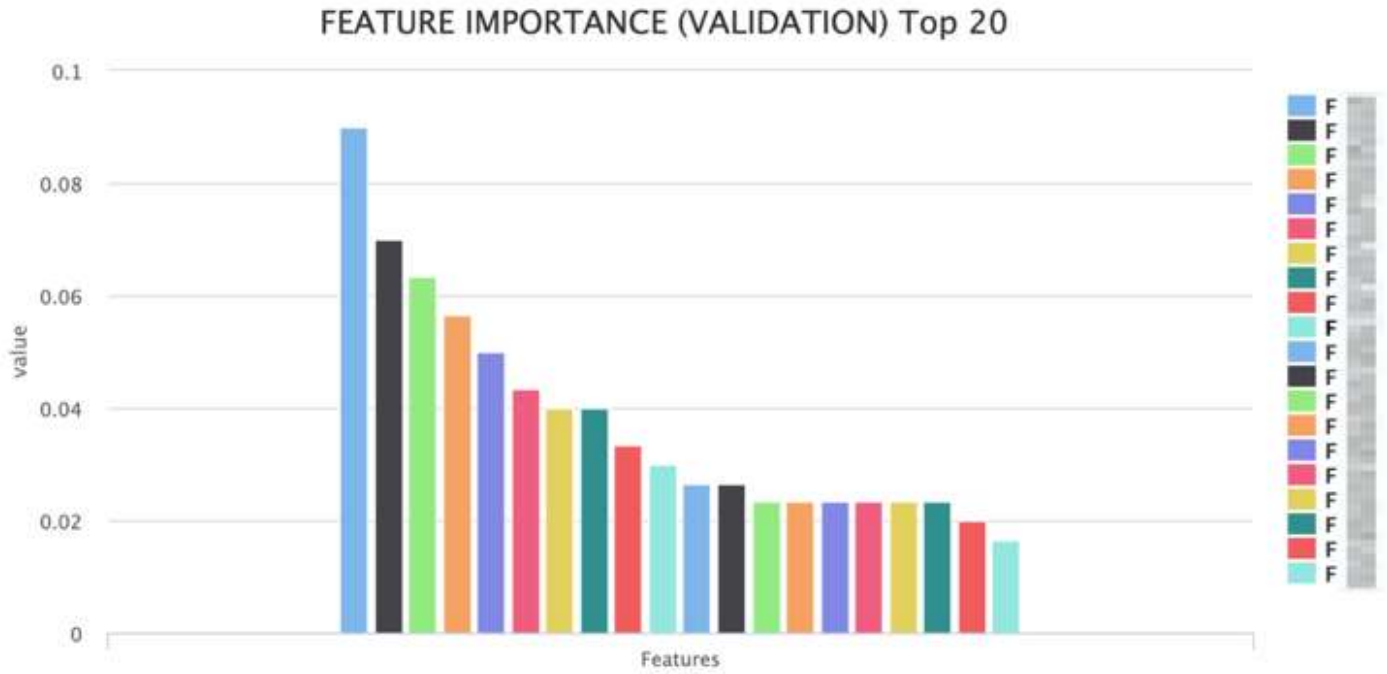


Modeling Approaches

- Pairwise XGBoost
- GLMix
- DNNs via TensorFlow

- Optimization Criteria: inMail Accepts
  - Positive: inMail sent by recruiter, and positively responded by candidate
  - Mutual interest between the recruiter and the candidate

Feature Importance in XGBoost



How We Utilize Feature Importances for GBDT

- Understanding feature digressions
  - Which a feature that was impactful no longer is?
  - Should we debug feature generation?
- Introducing new features in bulk and identifying effective ones
  - An activity feature for last 3 hours, 6 hours, 12 hours, 24 hours introduced (costly to compute)
  - Should we keep all such features?
- Separating the factors for that caused an improvement
  - Did an improvement come from a new feature, or a new labeling strategy, data source?
  - Did the ordering between features change?
- Shortcoming: A global view, not case by case

GLMix Models

- Generalized Linear Mixed Models
  - Global: Linear Model
  - Per-contract: Linear Model
  - Per-recruiter: Linear Model

$$g(\underbrace{P(r,c,re,ca,co)}_{\text{Positive Response Prob.}}) = \underbrace{\beta_{global} \cdot f_{all}}_{\text{Global model}} + \underbrace{\beta_{re} \cdot f_{all}}_{\text{Per-recruiter model}} + \underbrace{\beta_{co} \cdot f_{all}}_{\text{Per-contract model}}$$

- Lots of parameters overall
  - For a specific recruiter or contract the weights can be summed up
- Inherently explainable
  - Contribution of a feature is “weight x feature value”
  - Can be examined in a case-by-case manner as well

TensorFlow Models in Recruiter and Explaining Them

- We utilize the Integrated Gradients [ICML 2017] method

- How do we determine the baseline example?
  - Every query creates its own feature values for the same candidate
  - Query match features, time-based features
  - Recruiter affinity, and candidate affinity features
  - A candidate would be scored differently by each query
  - Cannot recommend a “Software Engineer” to a search for a “Forensic Chemist”
  - There is no globally neutral example for comparison!

Query-Specific Baseline Selection

- For each query:
  - Score examples by the TF model
  - Rank examples
  - Choose one example as the baseline
  - Compare others to the baseline example
- How to choose the baseline example
  - Last candidate
  - Kth percentile in ranking
  - A random candidate
  - Request by user (answering a question like: “Why was I presented candidate x above candidate y?”)

Example

Example - Detailed

Feature	Description	Difference (1 vs 2)	Contribution
Feature…….	Description…….	-2.0476928	-2.144455602
Feature…….	Description…….	-2.3223877	1.903594618
Feature…….	Description…….	0.11666667	0.2114946752
Feature…….	Description…….	-2.1442587	0.2060414469
Feature…….	Description…….	-14	0.1215354111
Feature…….	Description…….	1	0.1000282466
Feature…….	Description…….	-92	-0.085286277
Feature…….	Description…….	0.9333333	0.0568533262
Feature…….	Description…….	-1	-0.051796317
Feature…….	Description…….	-1	-0.050895940

Pros & Cons

- Explains potentially very complex models
- Case-by-case analysis
  - Why do you think candidate x is a better match for my position?
  - Why do you think I am a better fit for this job?
  - Why am I being shown this ad?
  - Great for debugging real-time problems in production
- Global view is missing
  - Aggregate Contributions can be computed
  - Could be costly to compute

Lessons Learned and Next Steps

- Global explanations vs. Case-by-case Explanations
  - Global gives an overview, better for making modeling decisions
  - Case-by-case could be more useful for the non-technical user, better for debugging
- Integrated gradients worked well for us
  - Complex models make it harder for developers to map improvement to effort
  - Use-case gave intuitive results, on top of completely describing score differences
- Next steps
  - Global explanations for Deep Models

Case Study:

Model Interpretation for Predictive Models in B2B Sales Predictions

Jilei Yang, Wei Di, Songtao Guo

Problem Setting

- Predictive models in B2B sales prediction
  - E.g.: random forest, gradient boosting, deep neural network, …
  - High accuracy, low interpretability
- Global feature importance → Individual feature reasoning

① What are top driver features for a certain company to have high/low probability to upsell/churn?

① Feature Contributor

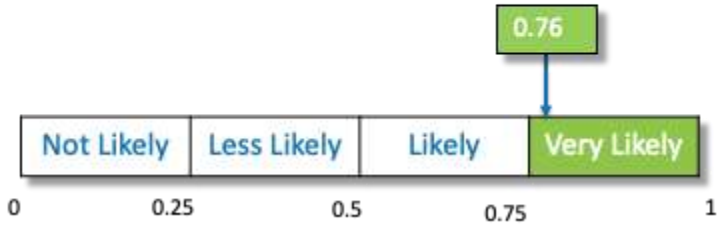
② Which top driver features can be perturbed if we want to increase/decrease probability for a certain company?

② Feature Influencer

Example

Company: CompanyX

Upsell LCP (LinkedIn Career Page)



Top Feature Contributor

- f1: 430.5
- f2: 216
- f3: 10097.57
- f4: 15

Top Feature Influencer (Positive)

f5: 0 → 5.4, ↑ 0.03

f6: 168 → 0, ↑ 0.03

f7: 0 → 0.24, ↑ 0.02

Top Feature Influencer (Negative)

f1: 430.5 → 148.7, ↓ 0.20

f2: 216 → 0, ↓ 0.17

f8: 423 → 146.0, ↓ 0.07

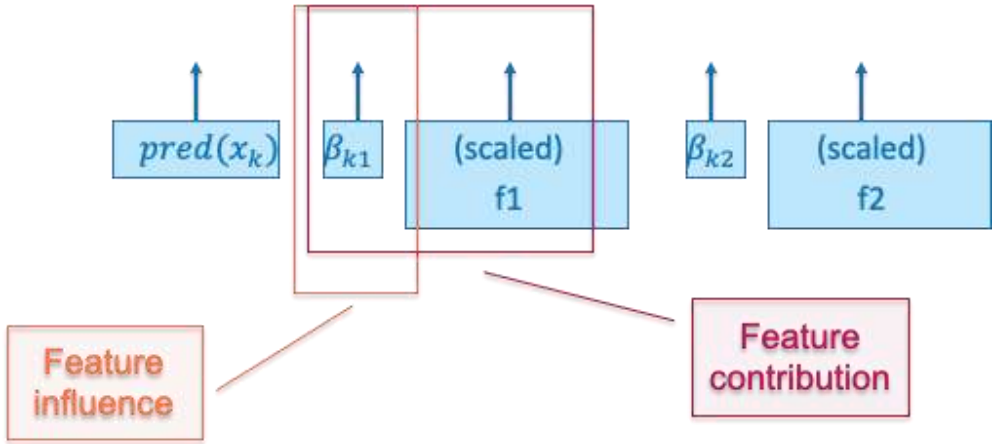
Revisiting LIME

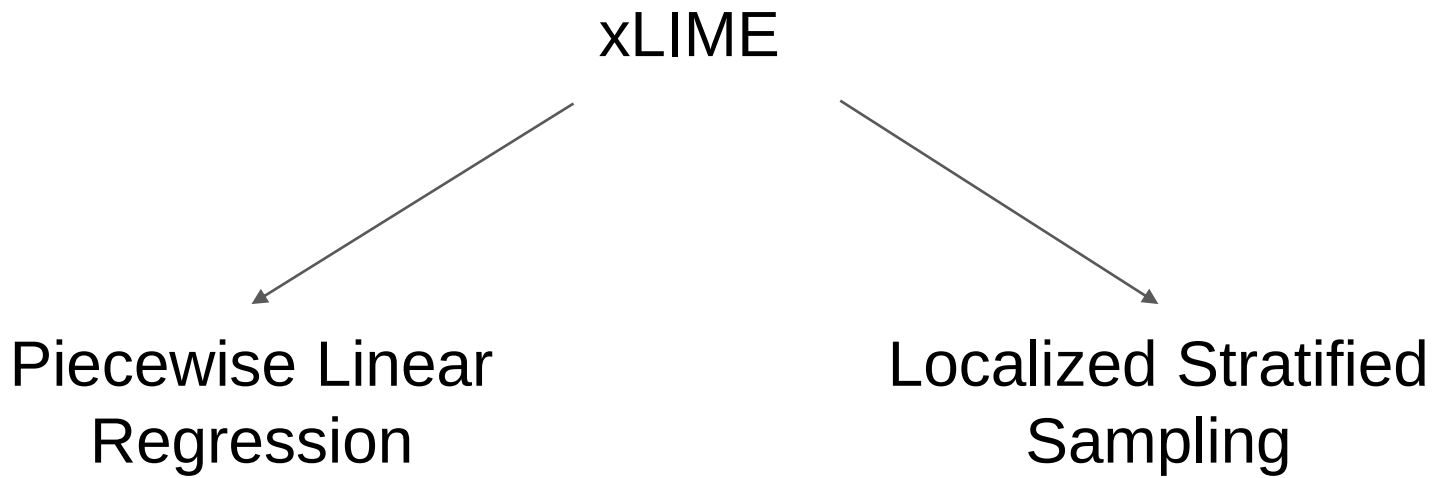
- Given a target sample x_k, approximate its prediction $pred(x_k)$ by building a sample-specific linear model:

$$pred(X) \approx \beta_{k1} X_1 + \beta_{k2} X_2 + \ldots, X \in neighbor(x_k)$$

- E.g., for company CompanyX:

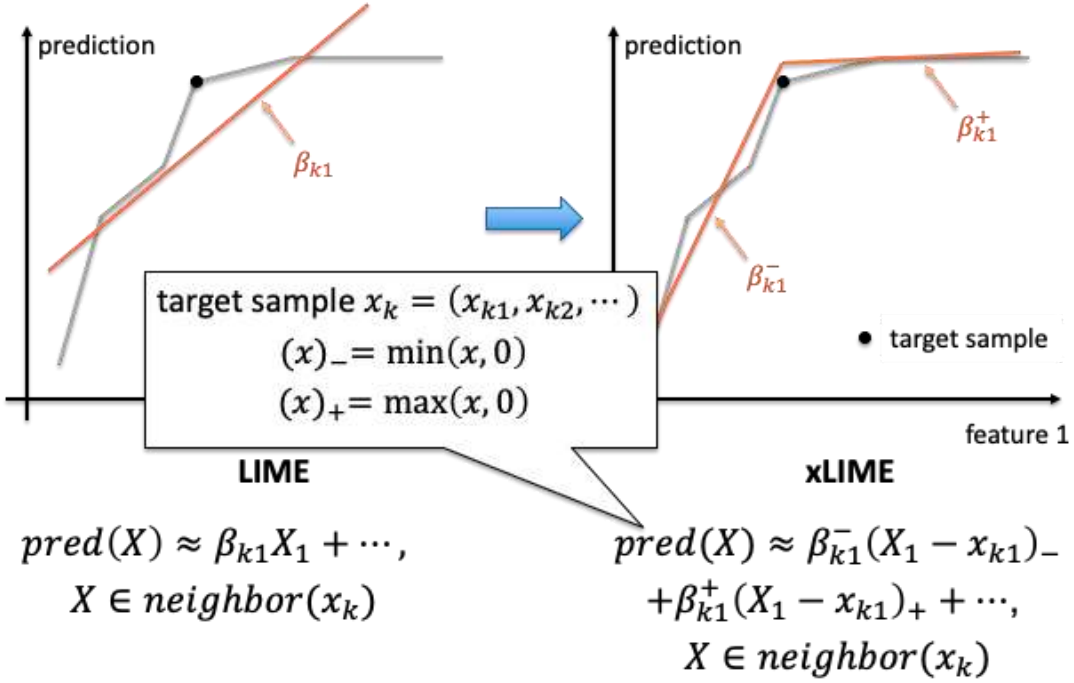
$$0.76 \approx 1.82 * 0.17 + 1.61 * 0.11 + \ldots$$




xLIME
Piecewise Linear Regression
Localized Stratified Sampling

Piecewise Linear Regression

Motivation: Separate top positive feature influencers and top negative feature influencers

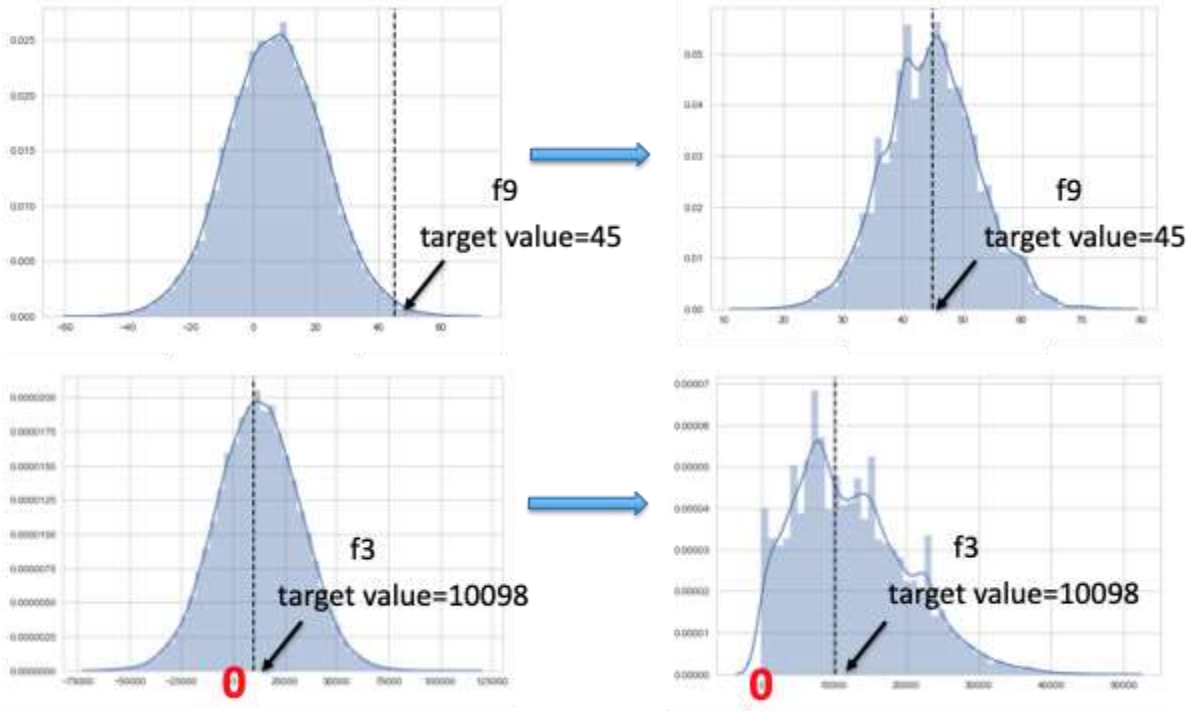


Impact of Piecewise Approach

- Target sample $x_k=(x_{k1}, x_{k2}, \cdots)$
- Top feature contributor
  - LIME: large magnitude of $\beta_{kj} \cdot x_{kj}$
  - xLIME: large magnitude of $\beta_{kj}^{-} \cdot x_{kj}$
- Top positive feature influencer
  - LIME: large magnitude of β_{kj}
  - xLIME: large magnitude of negative β_{kj}^{-} or positive β_{kj}^{+}
- Top negative feature influencer
  - LIME: large magnitude of β_{kj}
  - xLIME: large magnitude of positive β_{kj}^{-} or negative β_{kj}^{+}

Localized Stratified Sampling: Idea

Method: Sampling based on empirical distribution around target value at each feature level



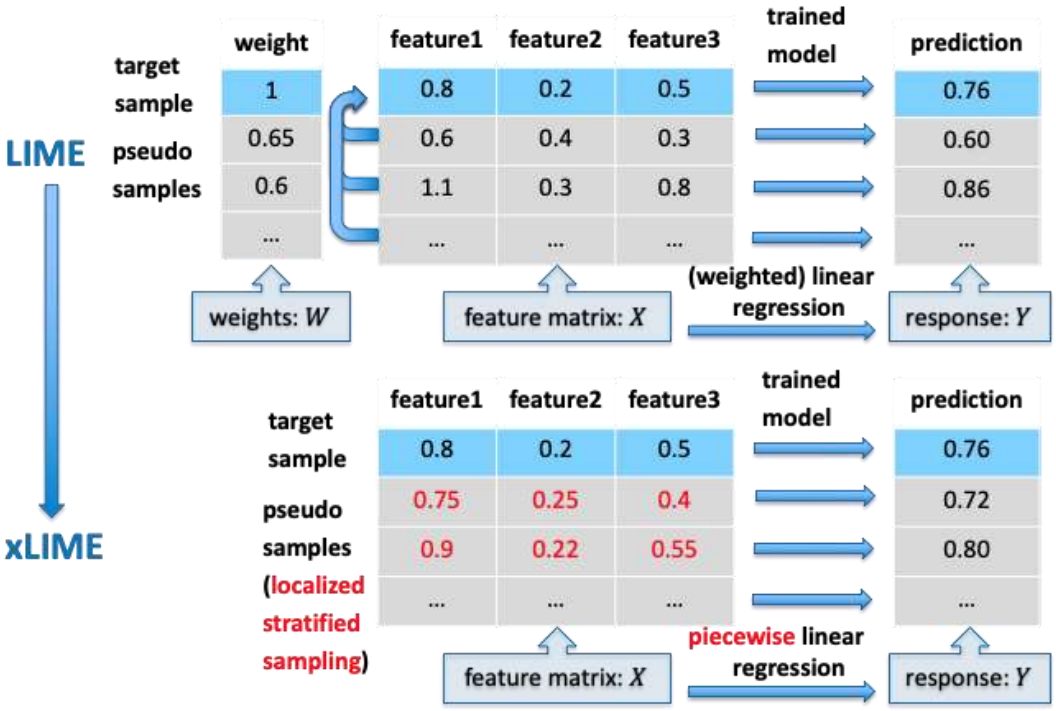
Localized Stratified Sampling: Method

- Sampling based on empirical distribution around target value for each feature
- For target sample x_k = (x_{k1} , x_{k2} , ⋯), sampling values of feature j according to

$$p_j\,(X_j) \cdot N(x_{kj}\,, (\alpha \cdot s_j\,)^2)$$

  - $p_j\,(X_j)$: empirical distribution.
  - x_{kj} : feature value in target sample.
  - s_j : standard deviation.
  - α : Interpretable range: tradeoff between interpretable coverage and local accuracy.
- In LIME, sampling according to $N(\bar{x_j}, {s_j}^2)$.

Summary


LIME
xLIME
target sample
pseudo samples
weight
feature1
feature2
feature3
trained model
prediction
1
0.65
0.6
...
0.8
0.2
0.5
0.6
0.4
0.3
1.1
0.3
0.8
...
...
...
0.76
0.60
0.86
...
weights: W
feature matrix: X
(weighted) linear regression
response: Y
target sample
pseudo samples (localized stratified sampling)
feature1
feature2
feature3
trained model
prediction
0.8
0.2
0.5
0.75
0.25
0.4
0.9
0.22
0.55
...
...
...
0.76
0.72
0.80
...
feature matrix: X
piecewise linear regression
response: Y

LTS LCP (LinkedIn Career Page) Upsell

- A subset of churn data
  - Total Companies: ~ 19K
  - Company features: 117
- **Problem:** Estimate whether there will be upsell given a set of features about the company’s utility from the product

Top Feature Contributor

Company : CompanyX

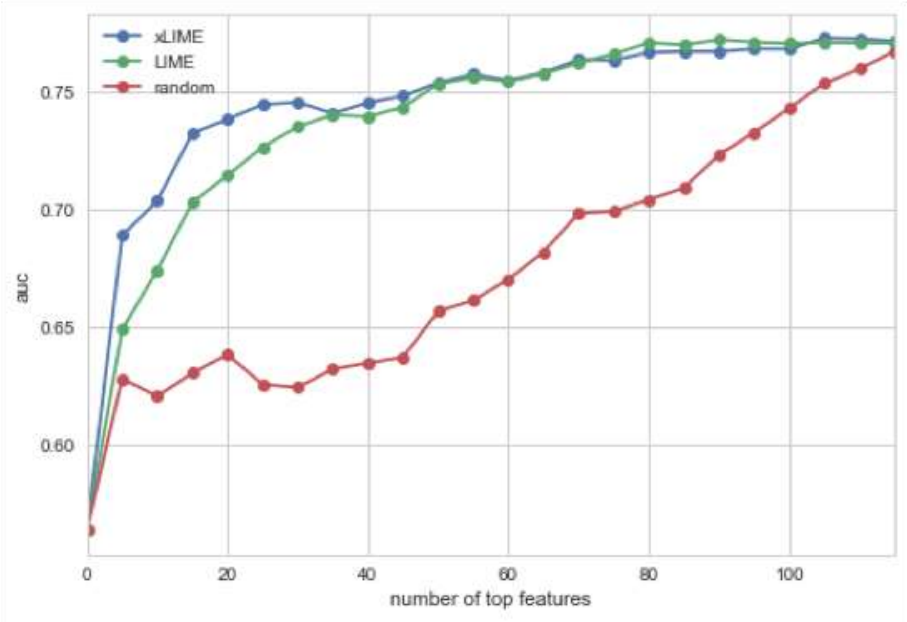
LIME

	name	value	quantile	contribution
	f9	45.0	98	-0.011
	f3	10097.6	66	0.011
	f10	16.5	94	0.010

xLIME

	name	value	quantile	contribution
	f1	430.5	59	0.246
	f2	216.0	40	0.161
	f3	10097.6	66	0.084

- **Explanation curve**: how classification performance varies if one considers only the top ranked feature contributors



Top Feature Influencers

Company: CompanyX

	Positive influencer			Negative influencer		
LIME	f1 +	430.5→712.3	.004	f1 -	430.5→148.7	.004
	f2 +	216.0→435.4	.004	f2 -	216.0→0.0	.004
	f11 +	9.8→13.2	.003	f11 -	9.8→6.3	.003
xLIME	f5 +	0.0→5.4	.032	f1 -	430.5→148.7	.201
	f6 -	168.0→0.0	.031	f2 -	216.0→0.0	.174
	f7 +	0.00→0.24	.016	f8 -	423.0→146.0	.071

Key Takeaways

- Looking at the explanation as contributor vs. influencer features is useful
  - Contributor: Which features end-up in the current outcome case-by-case
  - Influencer: **What needs to be done to improve likelihood, case-by-case**

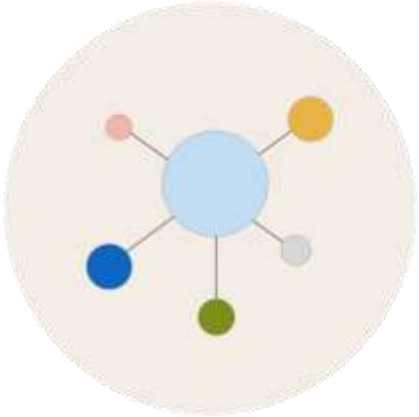
- xLIME aims to improve on LIME via:
  - Piecewise linear regression: More accurately describes local point, helps with finding correct influencers
  - Localized stratified sampling: More realistic set of local points
- Better captures the important features

Case Study:

Relevance Debugging and Explaining @ LinkedIn

Daniel Qiu, Yucheng Qian

Debugging Relevance Models

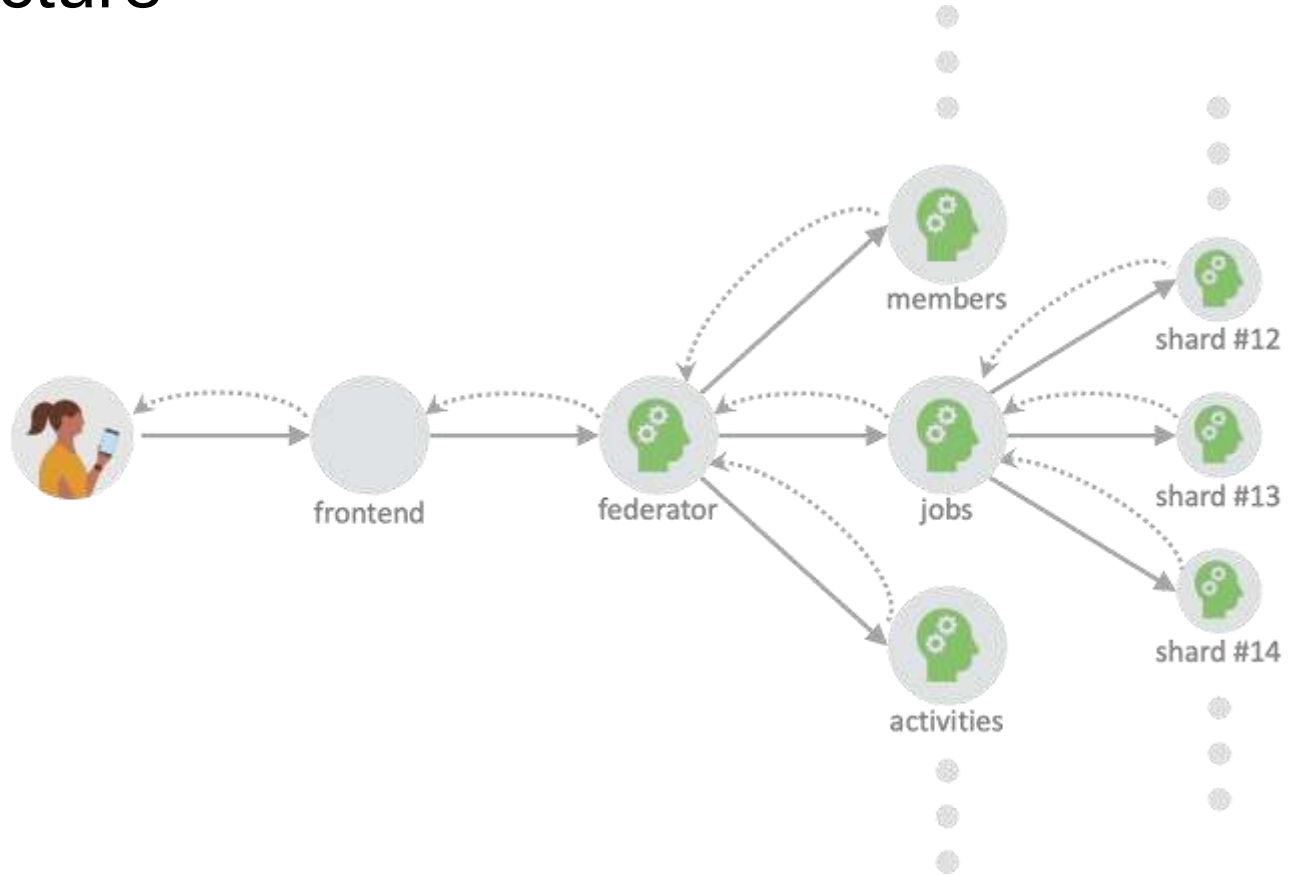


Modeling
Improve the machine learning model

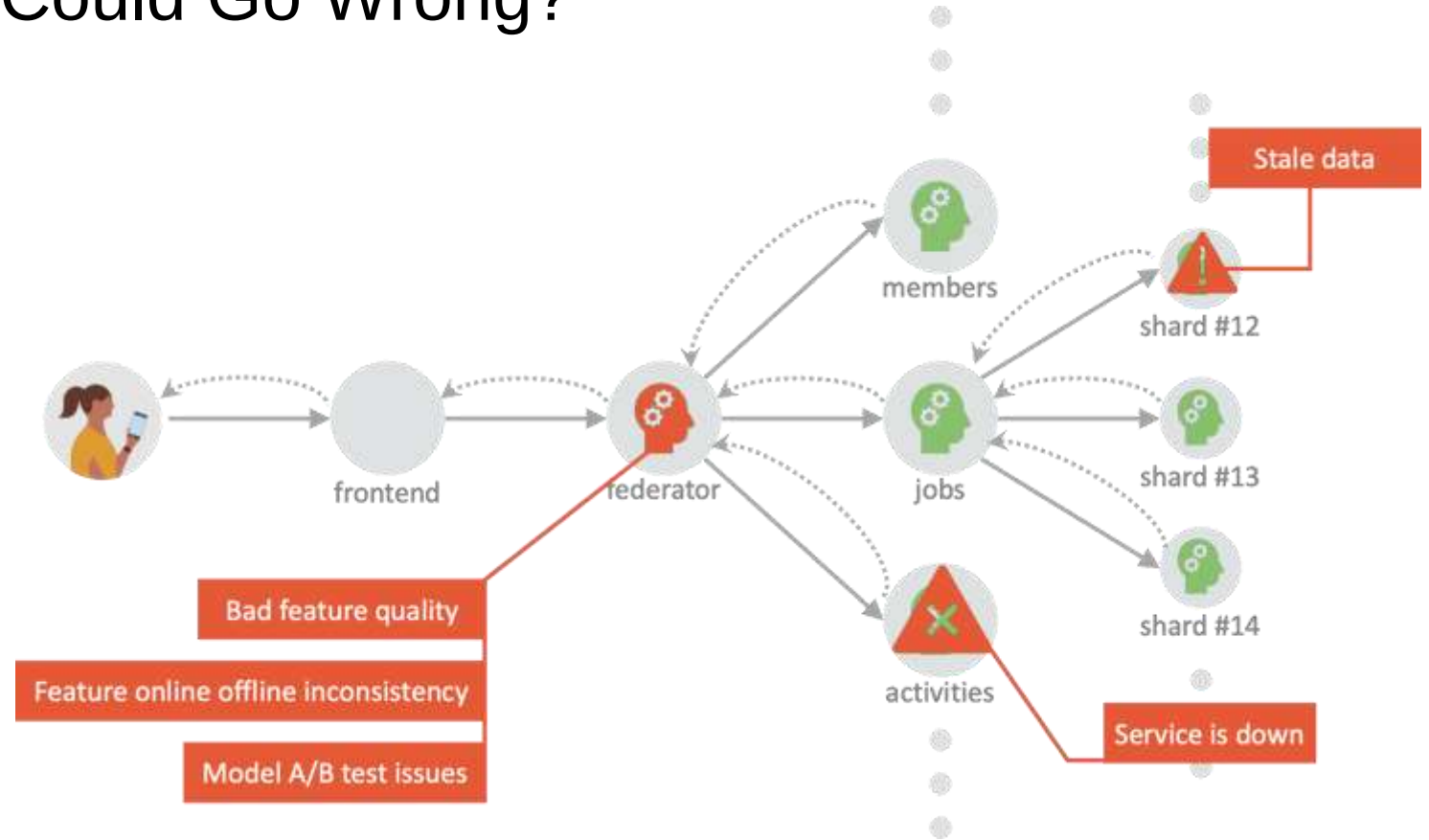
Value
Bring value to our members by providing relevant experience

Trust
Build trust with our members

Architecture



What Could Go Wrong?



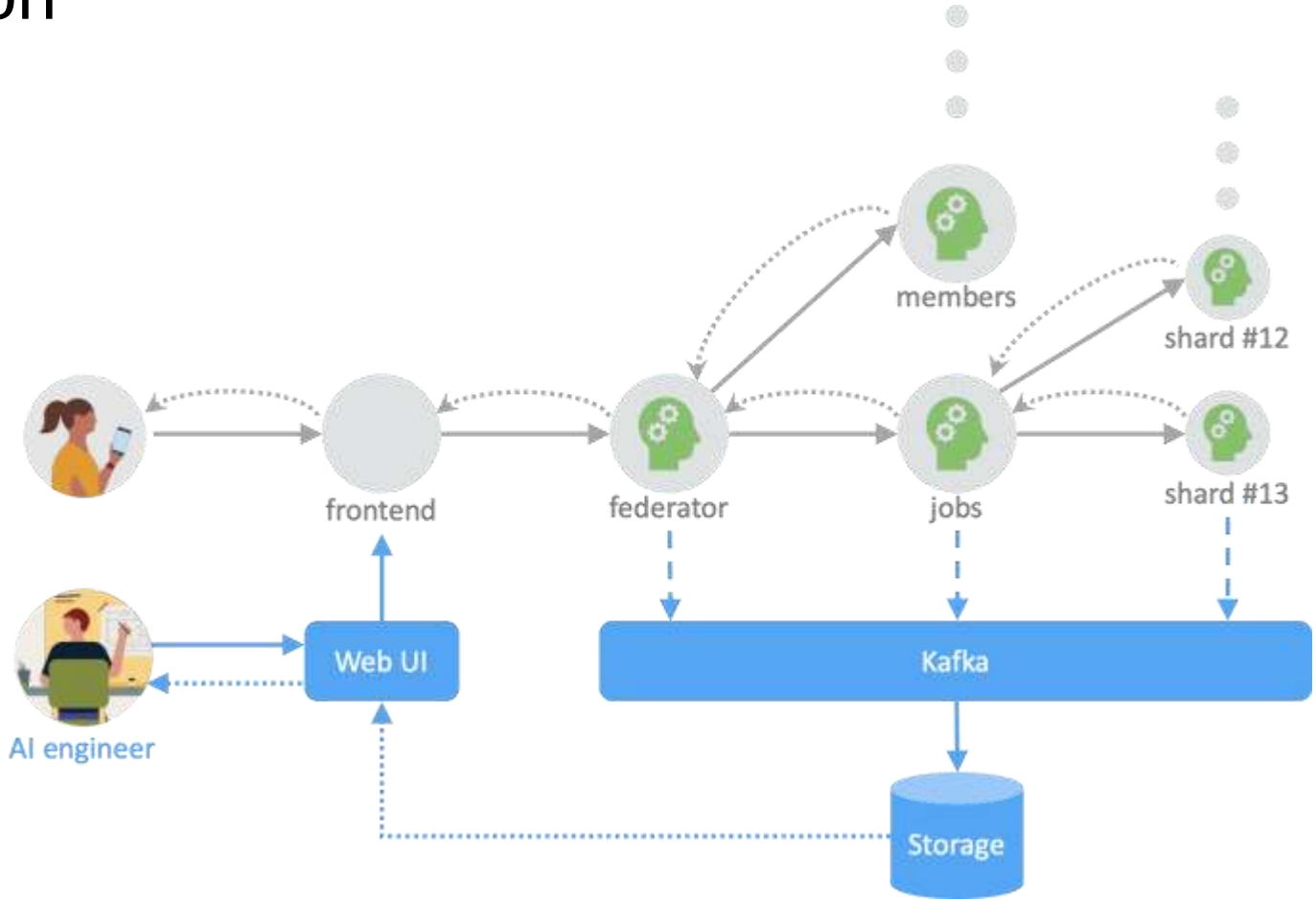
Challenges

Complex Infrastructure

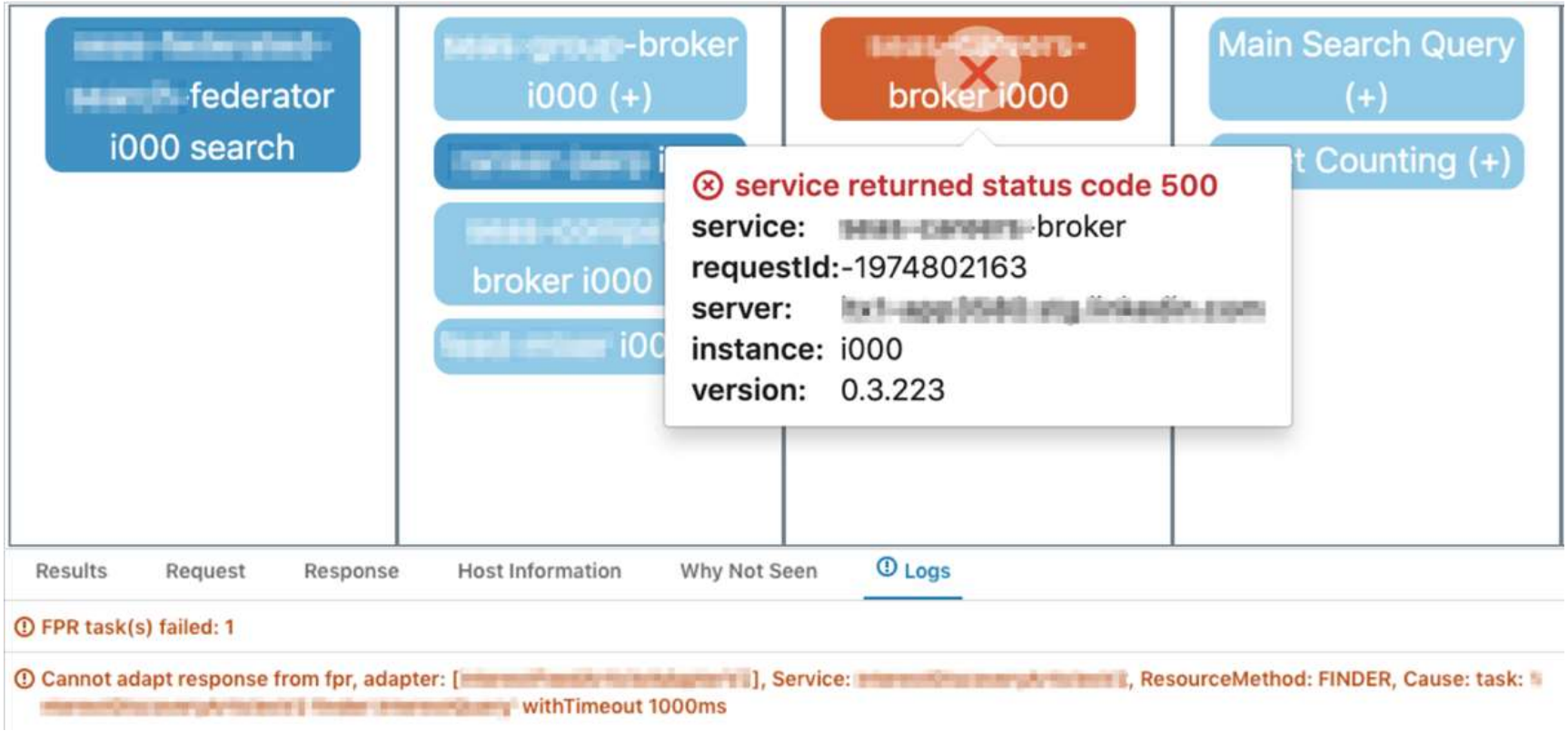
Hard to Reproduce

Time Consuming

Solution


members
shard #12
frontend
federator
jobs
shard #13
Web UI
Kafka
AI engineer
Storage

Call Graph

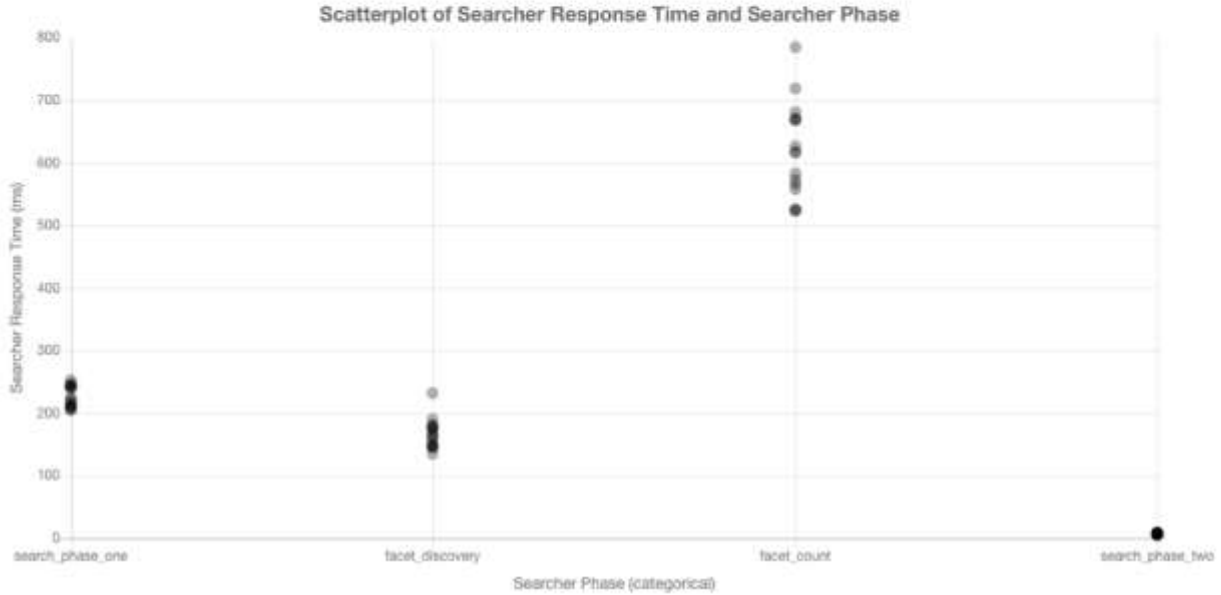

federator
i000 search
-broker
i000 (+)
broker i000
broker i000
Main Search Query
(+)
Counting (+)
service returned status code 500
service: -broker
requestId:-1974802163
server:
instance: i000
version: 0.3.223
Results
Request
Response
Host Information
Why Not Seen
Logs
FPR task(s) failed: 1
Cannot adapt response from fpr, adapter: [
], Service:
, ResourceMethod: FINDER, Cause: task:
withTimeout 1000ms

Timing

Total time (ms): 1041

Number of garbage collection events: 0

	Start Time	End Time	Total Time	Resent?	Partitions	Min	Max	p50	p90
search_phase_one	7	266	259	false	16	205	253	223.0	245.5
facet_discovery	13	240	227	true	16	135	232	164.0	186.0
facet_count	262	1041	779	true	16	523	785	617.0	700.0
search_phase_two	266	274	8	false	15	5	9	8.0	9.0



Features

Group	Feature	Value
SPR	activity_recent_click /	968
SPR	[illegible]	1
SPR	[illegible]	6.8762646
SPR	[illegible]	null
SPR	[illegible]	null
SPR	binary_activity_recent_click / |	1
SPR	[illegible]	null
SPR	log_activity_recent_click /	6.8762646
SPR	[illegible]	0
SPR	[illegible]	0

Advanced Use Cases

Perturbation

Comparison

Replay

Perturbation

1. Inject

Injected as part of the request

- Override A/B test settings
- Model selection
- Feature override

2. Relay

Passed to downstream service

3. Overwrite

Overwrite the system behavior

Comparison

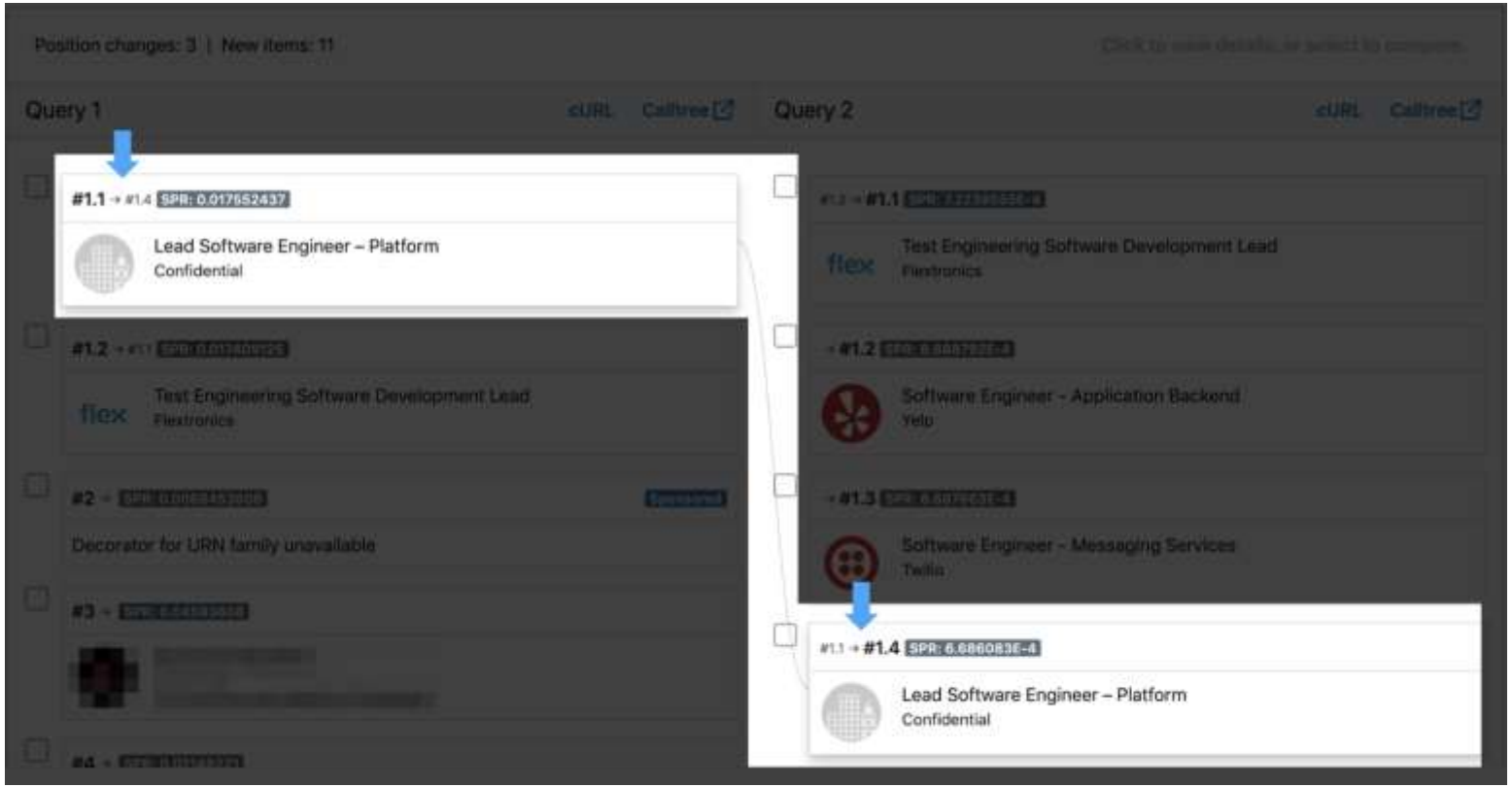
Compare Model

Compare results of 2 different queries/models

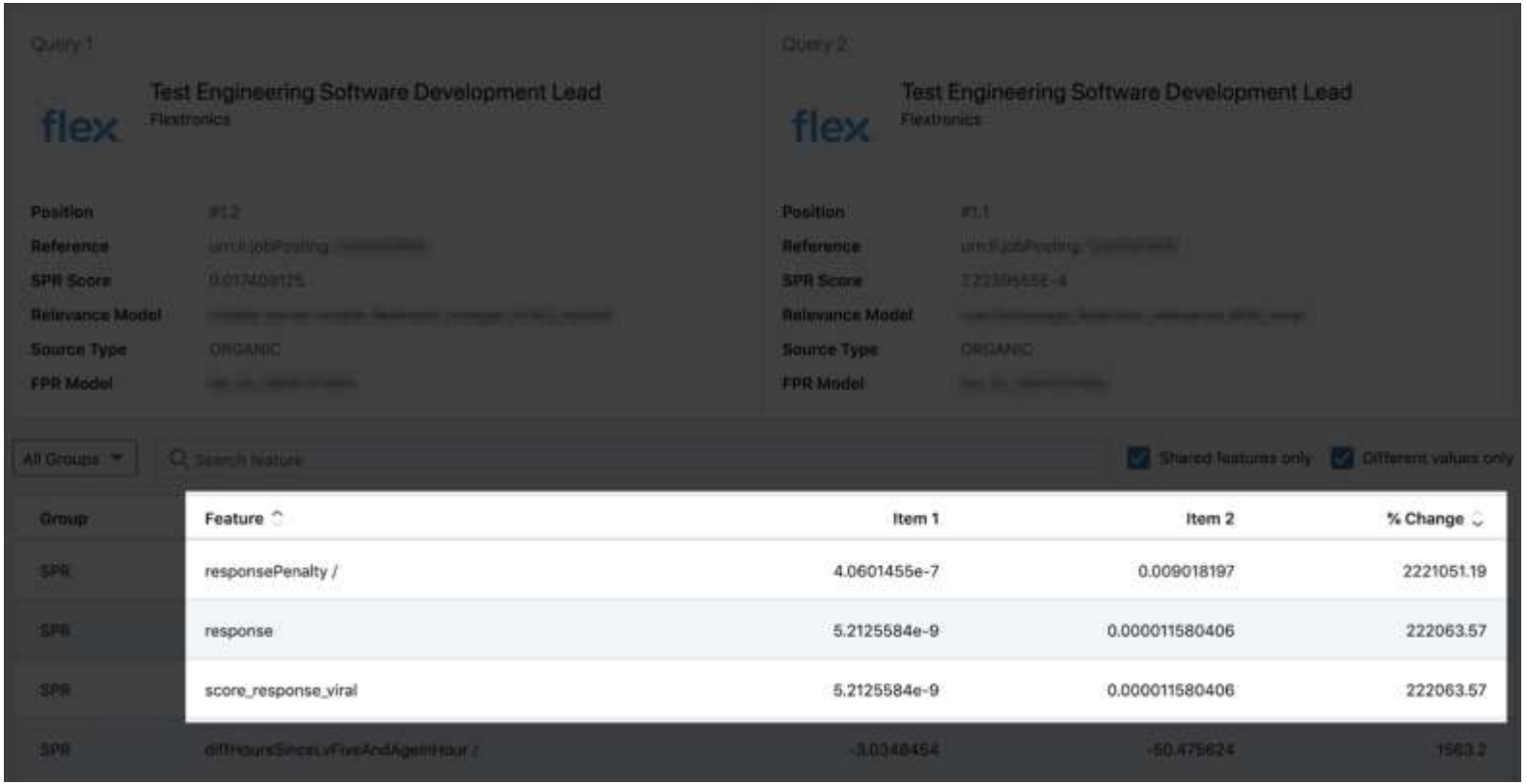
Compare Items

Compare features and scores of 2 different items, from the same query or different queries

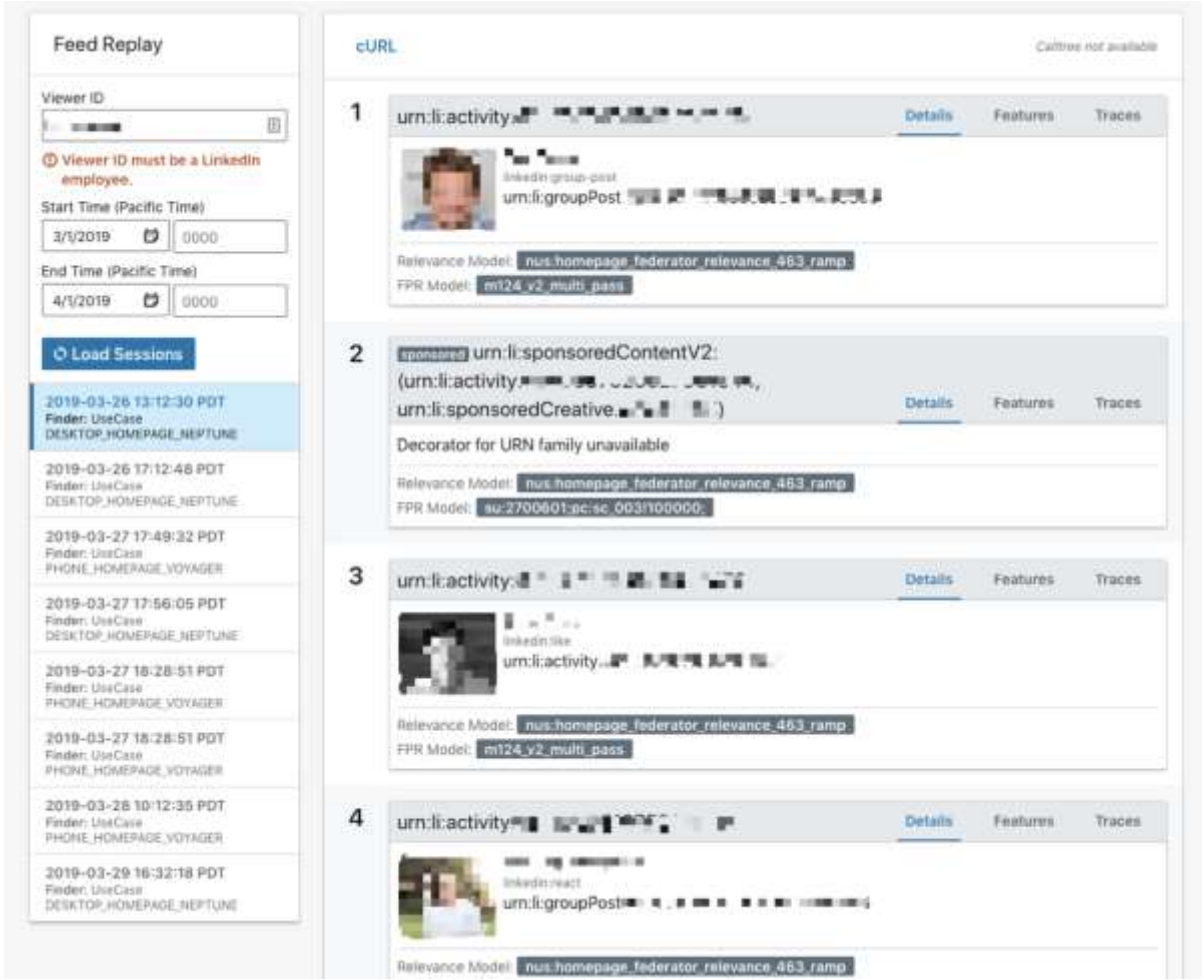
Holistic Comparison



Granular Comparison



Replay


Feed Replay
Viewer ID
Viewer ID must be a LinkedIn employee.
Start Time (Pacific Time)
3/1/2019
0000
End Time (Pacific Time)
4/1/2019
0000
Load Sessions
2019-03-26 13:12:30 PDT
Finder: UseCase
DESKTOP_HOMEPAGE_NEPTUNE
2019-03-26 17:12:48 PDT
Finder: UseCase
DESKTOP_HOMEPAGE_NEPTUNE
2019-03-27 17:49:32 PDT
Finder: UseCase
PHONE_HOMEPAGE_VOYAGER
2019-03-27 17:56:05 PDT
Finder: UseCase
DESKTOP_HOMEPAGE_NEPTUNE
2019-03-27 18:28:51 PDT
Finder: UseCase
PHONE_HOMEPAGE_VOYAGER
2019-03-27 18:28:51 PDT
Finder: UseCase
PHONE_HOMEPAGE_VOYAGER
2019-03-28 10:12:35 PDT
Finder: UseCase
PHONE_HOMEPAGE_VOYAGER
2019-03-29 16:32:18 PDT
Finder: UseCase
DESKTOP_HOMEPAGE_NEPTUNE
cURL
1
urn:li:activity
Details
Features
Traces
urn:li:groupPost
Relevance Model: nus:homepage_federator_relevance_463_ramp
FPR Model: m124_v2_multi_pass
2
sponsored urn:li:sponsoredContentV2:
(urn:li:activity
urn:li:sponsoredCreative.
Details
Features
Traces
Decorator for URN family unavailable
Relevance Model: nus:homepage_federator_relevance_463_ramp
FPR Model:
3
urn:li:activity:
Details
Features
Traces
urn:li:activity
Relevance Model: nus:homepage_federator_relevance_463_ramp
FPR Model: m124_v2_multi_pass
4
urn:li:activity
Details
Features
Traces
urn:li:groupPost
Relevance Model: nus:homepage_federator_relevance_463_ramp

Teams

- Search
- Feed
- Comments
- People you may know
- Jobs you may be interested in
- Notification

Case Study:

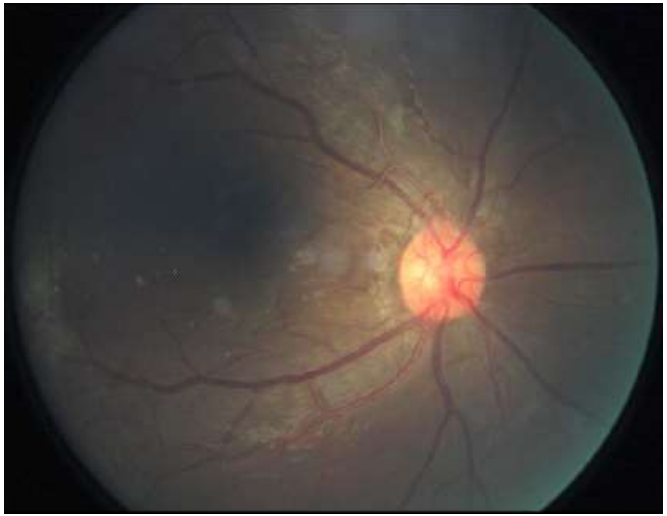
Integrated Gradients for Explaining Diabetic Retinopathy Predictions

Ankur Taly** (Fiddler labs)

(Joint work with Mukund Sundararajan, Kedar Dhamdhere, Pramod Mudrakarta)

**This research was carried out at Google Research

Retinal Fundus Image



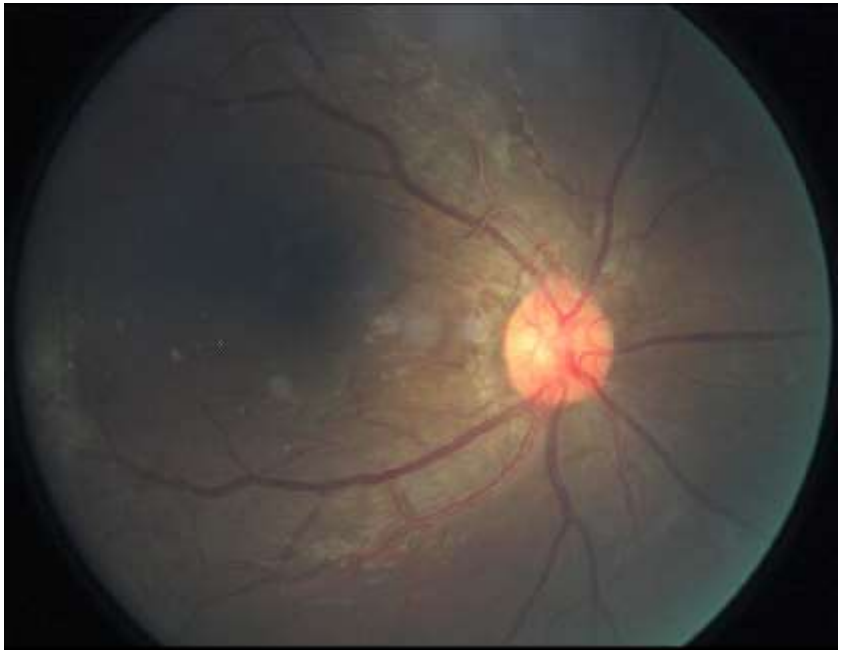
⇨ Prediction: **“proliferative”** DR[1]

- Proliferative implies vision-threatening

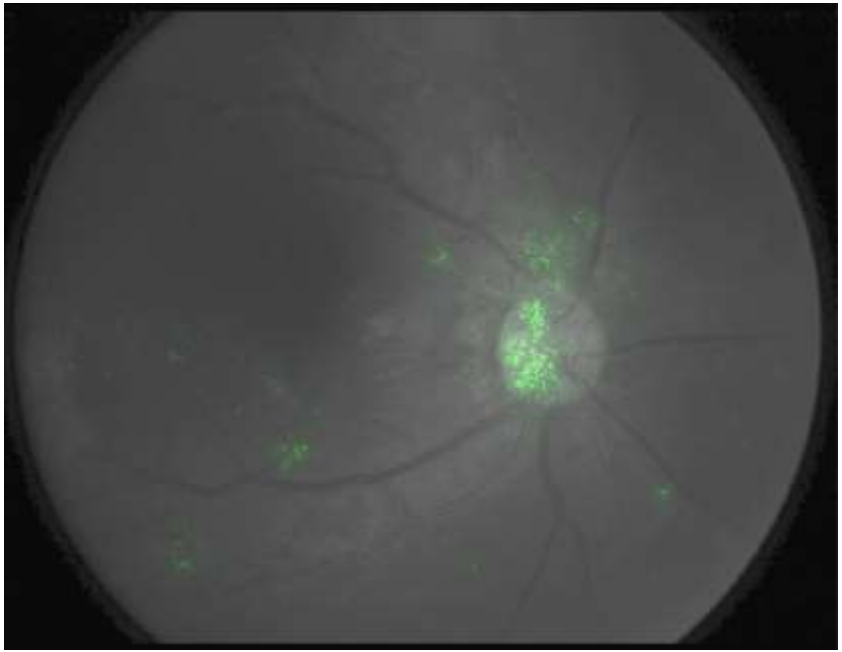
Can we provide an explanation to the doctor with supporting evidence for **“proliferative”** DR?

[1]**Diabetic Retinopathy (DR)** is a diabetes complication that affects the eye. Deep networks can predict DR grade from retinal fundus images with high accuracy (AUC ~0.97) [JAMA, 2016].

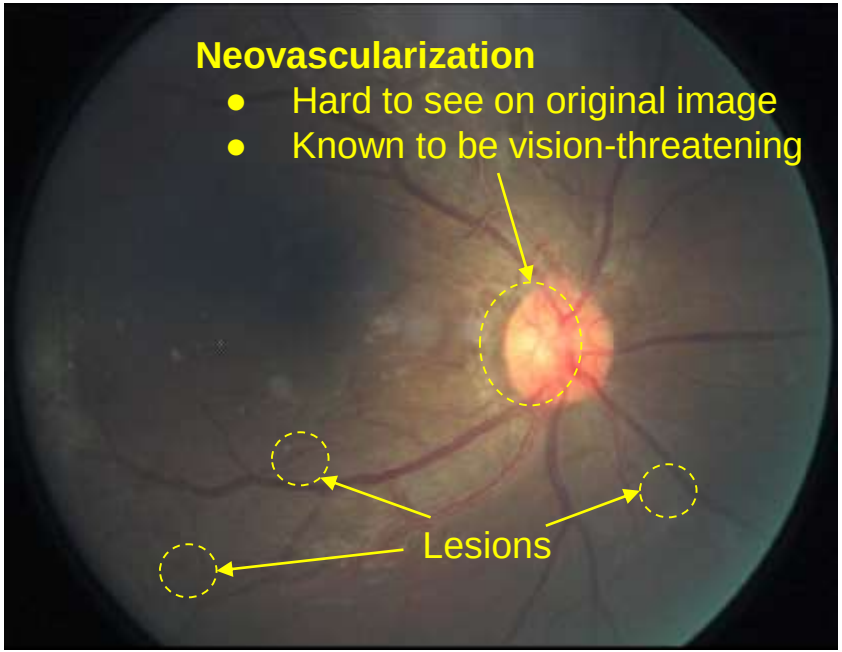
Retinal Fundus Image



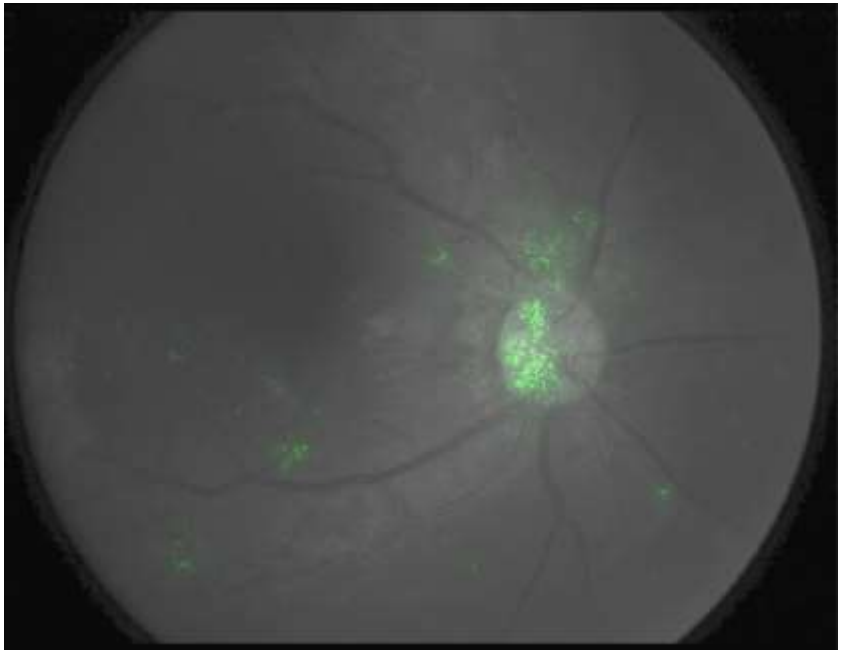
Integrated Gradients for label: “proliferative”
Visualization: Overlay heatmap on green channel



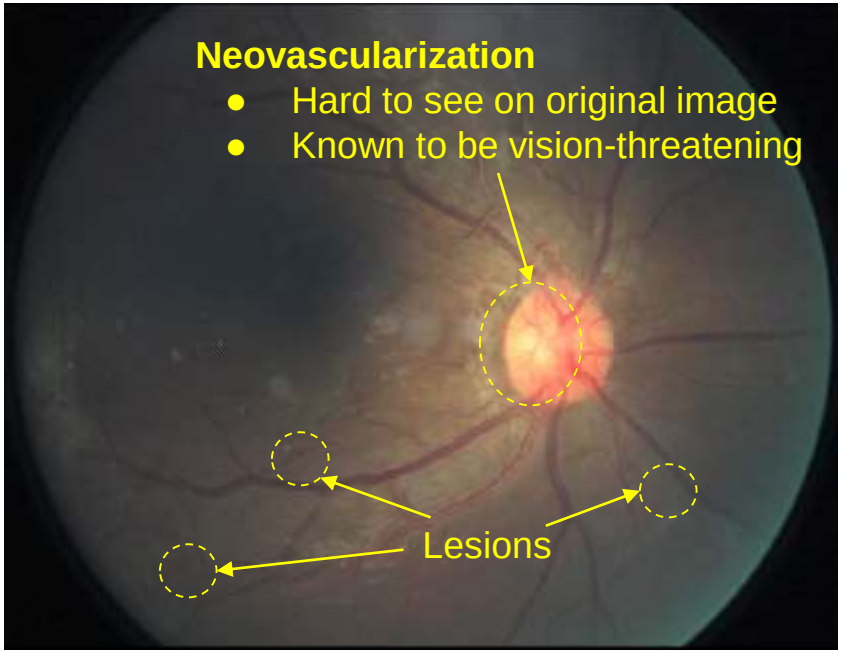
Retinal Fundus Image



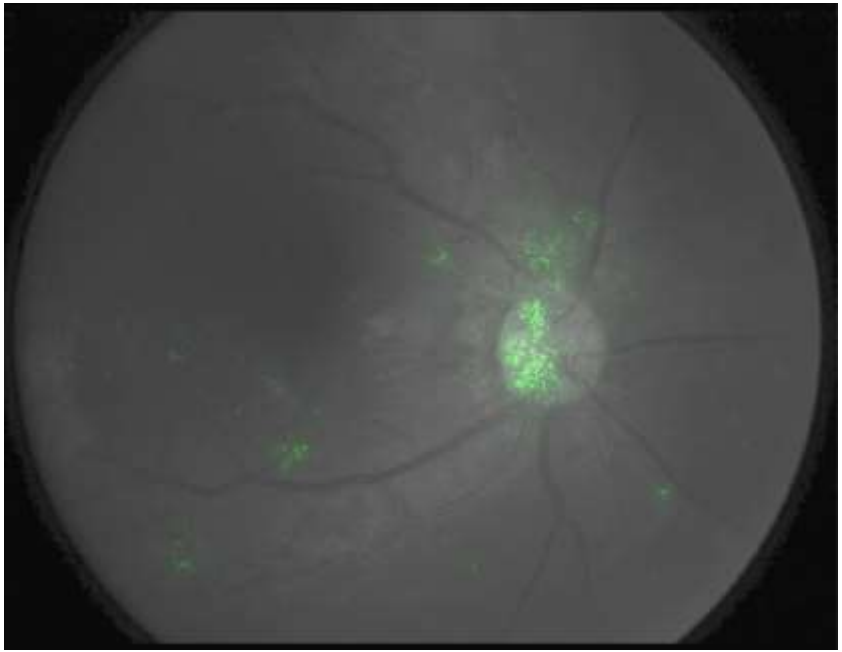
Integrated Gradients for label: “proliferative”
Visualization: Overlay heatmap on green channel



Retinal Fundus Image



Integrated Gradients for label: “proliferative”
Visualization: Overlay heatmap on green channel



Does attributions help improve doctors better diagnose diabetic retinopathy?

Assisted-read study

9 doctors grade 2000 images under three different conditions

A. Image only
B. Image + Model’s prediction scores
C. Image + Model’s prediction scores + Explanation (Integrated Gradients)

Assisted-read study

9 doctors grade 2000 images under three different conditions

A. Image only
B. Image + Model's prediction scores
C. Image + Model's prediction scores + Explanation (Integrated Gradients)

Findings:

- Model's predictions (B) significantly improve accuracy vs. image only (A) ($p < 0.001$)
- Both forms of assistance (B and C) improved sensitivity without hurting specificity
- Explanations (C) improved accuracy of cases with DR ($p < 0.001$) but hurt accuracy of cases without DR ($p = 0.006$)
- Both B and C increase doctor ↔ model agreement

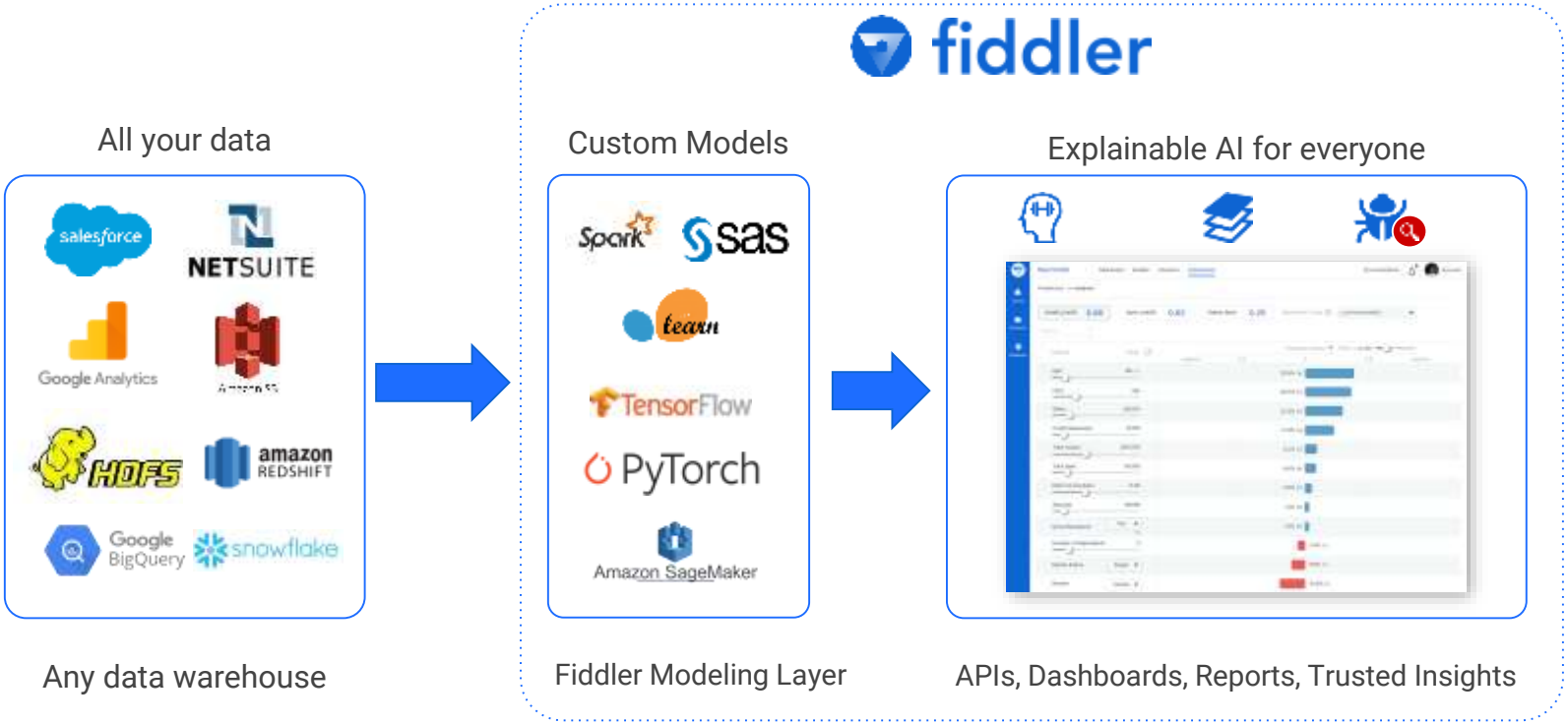
Paper: Using a deep learning algorithm and integrated gradients explanation to assist grading for diabetic retinopathy --- Journal of Ophthalmology [2018]

Case Study:

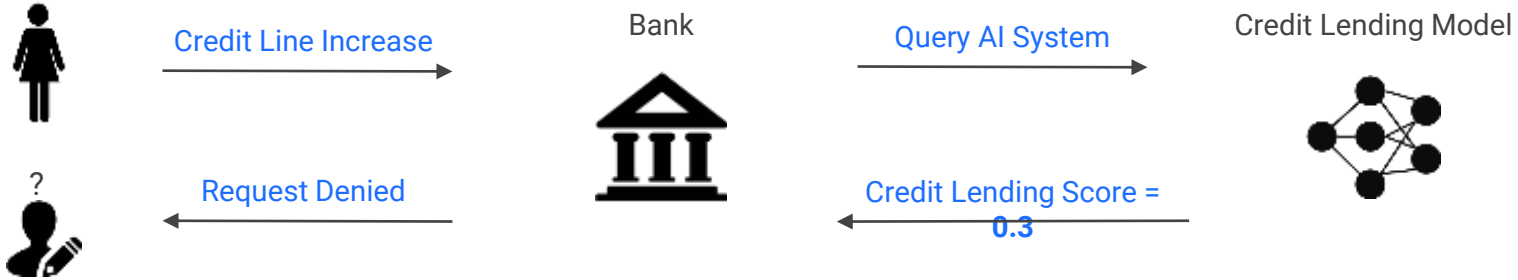
Building an Explainable AI Engine @  fiddler

Fiddler's Explainable AI Engine

Mission: Unlock Trust, Visibility and Insights by making AI Explainable in every enterprise



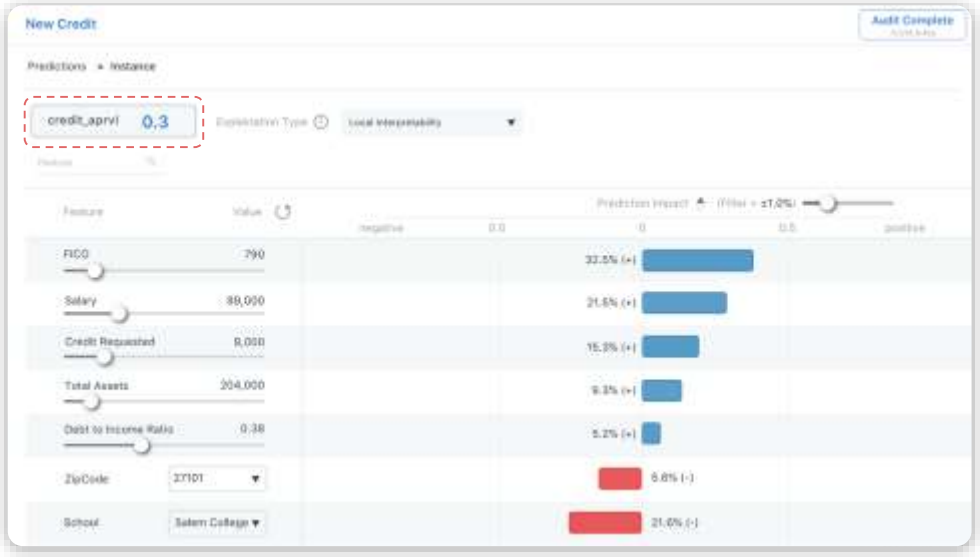
Example: Credit Lending in a black-box ML world



Why? Why not? How?

Fair lending laws [ECOA, FCRA] require credit decisions to be explainable

Explain individual predictions (using Shapley Values)



How Can This Help…

Customer Support

Why was a customer loan rejected?

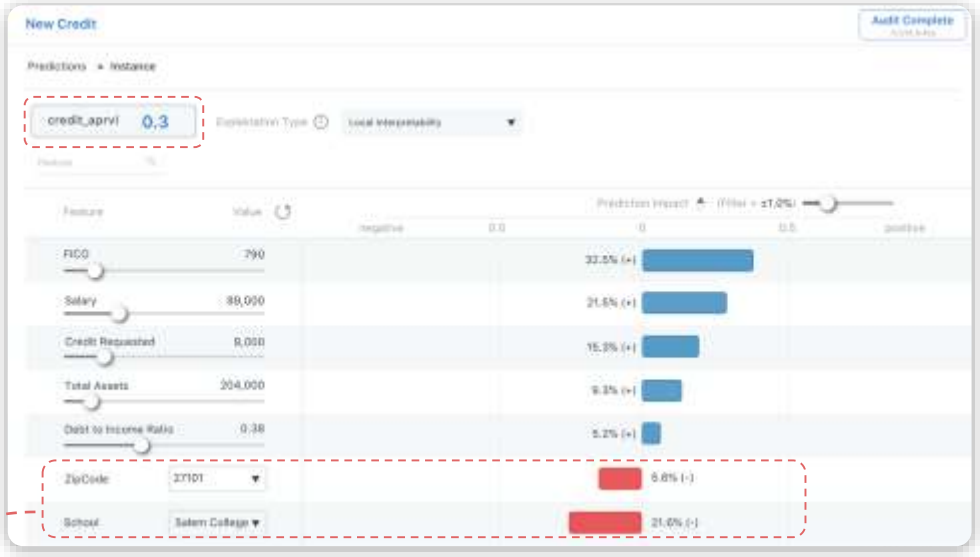
Bias & Fairness

How is my model doing across demographics?

Lending LOB

What variables should they validate with customers on “borderline” decisions?

Explain individual predictions (using Shapley Values)



How Can This Help…

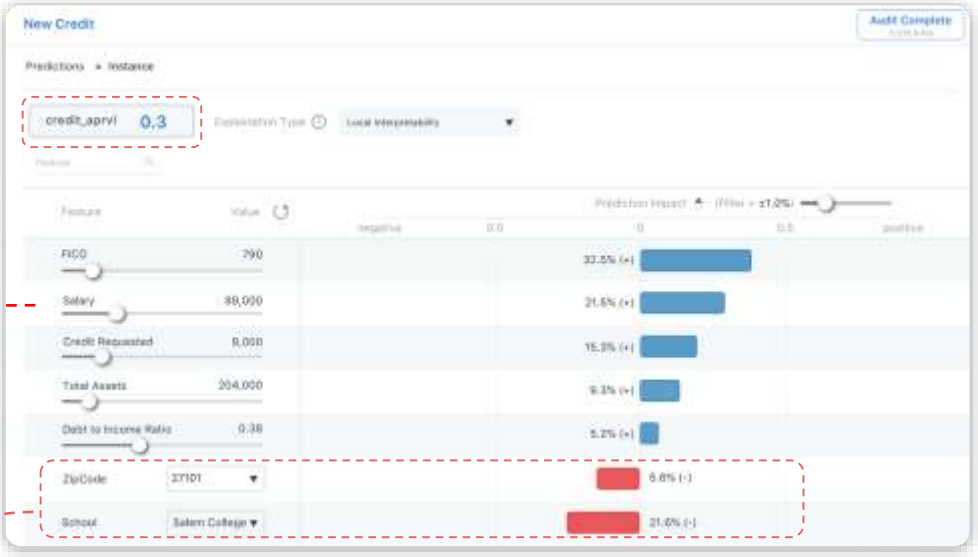
Customer Support
Why was a customer loan rejected?

Bias & Fairness
How is my model doing across demographics?

Lending LOB
What variables should they validate with customers on “borderline” decisions?

Explain individual predictions (using Shapley Values)

Probe the model on **counterfactuals**



How Can This Help…

Customer Support

Why was a customer loan rejected?

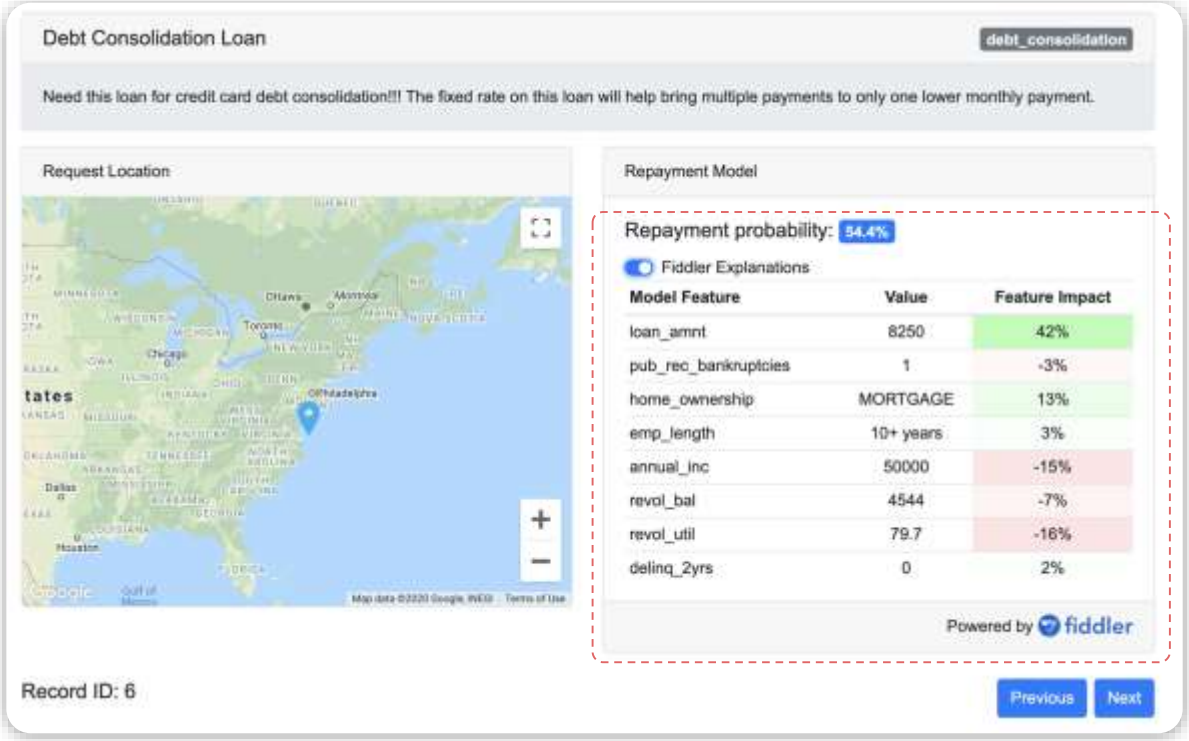
Bias & Fairness

How is my model doing across demographics?

Lending LOB

What variables should they validate with customers on “borderline” decisions?

Integrating explanations



How Can This Help…

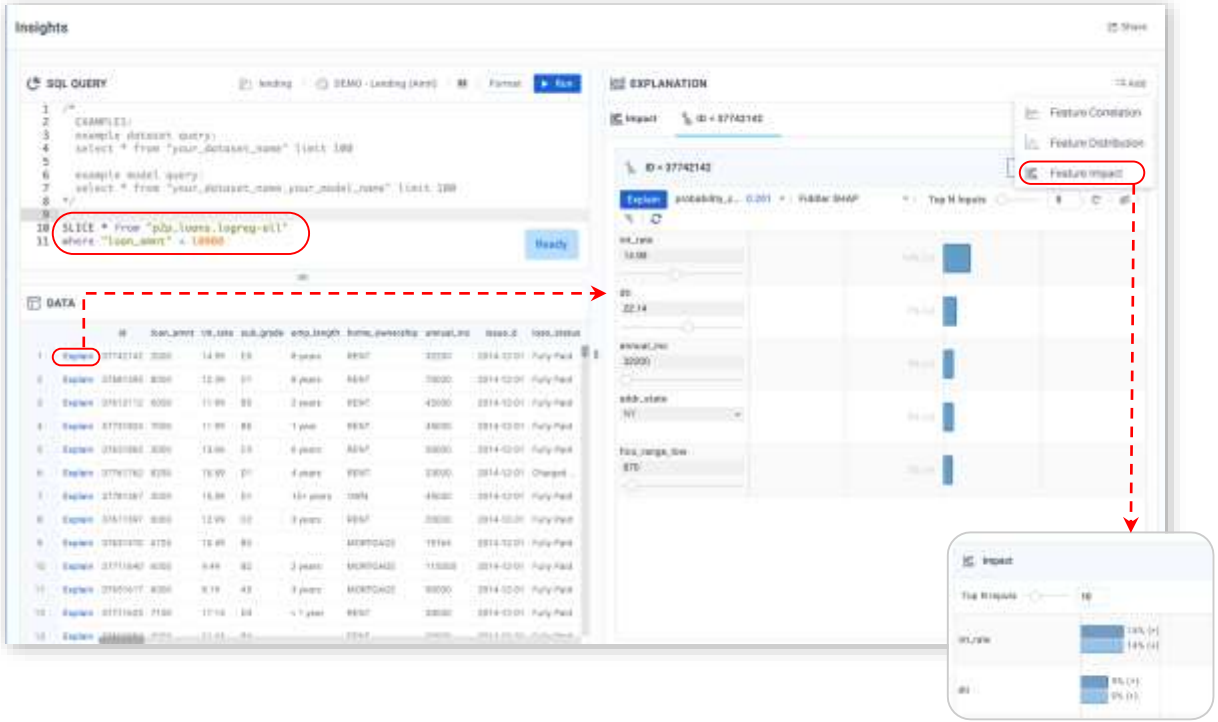
Customer Support

Why was a customer loan rejected?

Why was the credit card limit low?

Why was this transaction marked as fraud?

Slice & Explain



How Can This Help…

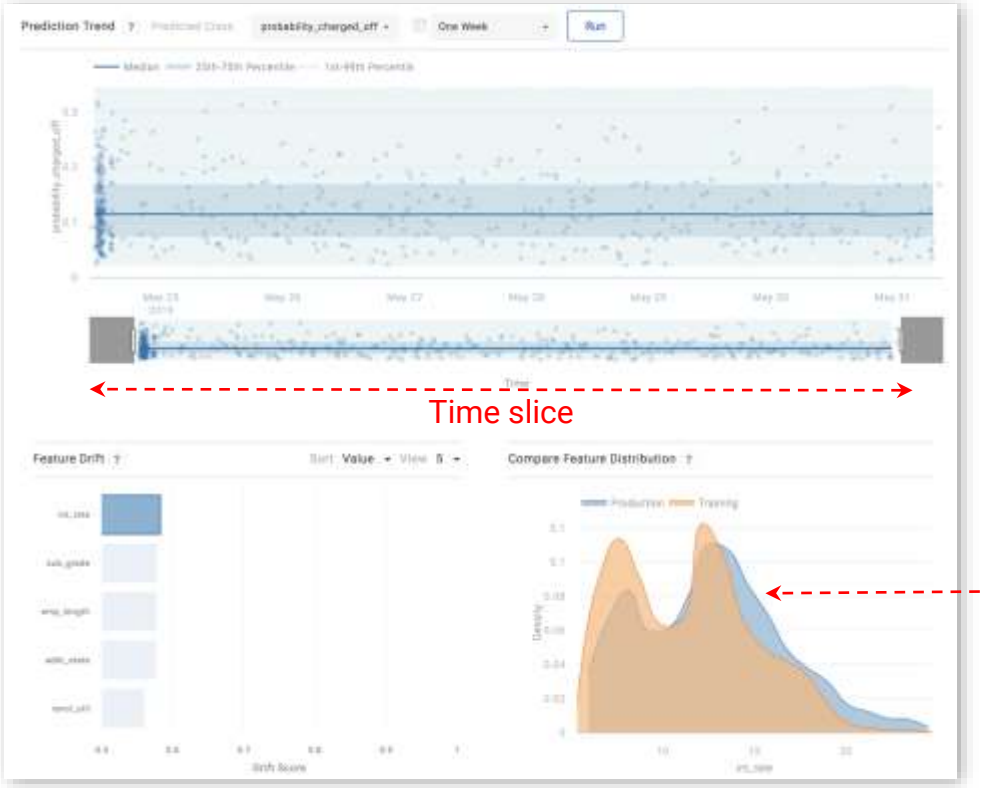
Global Explanations

What are the primary feature drivers of the dataset on my model?

Region Explanations

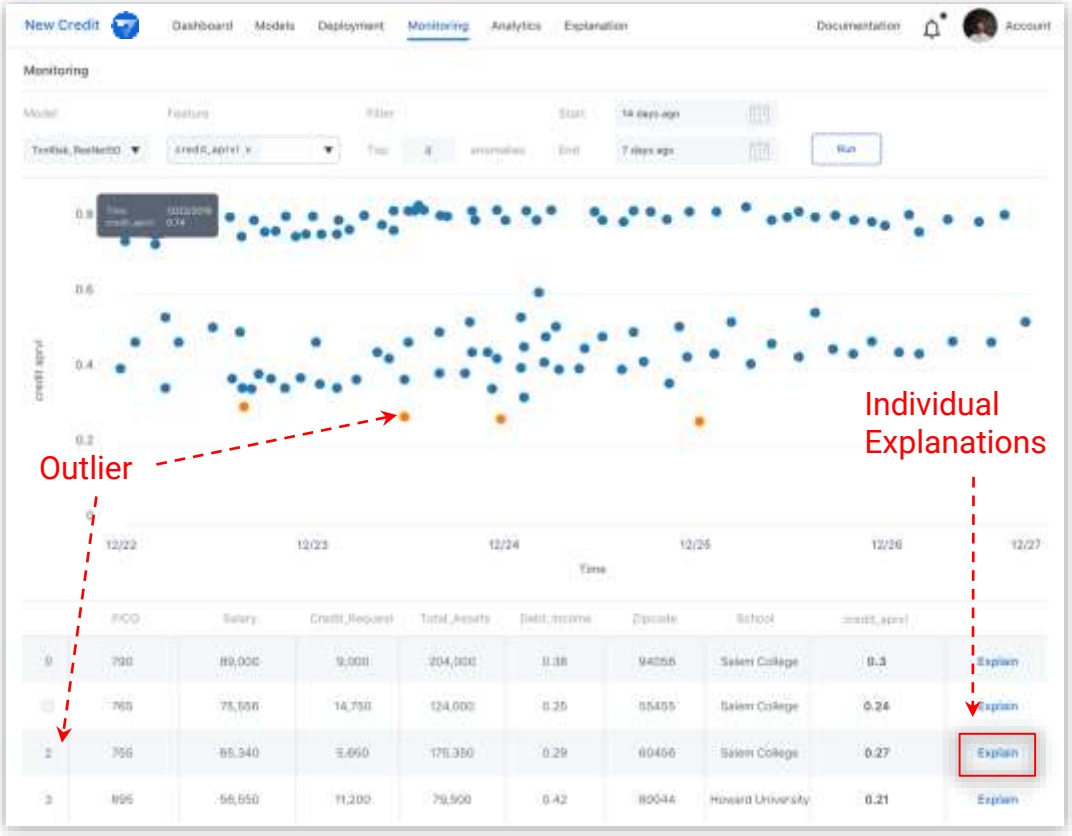
How does my model perform on a certain slice? Where does the model not perform well? Is my model uniformly fair across slices?

Model Monitoring: Feature Drift



Investigate Data Drift Impacting Model Performance

Model Monitoring: Outliers with Explanations



How Can This Help…

Operations

Why are there outliers in model predictions? What caused model performance to go awry?

Data Science

How can I improve my ML model? Where does it not do well?

Some lessons learned at Fiddler

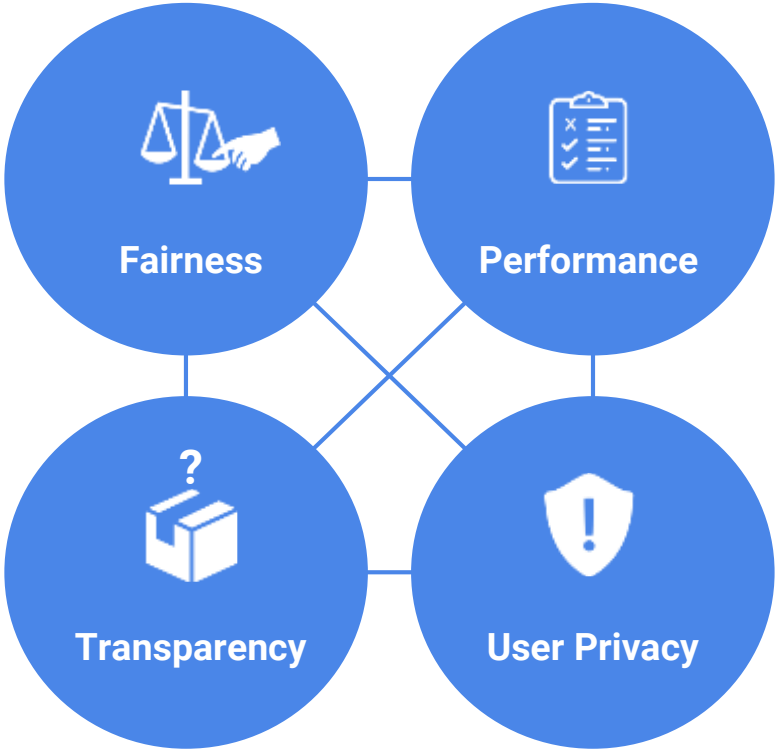
- Attributions are contrastive to their baselines
- Explaining explanations is important (e.g. good UI)
- In practice, we face engineering challenges as much as theoretical challenges

Recap

- Part I: Introduction and Motivation
  - Motivation and Need for Explainable AI
  - Challenges for Explainable AI @ Scale
- Part II: Explainable Machine Learning
  - Overview of Explainable AI Techniques
- Part III: Case Studies from Industry
  - Applications, Key Challenges, and Lessons Learned
- *Part IV: Open Problems, Research Challenges, and Conclusion*

Challenges & Tradeoffs

- Lack of standard interface for ML models makes pluggable explanations hard
- Explanation needs vary depending on the type of the user who needs it and also the problem at hand.
- The algorithm you employ for explanations might depend on the use-case, model type, data format, etc.
- There are trade-offs w.r.t. Explainability, Performance, Fairness, and Privacy.



Explainability in ML: Broad Challenges

Actionable explanations

Balance between explanations & model secrecy

Robustness of explanations to failure modes (Interaction between ML components)

Application-specific challenges
- Conversational AI systems: contextual explanations
- Gradation of explanations

Tools for explanations across AI lifecycle
- Pre & post-deployment for ML models
- Model developer vs. End user focused

Thanks! Questions?

- Feedback most welcome :-)
  - **krishna@fiddler.ai**, **sgeyik@linkedin.com**, **kenthk@amazon.com**, **vamithal@linkedin.com**, **ankur@fiddler.ai**
- Tutorial website: https://sites.google.com/view/www20-explainable-ai-tutorial
- To try Fiddler, please send an email to **info@fiddler.ai**