Lecture 8: Auditing and Explaining ML

CMSC 25910

Winter 2026

The University of Chicago

THE UNIVERSITY OF CHICAGO

The Evolution of the Right to an Explanation

US Equal Credit Opportunity Act (1974)

- ECOA requires creditors to provide notification about specific actions taken, as well as to provide an explanation
- “(2) *Statement of specific reasons.* The statement of **reasons for adverse action** required by paragraph (a)(2)(i) of this section **must be specific and indicate the principal reason(s)** for the adverse action. Statements that the adverse action was based on the creditor's internal standards or policies or that the applicant, joint applicant, or similar party failed to achieve a qualifying score on the creditor's credit scoring system are insufficient.”

See https://www.ecfr.gov/cgi-bin/text-idx?SID=1bb14fdfd1afc7d3f2d4756d223aeadb&mc=true&node=se12.8.1002_19

GDPR May Provide Such a Right

- “The data subject should have the right not to be subject to a decision…which is based solely on automated processing and which produces legal effects concerning him or her or similarly significantly affects him or her...”
- “In any case, such processing should be subject to suitable safeguards, which should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, **to obtain an explanation of the decision reached after such assessment** and to challenge the decision...”
- “…the controller should use **appropriate mathematical or statistical procedures** for the profiling, implement technical and organisational measures appropriate to ensure, in particular, that factors which result in inaccuracies in personal data are corrected and the risk of errors is minimised...”

See https://www.privacy-regulation.eu/en/recital-71-GDPR.htm

Counterfactuals and Recourse

- **Counterfactual:** Ideally small difference(s) in a data subject's set of features that would cause a different classification
  - Need a distance metric! But not all variables are created equal.
- **Recourse:** The ability for a data subject to change particular predictor variables
  - Contrast using "the timeliness of credit card payments" versus "the number of years of credit history" versus "sex"
  - To what extent should models **nudge** (influence, but not force) particular behavior?

Example Approaches to “Explain” Ads

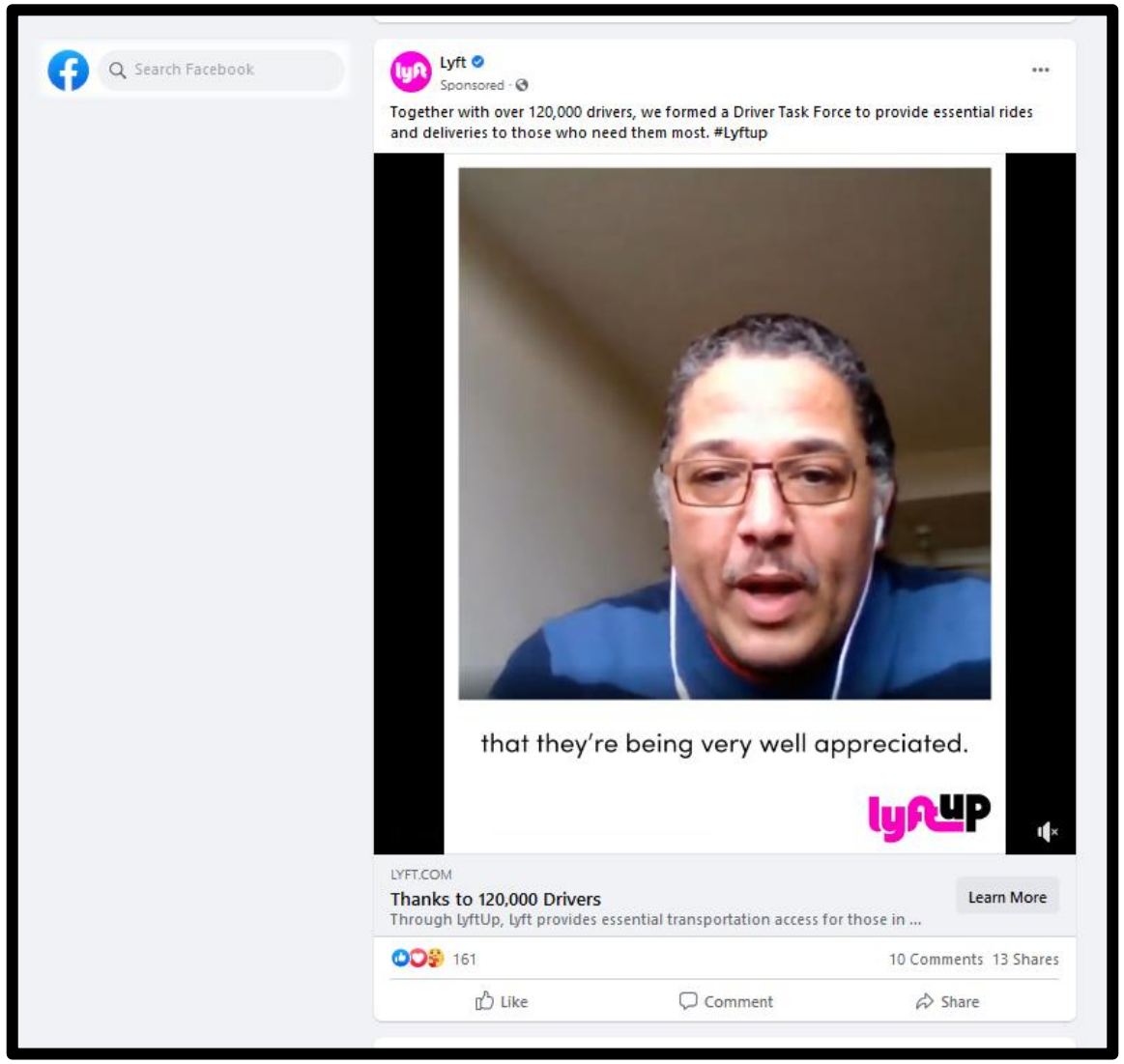
Disclose That An Ad is an Ad (Web)

Ad Consumer Attention

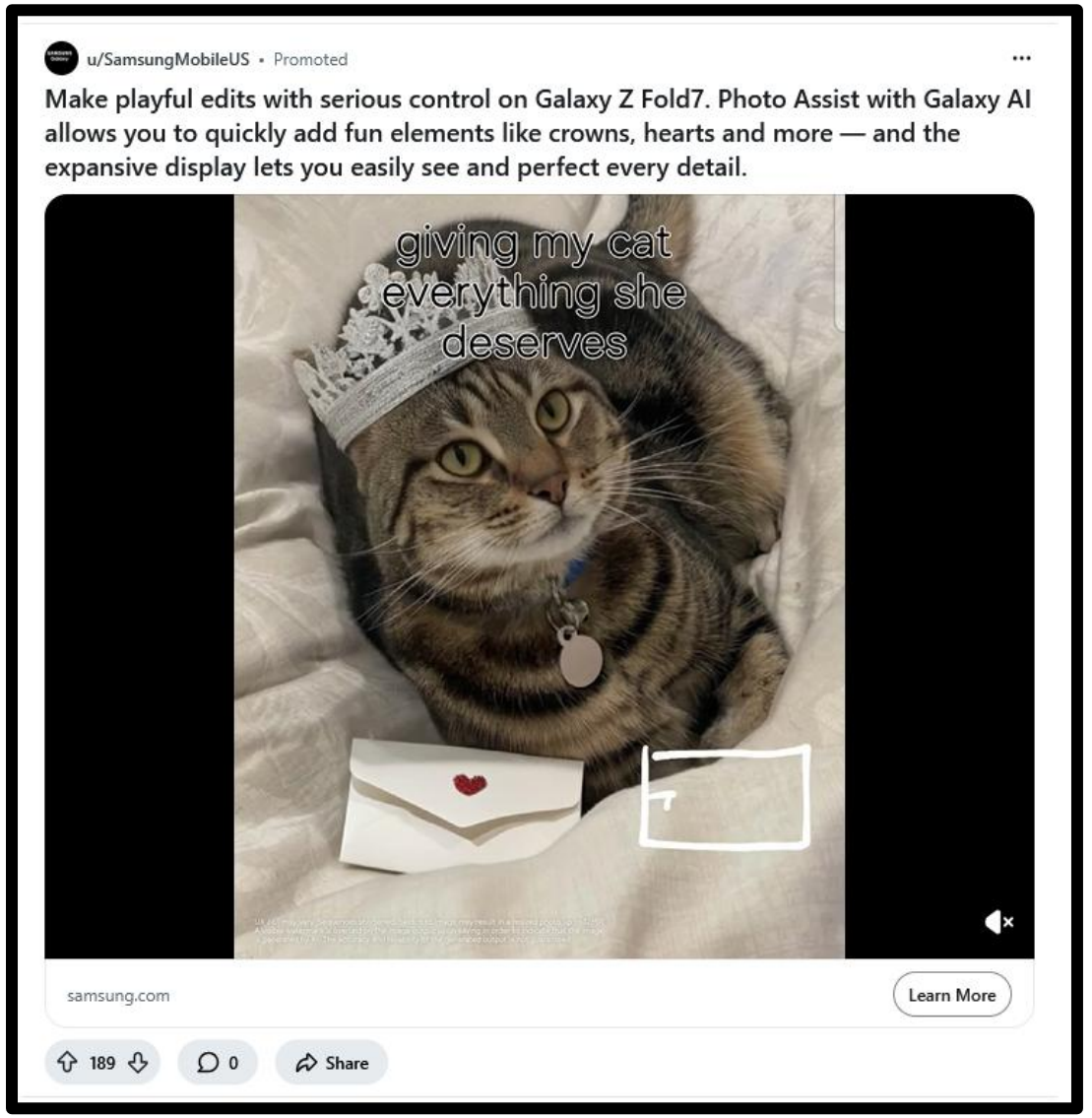
Illinois: Zantac Users May Get Cash Settlement In Lawsuit

Have you used Zantac and been diagnosed with cancer? You may qualify for significant compensation. See how.

Disclose That An Ad is an Ad (Facebook)



Disclose That An Ad is an Ad (Reddit)



Explaining One Ad (Local)

Ad Consumer Attention

Illinois: Zantac Users May Get Cash
Lawsuit

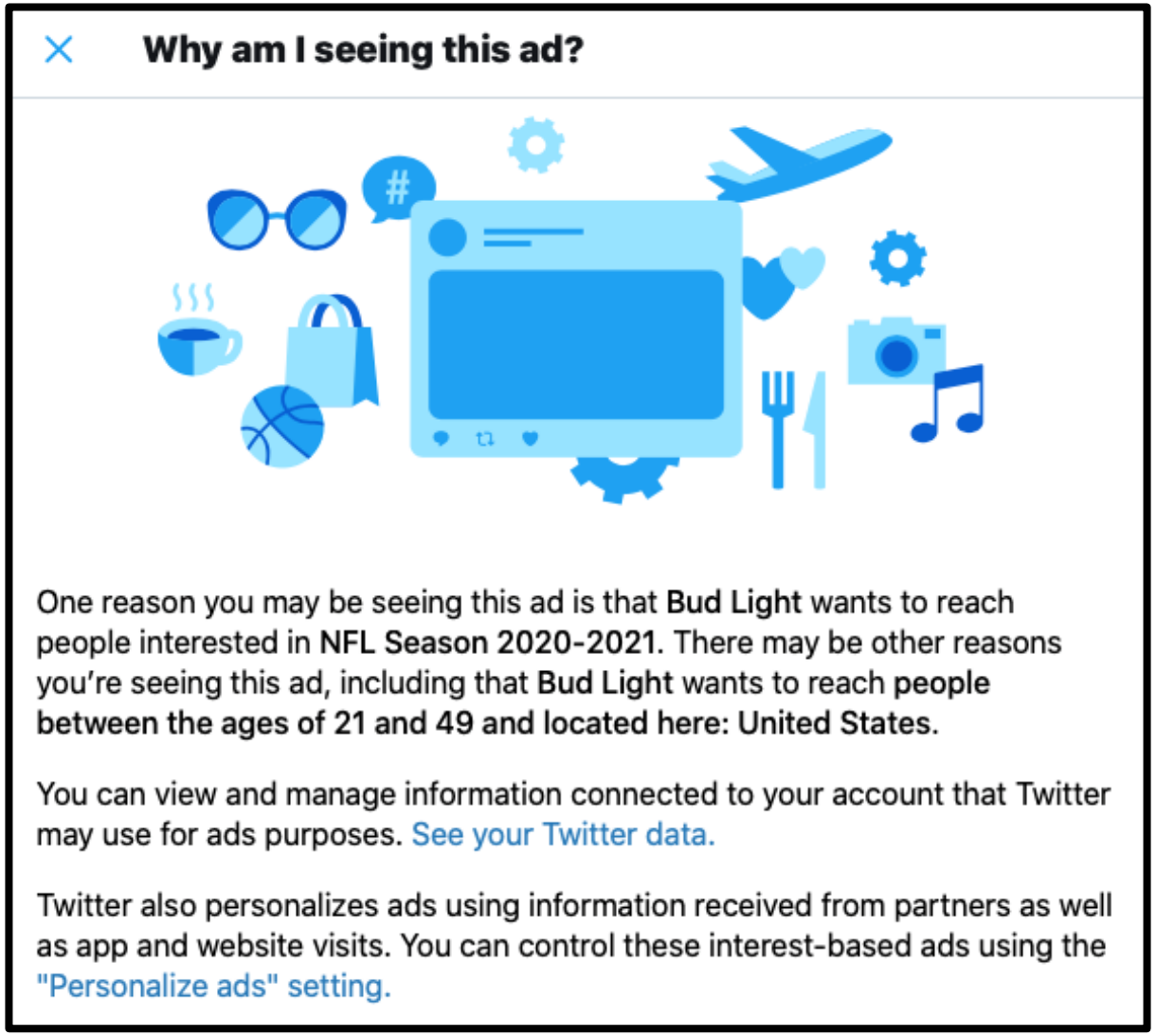
Have you used Zantac and been diagnosed with ca
significant compensation. See how.

Why this ad?

Ad Feedback

Advertise with us

Explaining One Ad (Local)



Explaining One Ad (Local)

Why This Ad?

verizon media

For Consumers

- The sites and apps you use work with online advertising companies to provide you with advertising that is as relevant and useful as possible. Personalization may be informed by various factors such as the content of the site or app you are using, information you provide, historical searches you conduct, what your friends or contacts recommend to you, apps on your device, or based on your other interests. Read about Verizon Media's privacy and advertising practices to learn more about how Verizon Media selects the ads you see.

Who placed this ad?

- This ad was served by Verizon Media or one of Verizon Media's advertising partners.

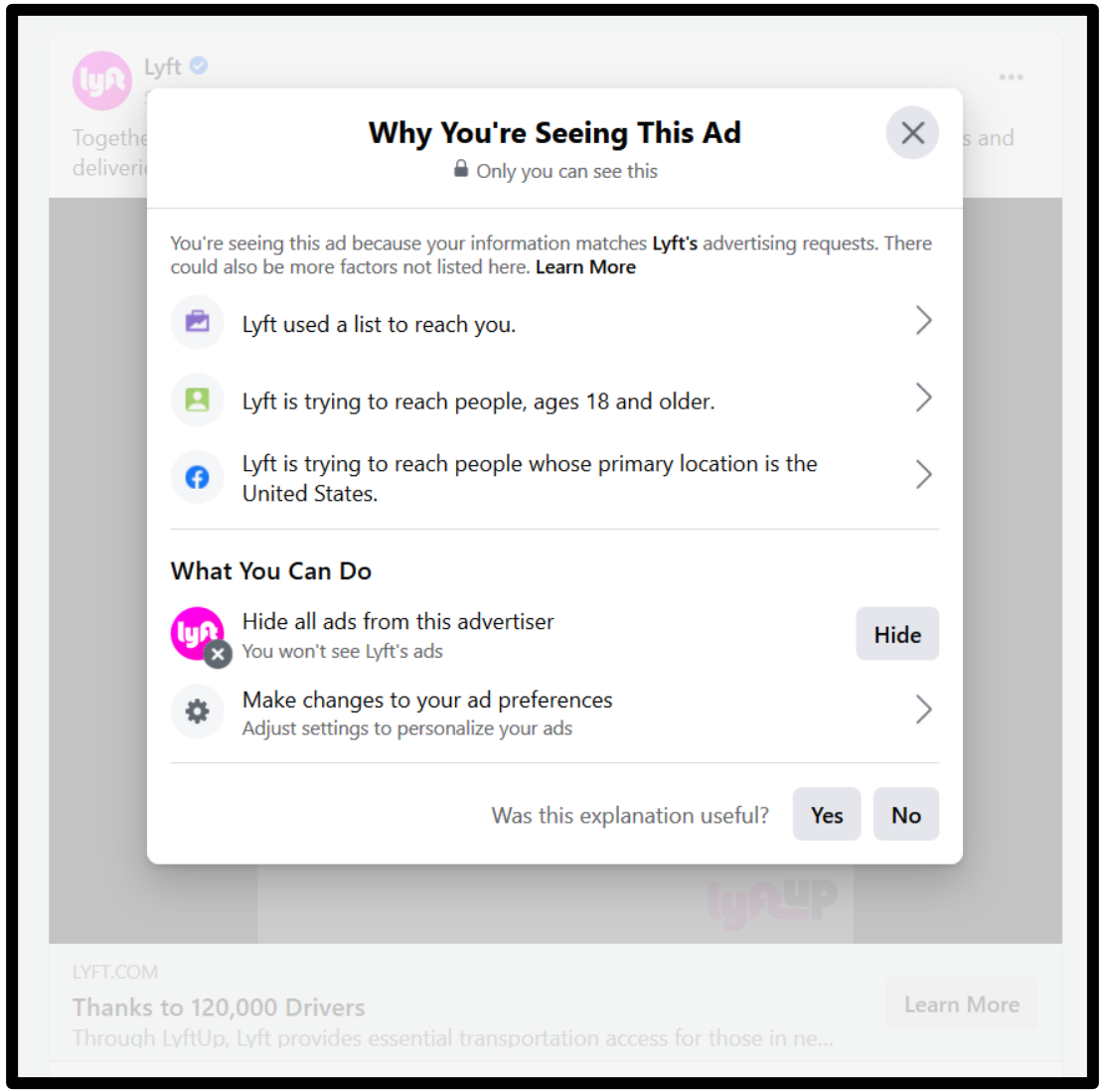
Why was this ad served?

- Certain factors like your activity, searches, demographic data, apps on your device, and location information may be used to select the ads you see.

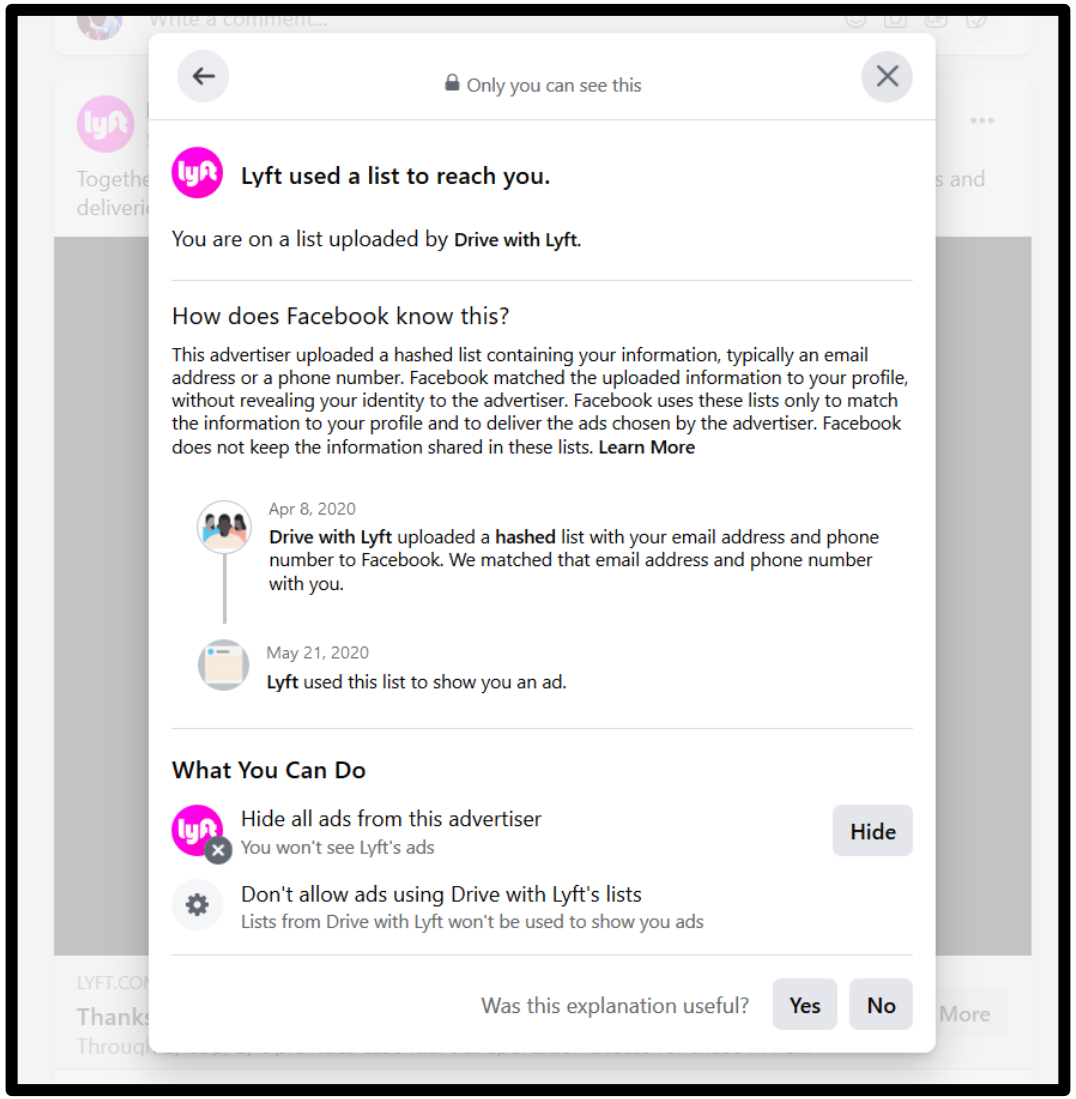
What choices do I have?

- Manage interest-based advertising categories, or opt-out of all categories, from Verizon Media.
- View our other privacy controls.
- Visit the Network Advertising Initiative (US) and the Digital Advertising Alliance Ad Choices - DAA (US), EDAA (EU), DAAC (Canada), ADAA (AU/NZ) to see your opt-out choices from other participating companies.
- Explore other controls and tools to help set and maintain your privacy choices.
- If you are using Safari or a browser enabled with Intelligent Tracking Protection (ITP) or similar cookie-blocking technology, if you wish to opt out of receiving personalized ads, you will need to do so directly via the Verizon Media Privacy Center.

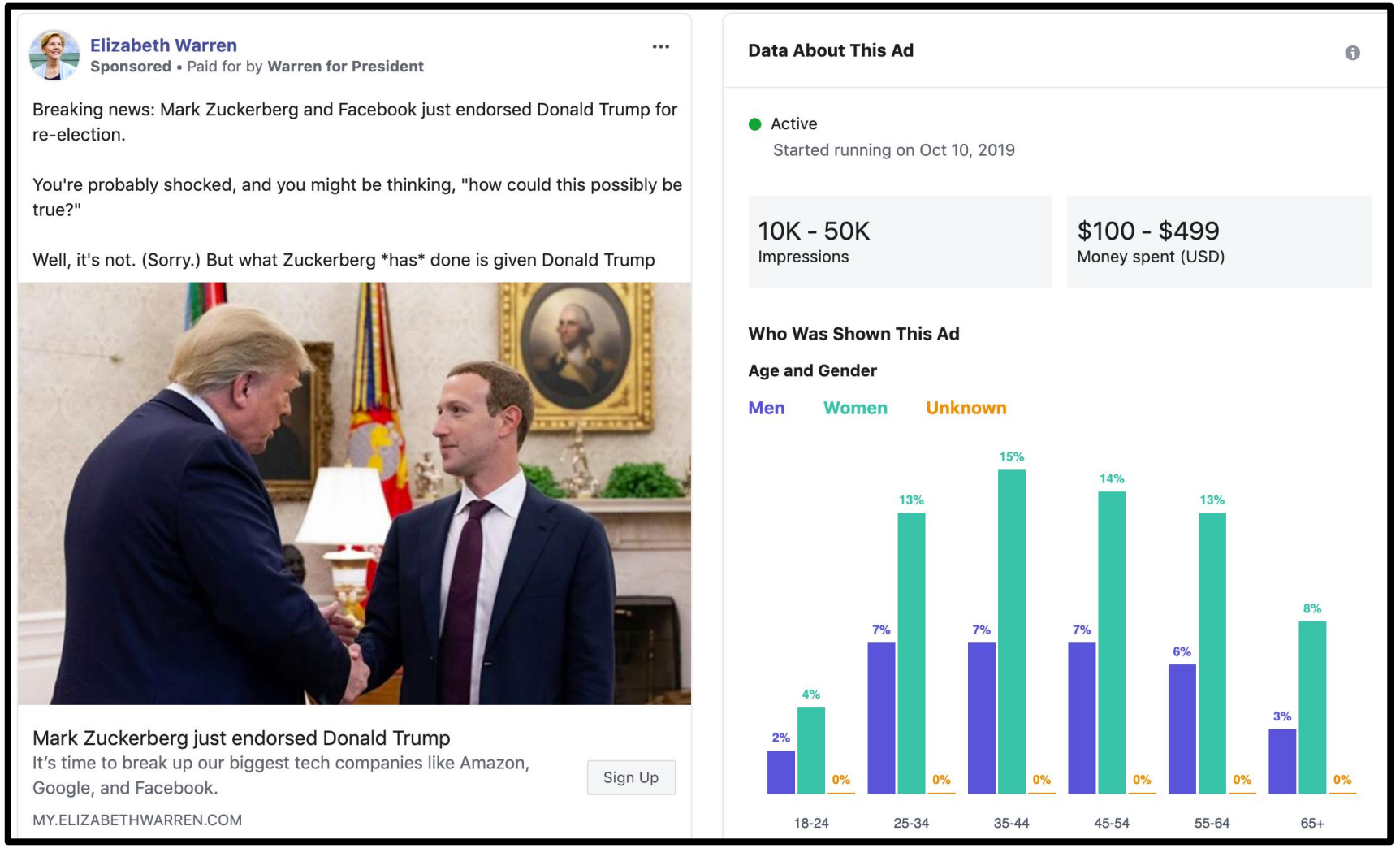
Explaining One Ad (Local)



Explaining One Ad (Local)

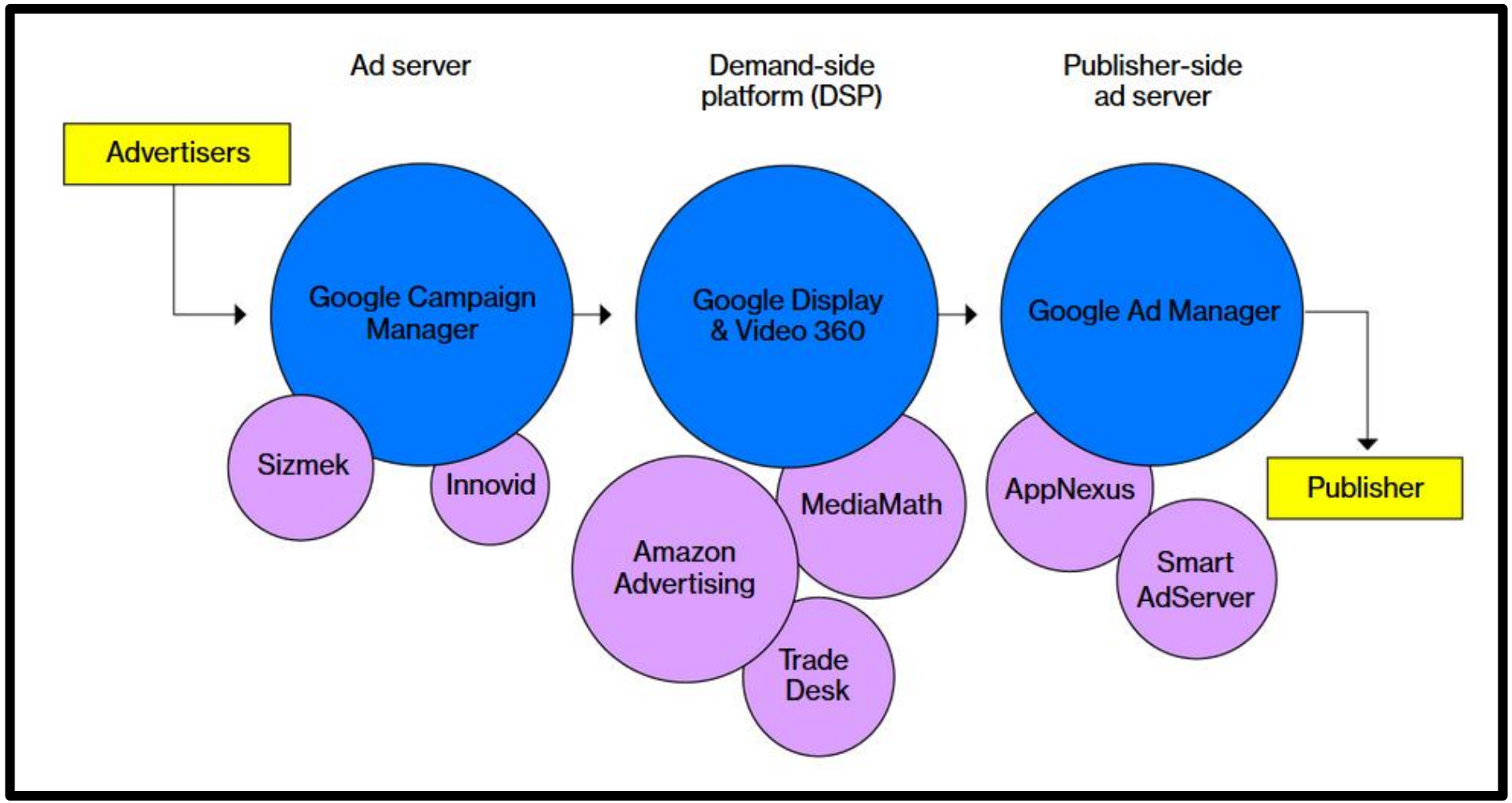


Explaining Ad Campaigns (Global)



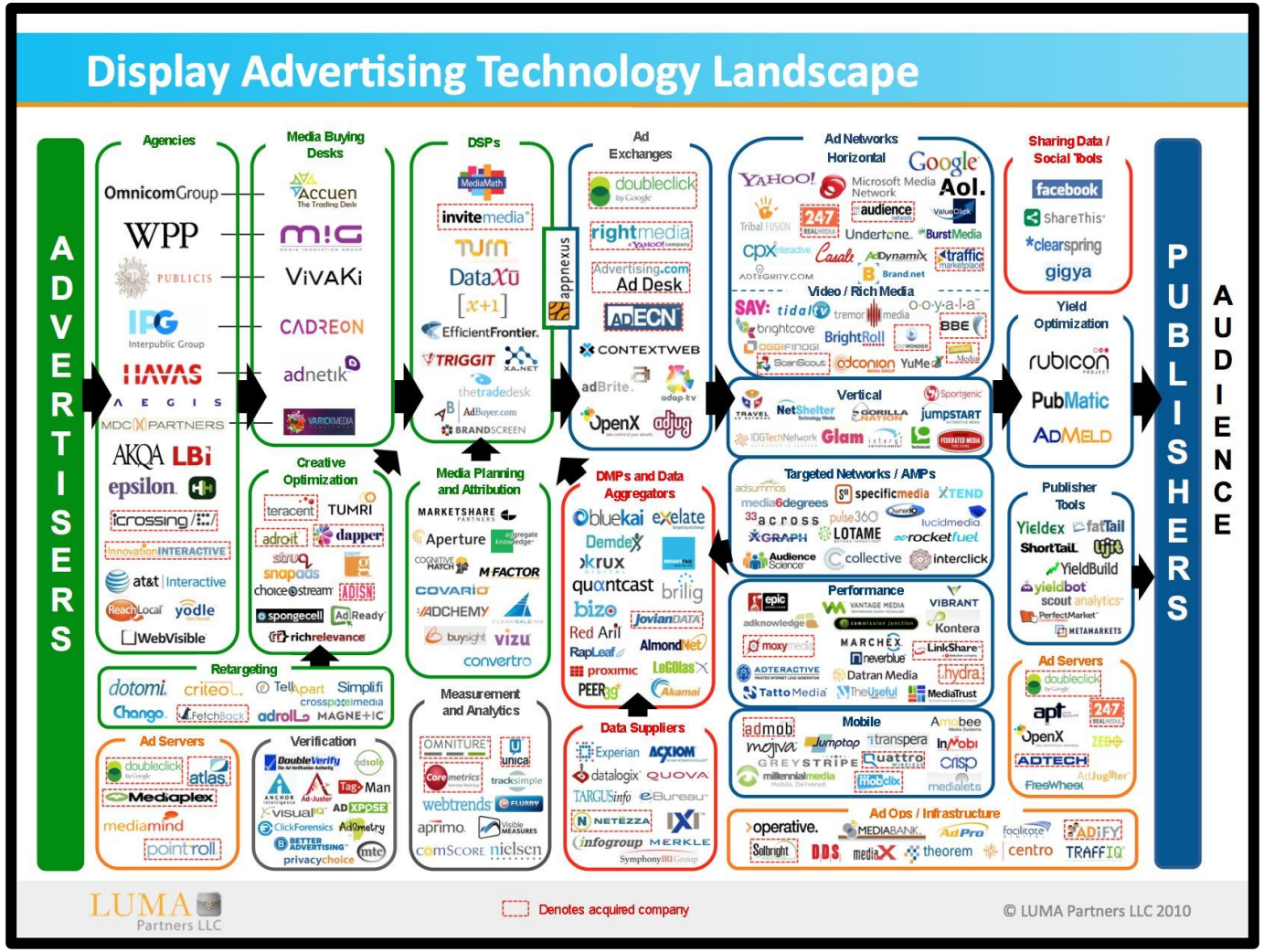
Approaches to “Explain” Models

Is This Enough? (Ad Ecosystem)



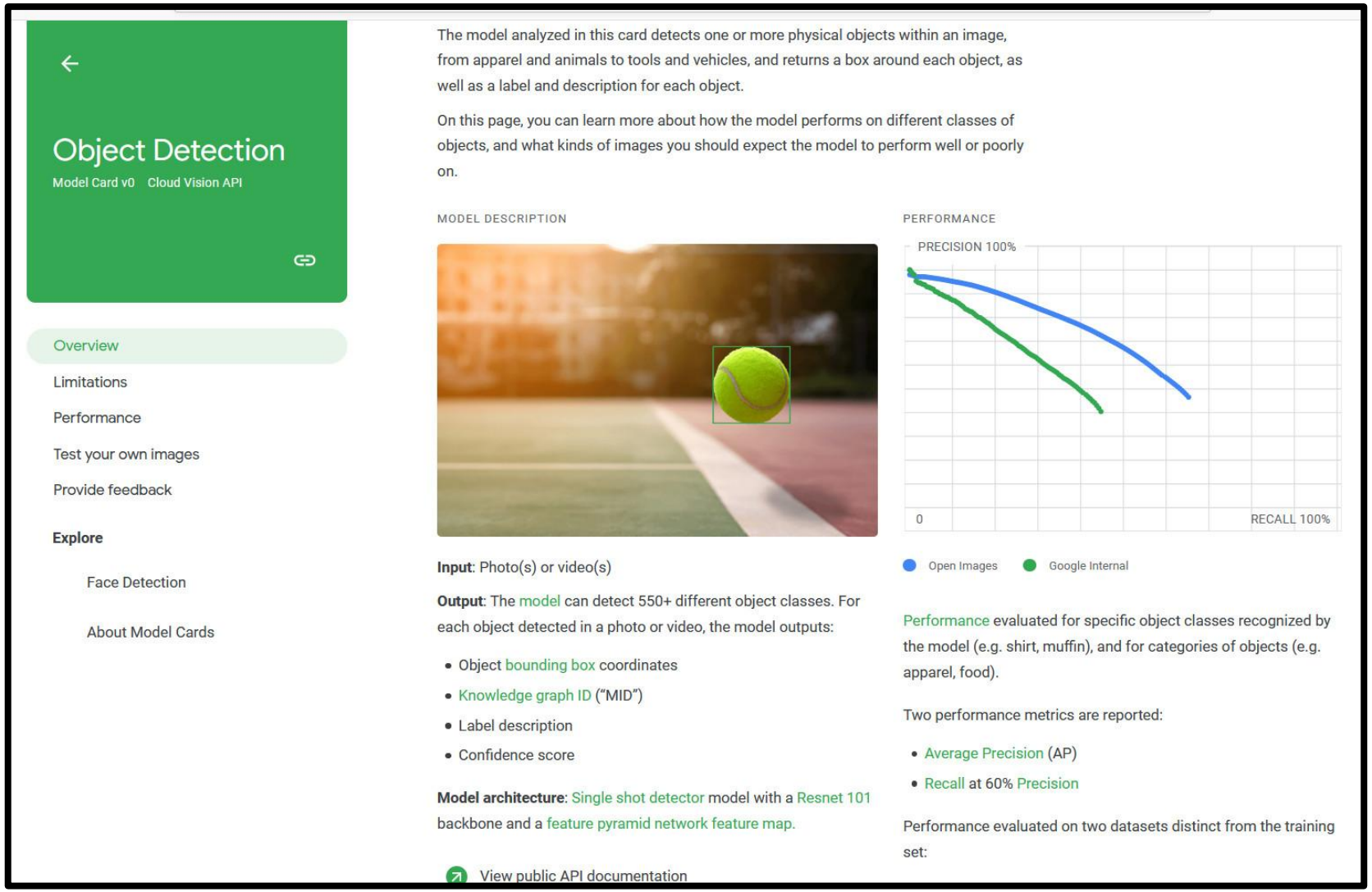
Taken from https://www.bloomberg.com/news/features/2019-10-24/how-google-s-ad-ecosystem-works

Is This Enough? (Ad Ecosystem)



Taken from https://www.adexchanger.com/venture-capital/luma-partners-ad-tech-ecosystem-map-the-december-2010-update/

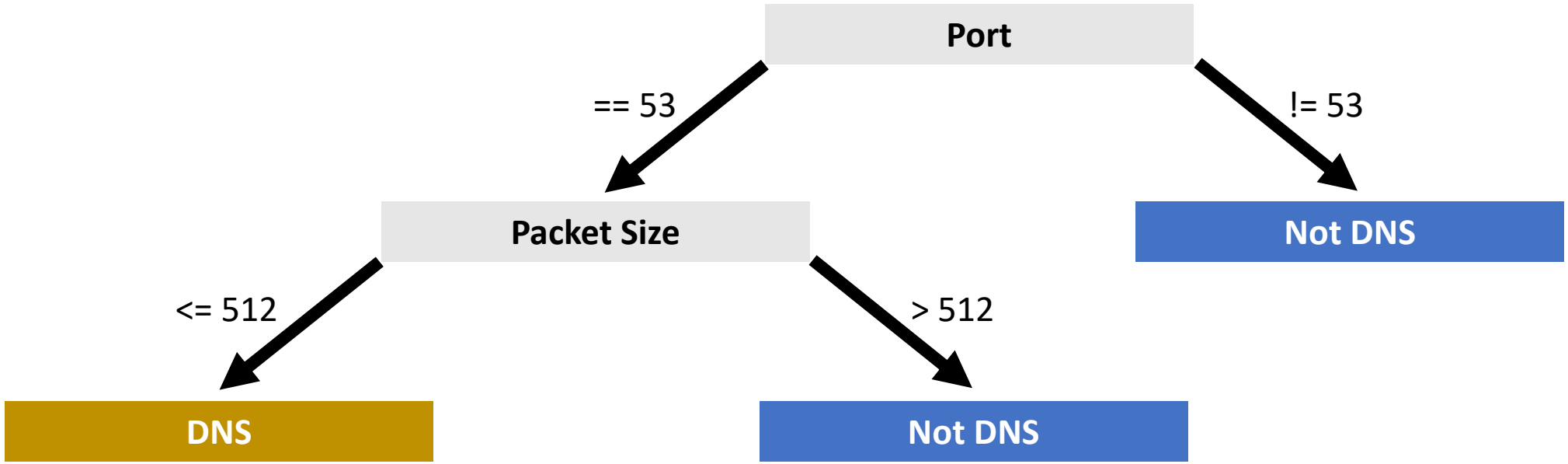
Explaining a Model (Global)



https://modelcards.withgoogle.com/ and https://arxiv.org/abs/1810.03993

Inherently Interpretable Models

- Example: decision trees



https://modelcards.withgoogle.com/ and https://arxiv.org/abs/1810.03993

Inherently Interpretable Models

- Example: regression models
  - Linear regression: coefficients
  - Logistic regression: odds ratio

Table 2: Linear regression with the number of scenarios the participant answered correctly as the dependent variable. Higher numbers correspond to more correct answers.

Factor	β	SE	t	p
(Intercept)	9.53	0.40	24.0	**<.001**
Condition: Brave	0.79	0.49	1.61	.108
Condition: Brave-Mobile	0.49	0.49	0.08	.940
Condition: Chrome	1.07	0.49	2.16	**.032**
Condition: Chrome-Mobile	0.62	0.50	1.25	.211
Condition: Chrome-Old	1.09	0.50	2.20	**.028**
Condition: Edge	0.05	0.50	0.10	.923
Condition: Firefox	0.88	0.59	1.80	.073
Condition: Firefox-Mobile	-0.30	0.50	-0.60	.550
Condition: Opera	0.57	0.50	1.15	.252
Condition: Opera-Mobile	-0.34	0.49	-0.70	.484
Condition: Safari	0.78	0.51	1.53	.127
Condition: Safari-Mobile	0.95	0.49	1.93	.055
Gender: Male	0.50	0.20	2.51	**.013**
Technical: Yes	0.49	0.31	1.60	.111
Age Range	-0.65	0.52	-1.24	.216
Browsing in Private Mode (%)	-0.00	0.01	-0.26	.792
Reopened Disclosure (#)	0.19	0.16	1.19	.236

Taken from Wu et al. "Your Secrets Are Safe: How Browsers' Explanations Impact Misconceptions About Private Browsing Mode," WWW 2018. https://www.blaseur.com/papers/www18privatebrowsing.pdf

Highlight (Globally) Important Features

Category	Collection Method	List of Features
Metadata	Google Drive/Dropbox API	account size, used space, file size, file type (img, doc, etc.), extension (jpg, txt, etc.), last modified date, last modifying user, access type (owner, editor, etc.), sensitive filename, sharing status
Documents	Local text processing	bag of words for top 100 content keywords, LDA topic models, TF-IDF vectors, word2vec representations, table schemas for spreadsheets
Images	Google Vision API [20]	image object labels, adult, racy, medical, violent, logos, dominant RGB values, average RGB value
Sensitive Identifiers	Google DLP API [18]	***counts*** of the following identifiers in a file: name, gender, ethnic group, address, email, date of birth, drivers license #, passport #, credit card, SSN, bank account #, VIN

Table 3: A list of the features we automatically collected for each file using multiple APIs and custom code.

Taken from Khan et al. "Helping Users Automatically Find and Manage Sensitive, Expendable Files in Cloud Storage," USENIX Security 2021. https://www.blaseur.com/papers/usenix21-aletheia.pdf

Highlight (Globally) Important Features

Task		Features
Sensitivity	Documents	gender; fraction of ethnic/VIN/location files; credit card; date of birth; email
	Images	fraction of gender/SSN/ethnic/location files; adult; credit card; racy; passport
Usefulness	Documents	access type; last modifying user; finance keywords; report & journal keywords
	Images	file size; finance keywords; access type; last modifying user; medical keywords
File Management	All Files	usefulness; sensitivity; spoof; account size; used space; finance keywords; medical keywords

Table 8: Top features for prediction tasks. Italicized *keywords* were top terms identified via the bag of words collections.

Taken from Khan et al. "Helping Users Automatically Find and Manage Sensitive, Expendable Files in Cloud Storage," USENIX Security 2021. https://www.blaseur.com/papers/usenix21-aletheia.pdf

Retrospective Explanations

Explaining Text Classification

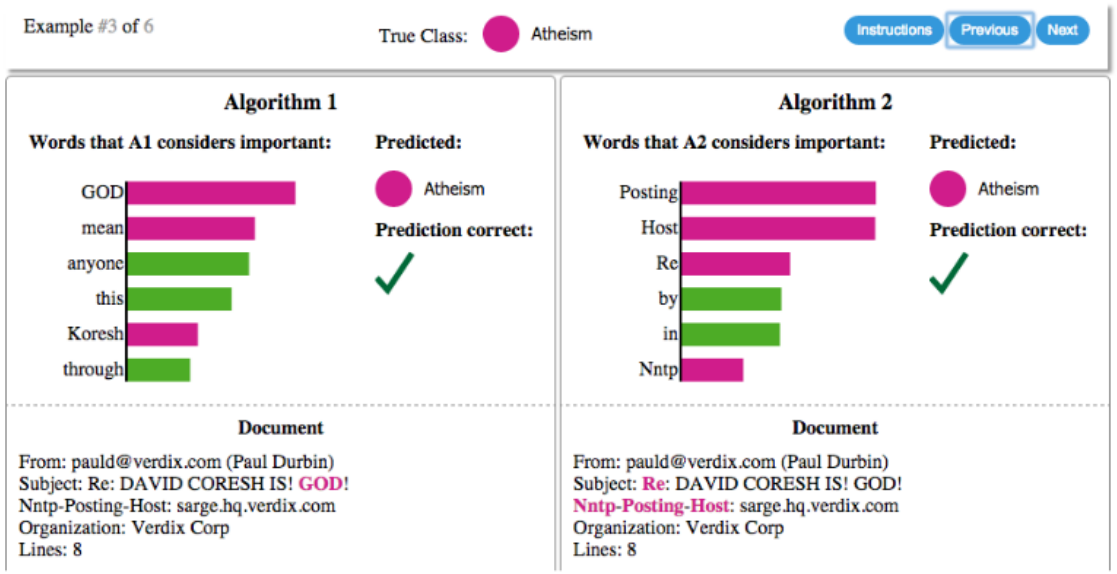
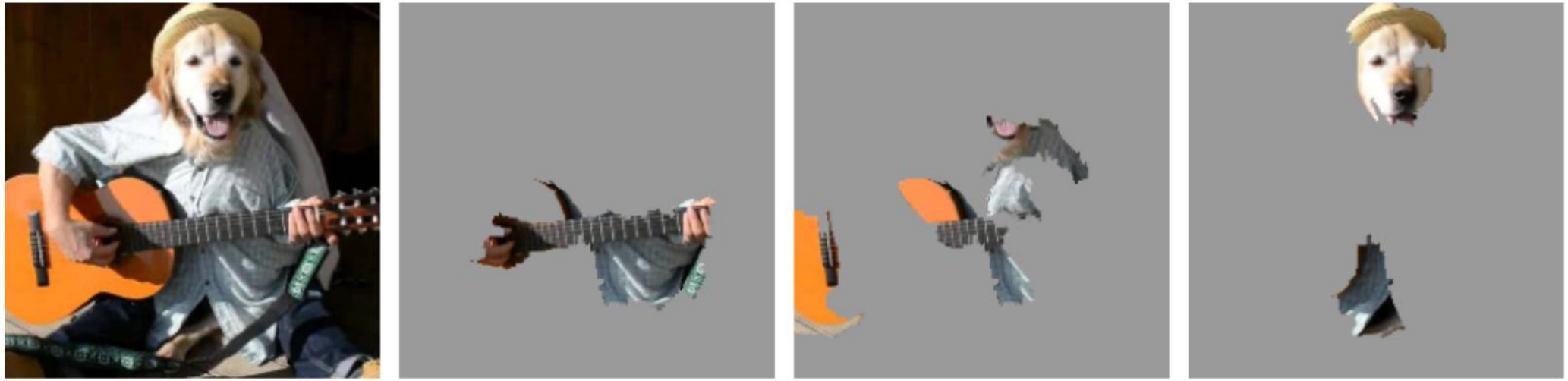


Figure 2: Explaining individual predictions of competing classifiers trying to determine if a document is about "Christianity" or "Atheism". The bar chart represents the importance given to the most relevant words, also highlighted in the text. Color indicates which class the word contributes to (green for "Christianity", magenta for "Atheism").

Taken from Ribiero et al. "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," KDD 2016
https://dl.acm.org/doi/pdf/10.1145/2939672.2939778

Explaining Image Classifications

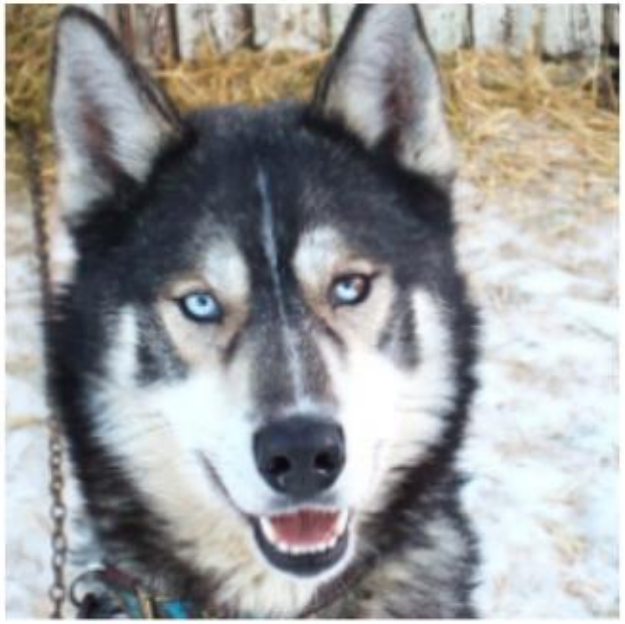


(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

Figure 4: Explaining an image classification prediction made by Google's Inception neural network. The top 3 classes predicted are "Electric Guitar" ($p = 0.32$), "Acoustic guitar" ($p = 0.24$) and "Labrador" ($p = 0.21$)

Taken from Ribiero et al. "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," KDD 2016
https://dl.acm.org/doi/pdf/10.1145/2939672.2939778

Explaining Image Classifications



(a) Husky classified as wolf

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

Taken from Ribiero et al. "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," KDD 2016
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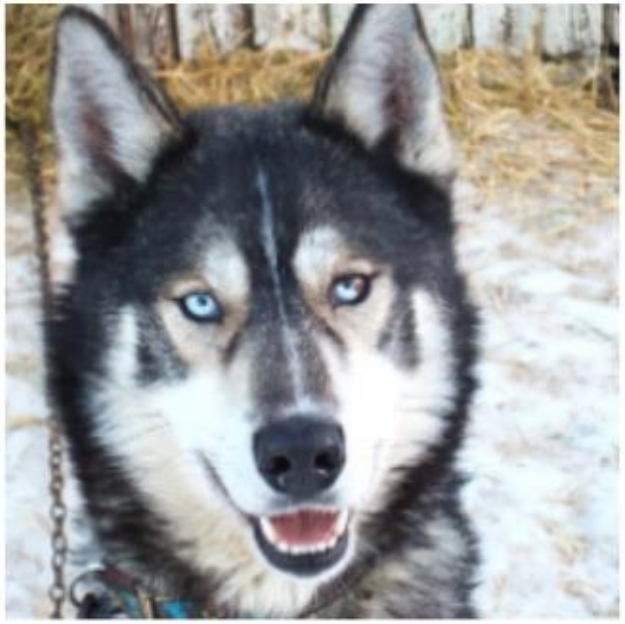
Explaining Image Classifications



(a) Husky classified as wolf

(b) Explanation

Figure 11: Raw data and explanation of a bad model's prediction in the "Husky vs Wolf" task.

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LIME

- Local Interpretable Model-agnostic Explanations
- Overall goal: “identify an interpretable model over the interpretable representation that is locally faithful to the classifier.”
- Distinguishes between **features** (used by the model) and **interpretable representation** (used to explain to a human)
- “We also propose a method to explain models by presenting representative individual predictions and their explanations in a non-redundant way… We demonstrate the flexibility of these methods by explaining different models for text (e.g. random forests) and image classification (e.g. neural networks).”

Ribiero et al. "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," KDD 2016
https://dl.acm.org/doi/pdf/10.1145/2939672.2939778

LIME Overview

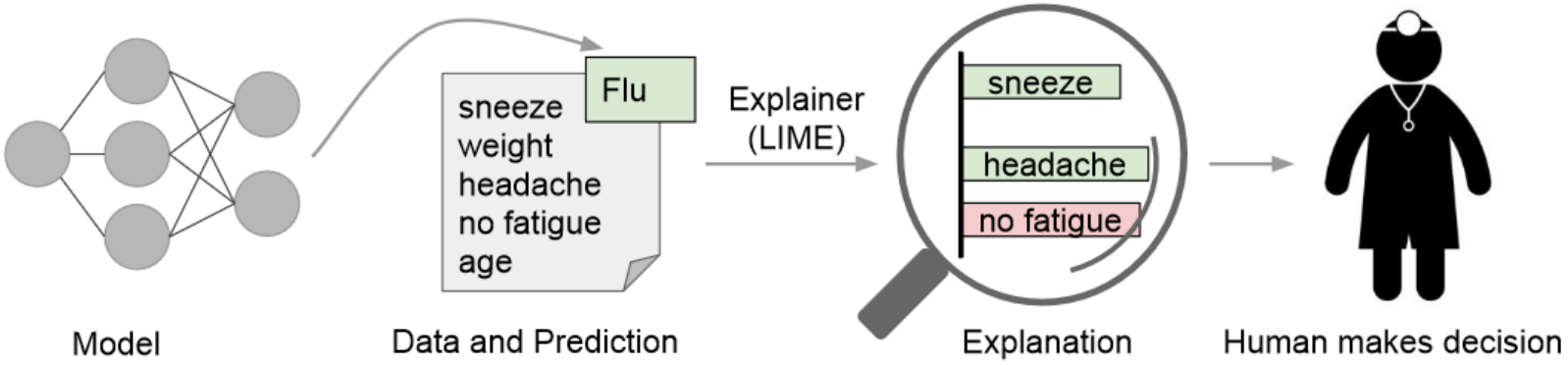

Figure 1: Explaining individual predictions. A model predicts that a patient has the flu, and LIME highlights the symptoms in the patient's history that led to the prediction. Sneeze and headache are portrayed as contributing to the "flu" prediction, while "no fatigue" is evidence against it. With these, a doctor can make an informed decision about whether to trust the model's prediction.

Taken from Ribiero et al. "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," KDD 2016
https://dl.acm.org/doi/pdf/10.1145/2939672.2939778

Local vs. Global Explanations

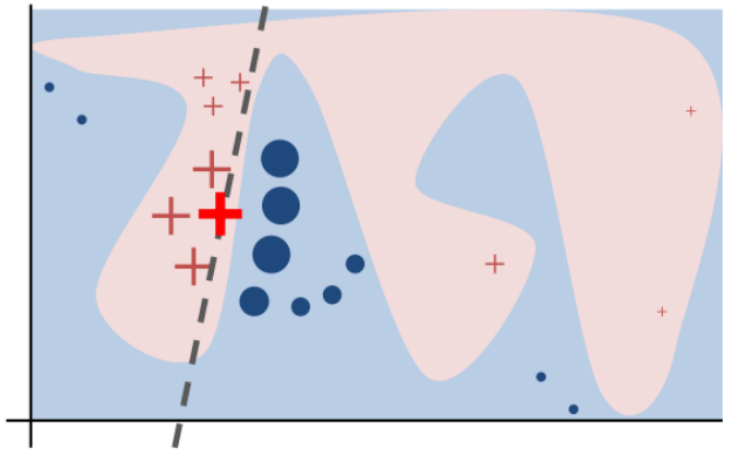

Figure 3: Toy example to present intuition for LIME. The black-box model's complex decision function f (unknown to LIME) is represented by the blue/pink background, which cannot be approximated well by a linear model. The bold red cross is the instance being explained. LIME samples instances, gets predictions using f, and weighs them by the proximity to the instance being explained (represented here by size). The dashed line is the learned explanation that is locally (but not globally) faithful.

Taken from Ribiero et al. "'Why Should I Trust You?' Explaining the Predictions of Any Classifier," KDD 2016
https://dl.acm.org/doi/pdf/10.1145/2939672.2939778

Recap: The Form an Explanation Could Take

Potential Audiences

- Individual data subjects
- All data subjects
- Regulators / policymakers
- Third parties who receive explanations from individual data subjects (e.g., journalists)

- **Global** (model, all data subjects) vs. **Local** (one data subject)

Potential Information

- The general approach taken
- The precise factors taken into account
  - Do we provide access to the data subject's own values?
  - Do we explain how those factors are combined?
  - Do we explain the ML model used?
  - Do we open-source the ML model?
- Counterfactuals – "If *X* had not occurred, *Y* would not have occurred"
  - What could a person have changed for a different classification?
  - Can we define some distance function and show the *smallest* change?

See https://docs.seldon.io/projects/alibi/en/stable/methods/CF.html

Category of Methods	Explanation Method	Definition	Algorithm Examples	Question Type
Explain the model (**Global**)	Global feature importance	Describe the weights of features used by the model (including visualization that shows the weights of features)	[41, 60, 69, 90]	**How**
	Decision tree approximation	Approximate the model to an interpretable decision-tree	[11, 47, 52]	**How**, Why, Why not, What if
	Rule extraction	Approximate the model to a set of rules, e.g., if-then rules	[26, 93, 102]	**How**, Why, Why not, What if
Explain a prediction (**Local**)	Local feature importance and saliency method	Show how features of the instance contribute to the model's prediction (including causes in parts of an image or text)	[61, 74, 83, 85, 101]	**Why**
	Local rules or trees	Describe the rules or a decision-tree path that the instance fits to guarantee the prediction	[39, 75, 99]	**Why**, **How to still be this**
Inspect counterfactual	Feature influence or relevance method	Show how the prediction changes corresponding to changes of a feature (often in a visualization format)	[8, 33, 36, 51]	**What if**, How to be that, How to still be this
	Contrastive or counterfactual features	Describe the feature(s) that will change the prediction if perturbed, absent or present	[27, 91, 100]	**Why**, **Why not**, **How to be that**
Example based	Prototypical or representative examples	Provide example(s) similar to the instance and with the same record as the prediction	[13, 48, 50]	**Why**, How to still be this
	Counterfactual example	Provide example(s) with small differences from the instance but with a different record from the prediction	[37, 55, 66]	**Why**, **Why not**, How to be that

Table 1. Taxonomy of XAI methods mapping to user question types. Questions in bold are the primary ones that the XAI method addresses. Questions in regular font are ones that only a subset of cases the XAI method can address. For example, while a global decision tree approximation can potentially answer *Why, Why not, and What if* questions for individual instances [58], the approximation may not cover certain instances.

Taken from Liao et al. "Questioning the AI: Informing Design Practices for Explainable AI User Experiences," CHI 2020. https://dl.acm.org/doi/pdf/10.1145/3313831.3376590

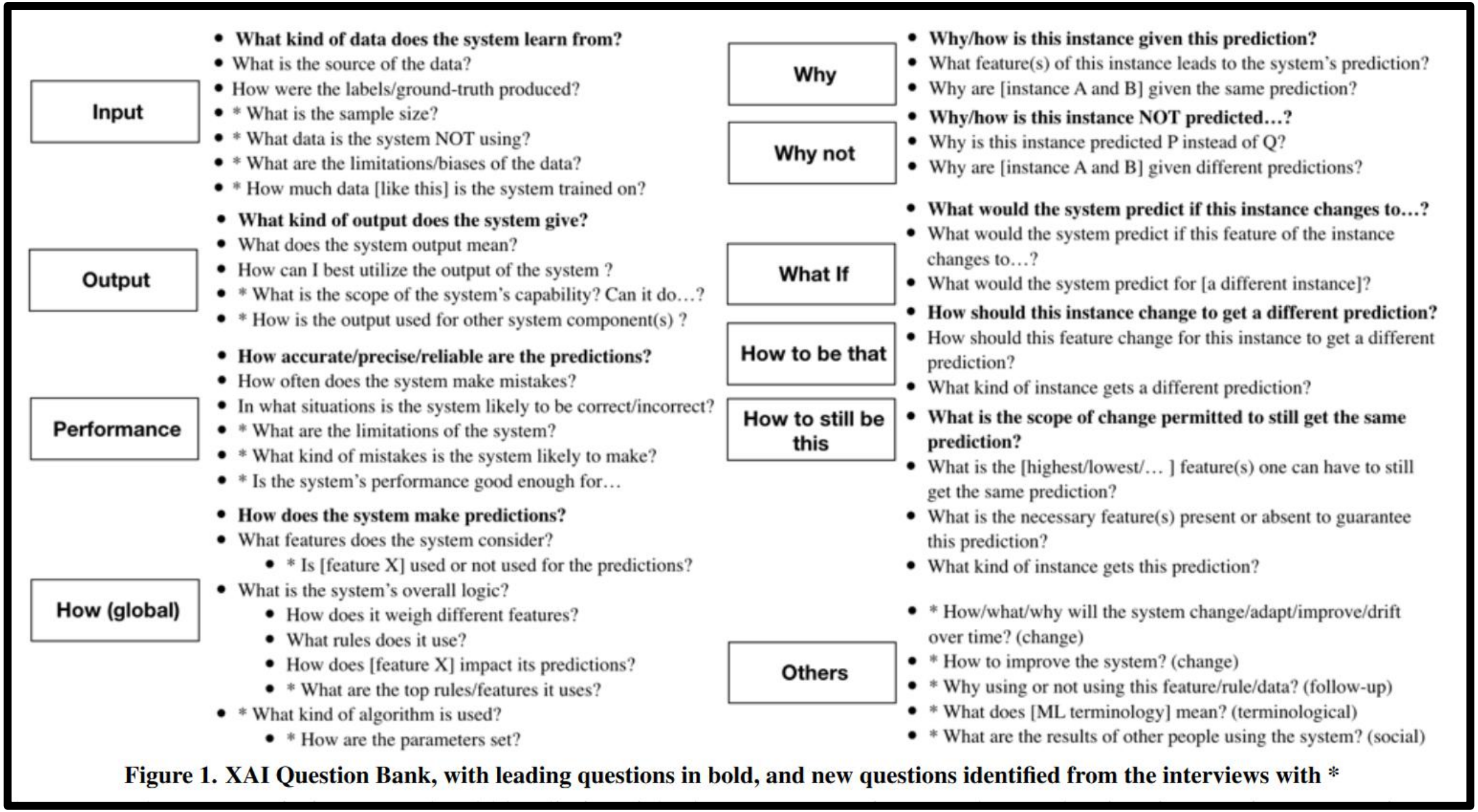

Figure 1. XAI Question Bank, with leading questions in bold, and new questions identified from the interviews with *

Taken from Liao et al. "Questioning the AI: Informing Design Practices for Explainable AI User Experiences," CHI 2020. https://dl.acm.org/doi/pdf/10.1145/3313831.3376590

Algorithmic Audits

What It Means to Audit an Algorithm

- Who? Typically an independent third party
- What? Systematically analyzes characteristics of an algorithm's output, such as its accuracy, fairness/bias, and compliance with laws or organizational policies
- Why? As one of the mechanisms to protect users/society and minimize the negative impacts of the algorithm and its underlying training data
- Key Challenge: What if the algorithm's creator doesn't want it to be audited and makes it difficult to do so?

See https://www.emerald.com/fthci/article-abstract/14/4/272/1320887/Auditing-Algorithms-Understanding-Algorithmic or https://dl.acm.org/doi/abs/10.1145/3351095.3372873

What It Means to Audit an Algorithm

See https://www.npr.org/2021/08/04/1024791053/facebook-boots-nyu-disinformation-researchers-off-its-platform-and-critics-cry-f

Do we have a right to an explanation from automated decision-making systems?

Should we?