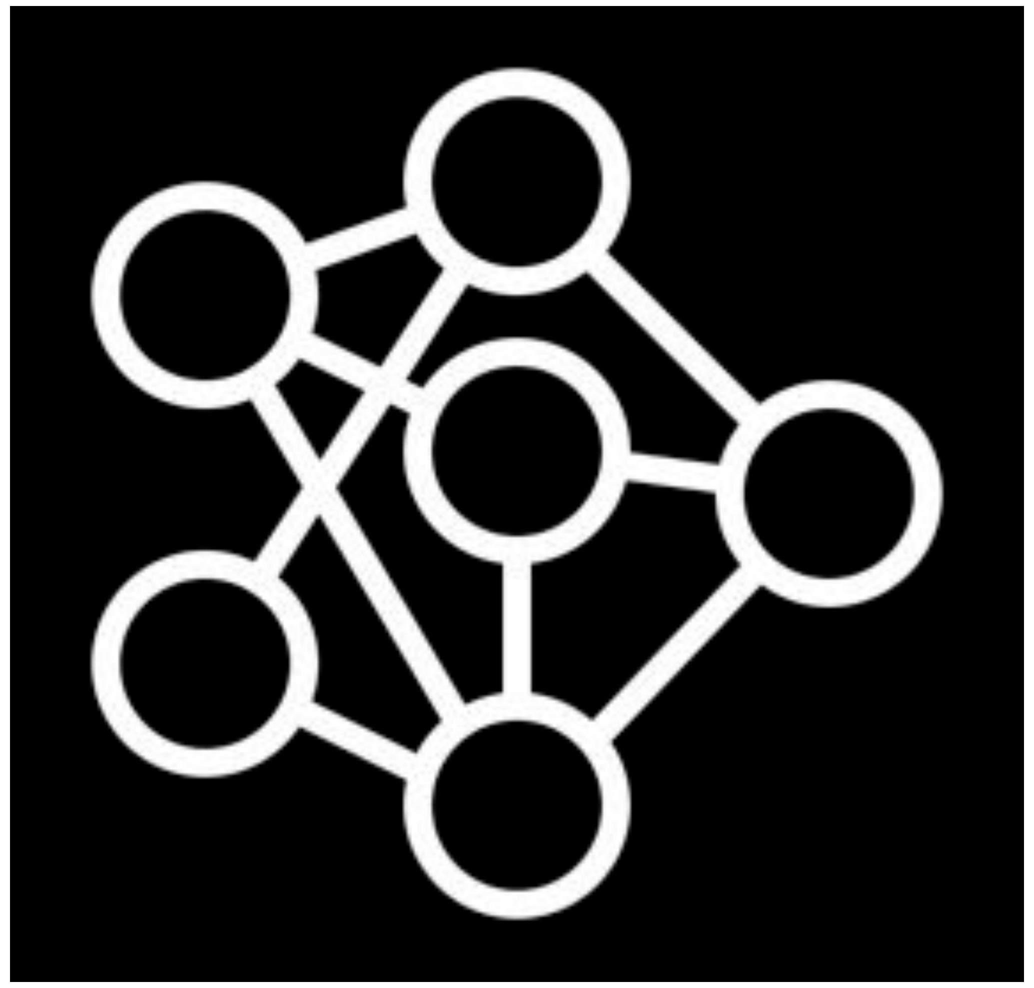
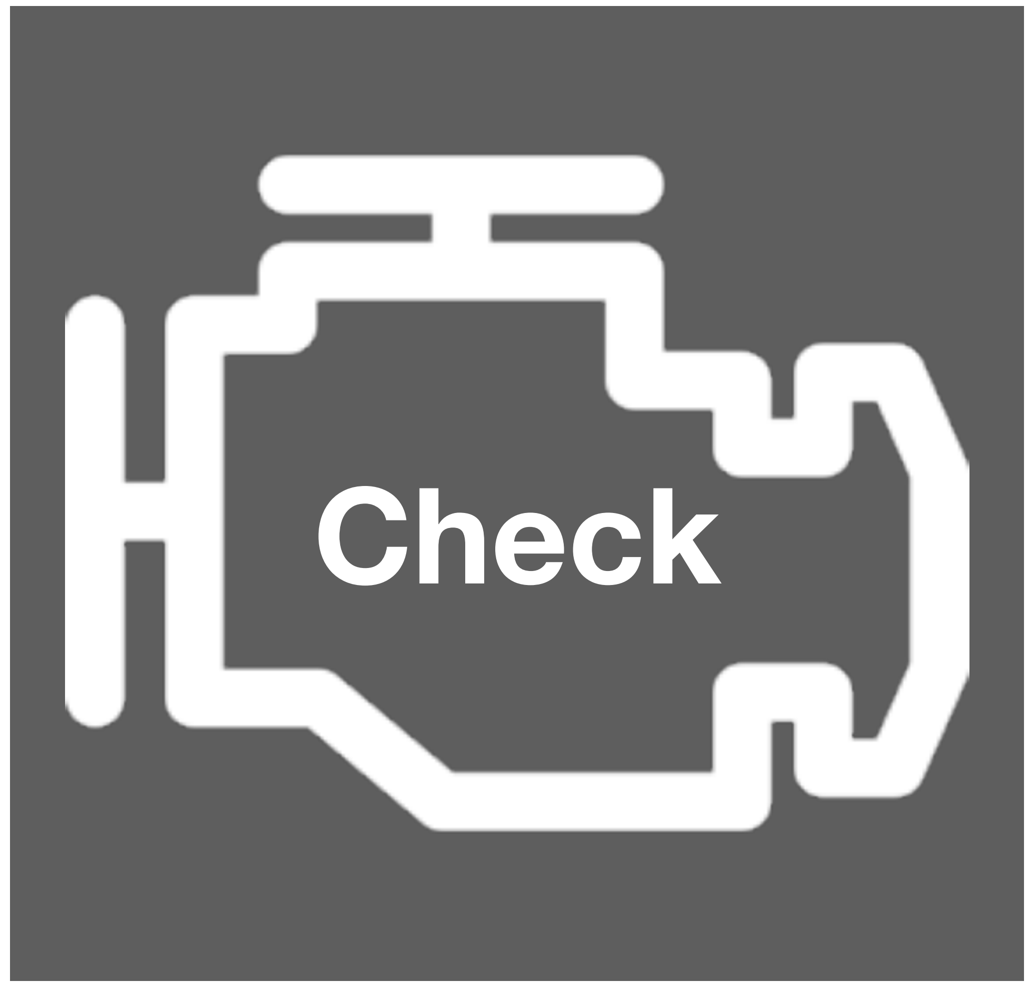
Explaining Explanations

Black-box



Imprecise



System-level

Leilani H. Gilpin - MIT

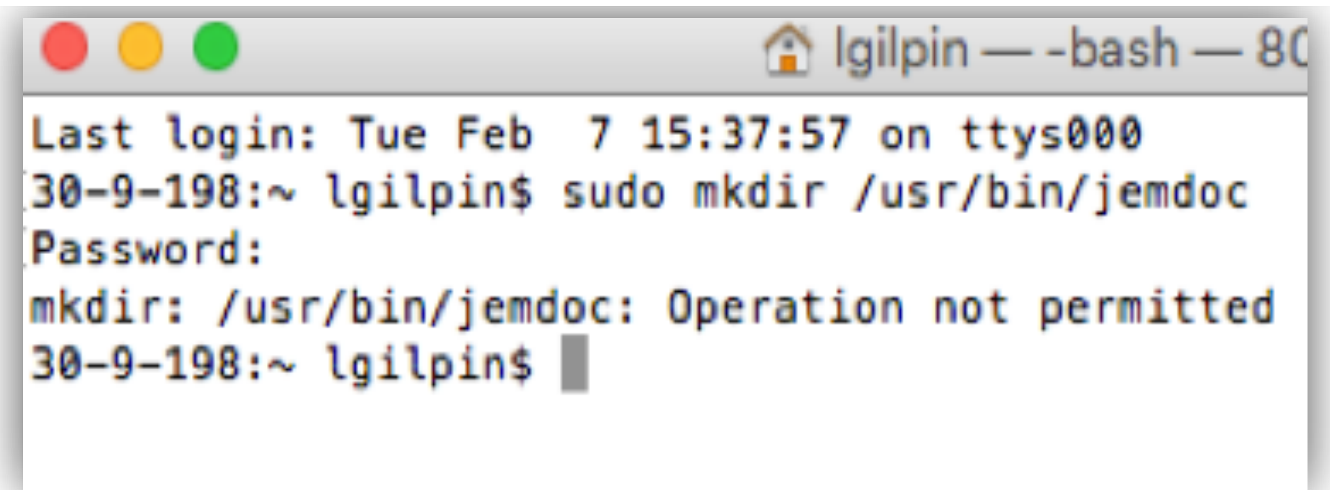
The Need for Explanations

No Explanation

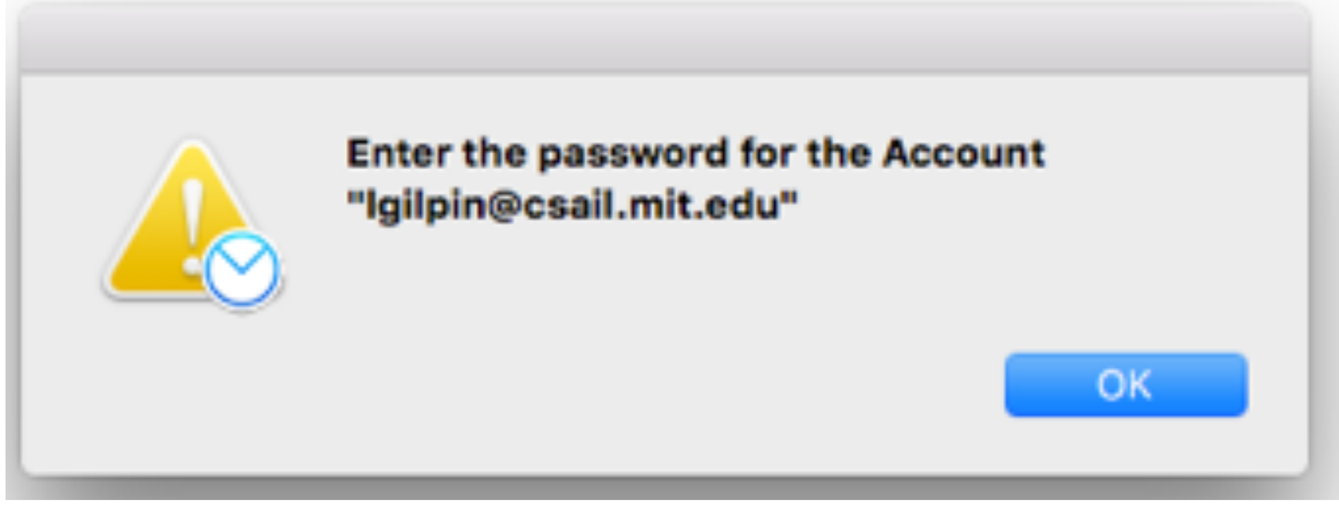

AI Mistakes Bus-Side Ad for Famous CEO, Charges Her With Jaywalking

By Tang Ziyi / Nov 22, 2018 04:17 PM / Society & Culture

No Commonsense



OS Upgrade (Version Skew)



Imprecise (Certificate Missing)

Users Need Explanations

What is Explainability?

From Darpa XAI

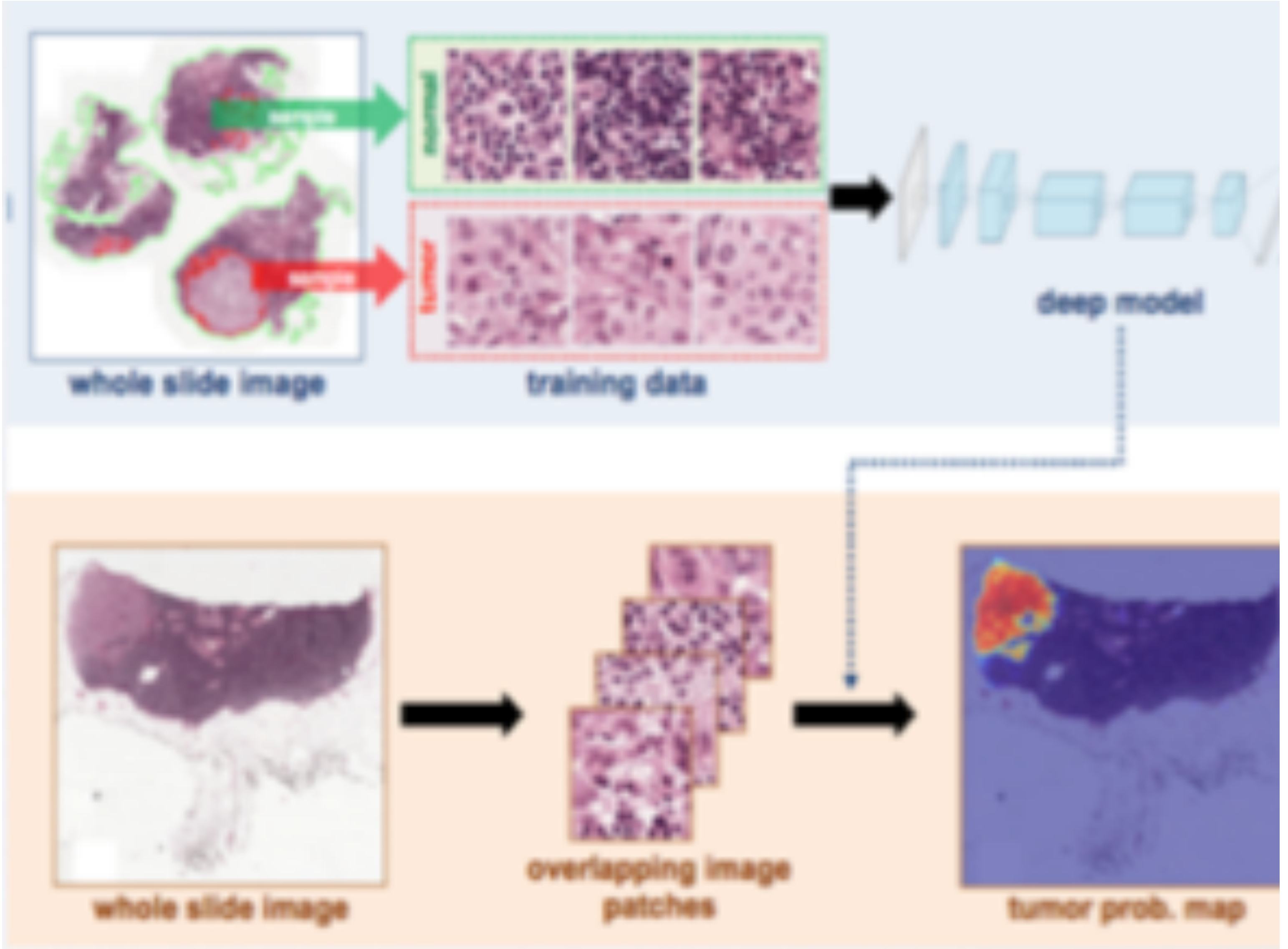
"Explanations…express answer to not just any questions but to questions that present the kind of **intellectual difficulty…**"

–Sylvain Bromberger, On What We Know We Don't Know

Deep Nets are Everywhere

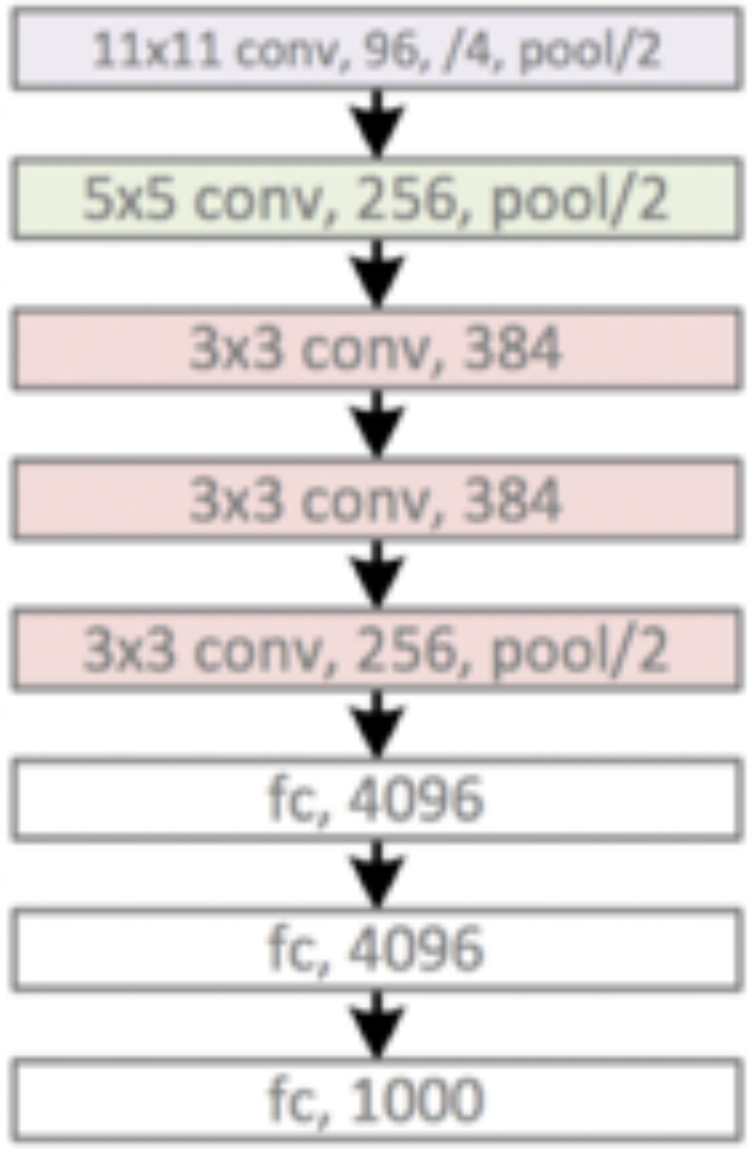
Self-driving Cars

Playing Go



Making Medical Decisions

Deep Nets are Not Understandable



input → → **output**

Middle “hidden” layers

Whenever correct: “whatever you did in the middle, do more.”
Whenever wrong: “whatever you did in the middle, do less.”

Overview

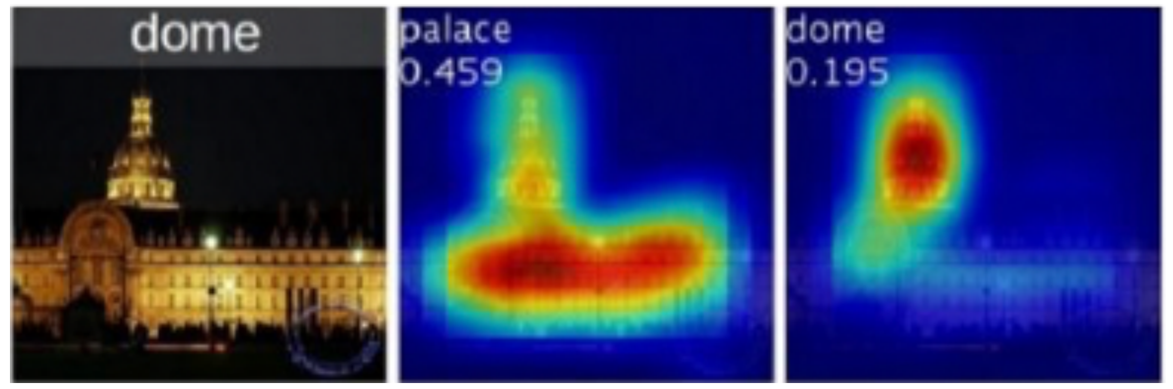
- Definitions
- Taxonomy
  - Survey: Literature review (87 papers) in computer science, artificial intelligence, and philosophy.
  - Recommendations for Evaluation
- How can Explanations Help (e.g. anomaly detection).
- Contributions and Future Work

Definitions

- Explainability != Interpretability
- **Interpretability** describes the internals of a system that is *understandable* to humans.
- **Completeness** describes operation in an *accurate* way.
- <u>An explanation needs **both.**</u>

What we Have

Visual cues

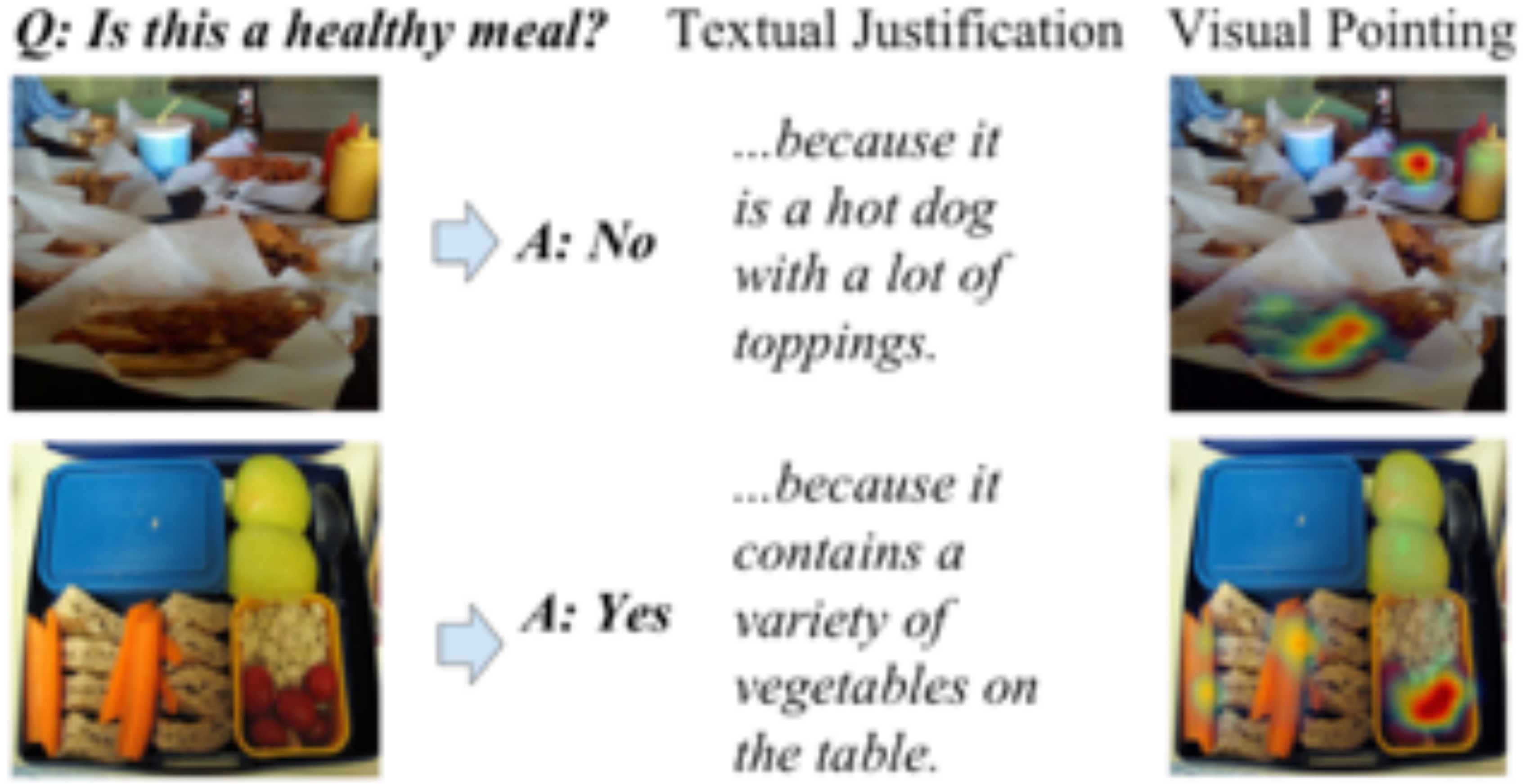


Interpretable,
not complete

Role of individual units

Complete,
not interpretable

Attention based



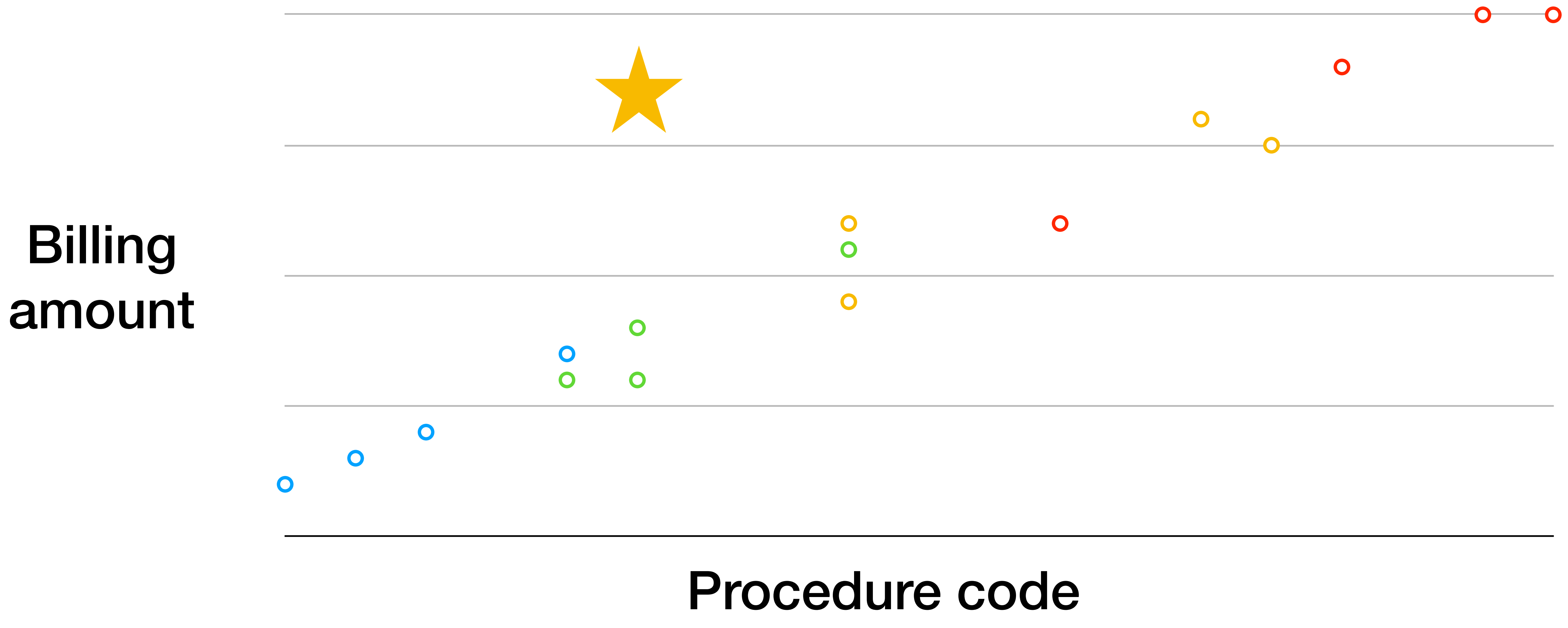
Interpretable,
not complete

Why this Matters

Interpretability

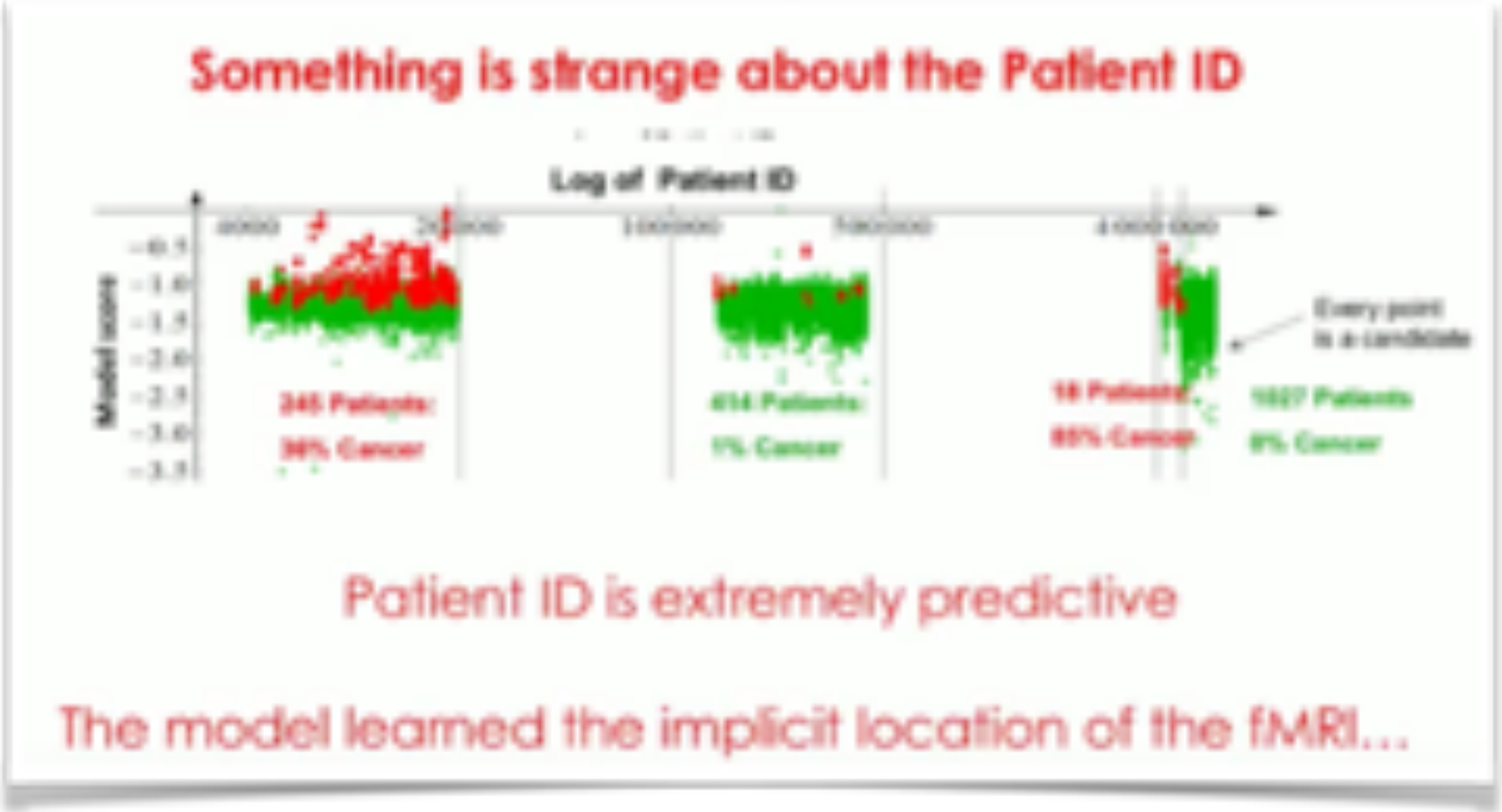
- GDPR
- Liability for decision making

Why this Matters



Completeness

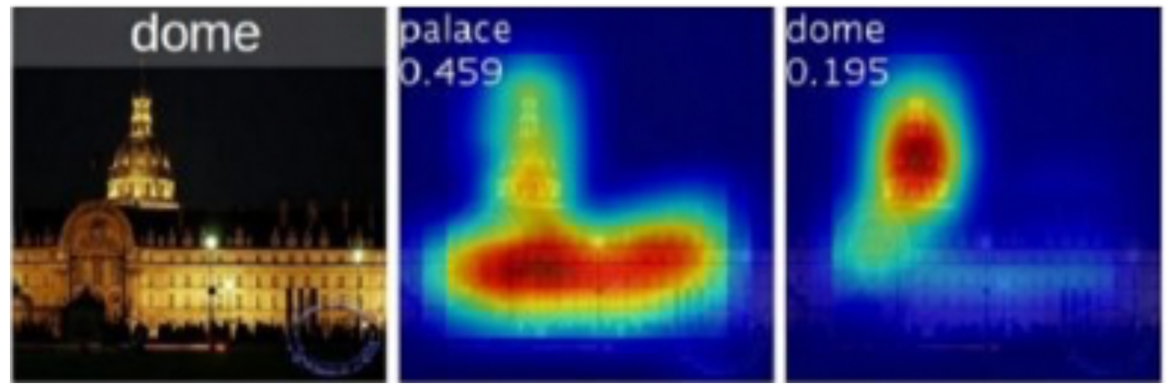
- Explaining the wrong thing.
- Making decisions for the wrong reasons.



From Claudia Perlich at *Women in Data Science* 2018.

What is Being Explained?

Visual cues

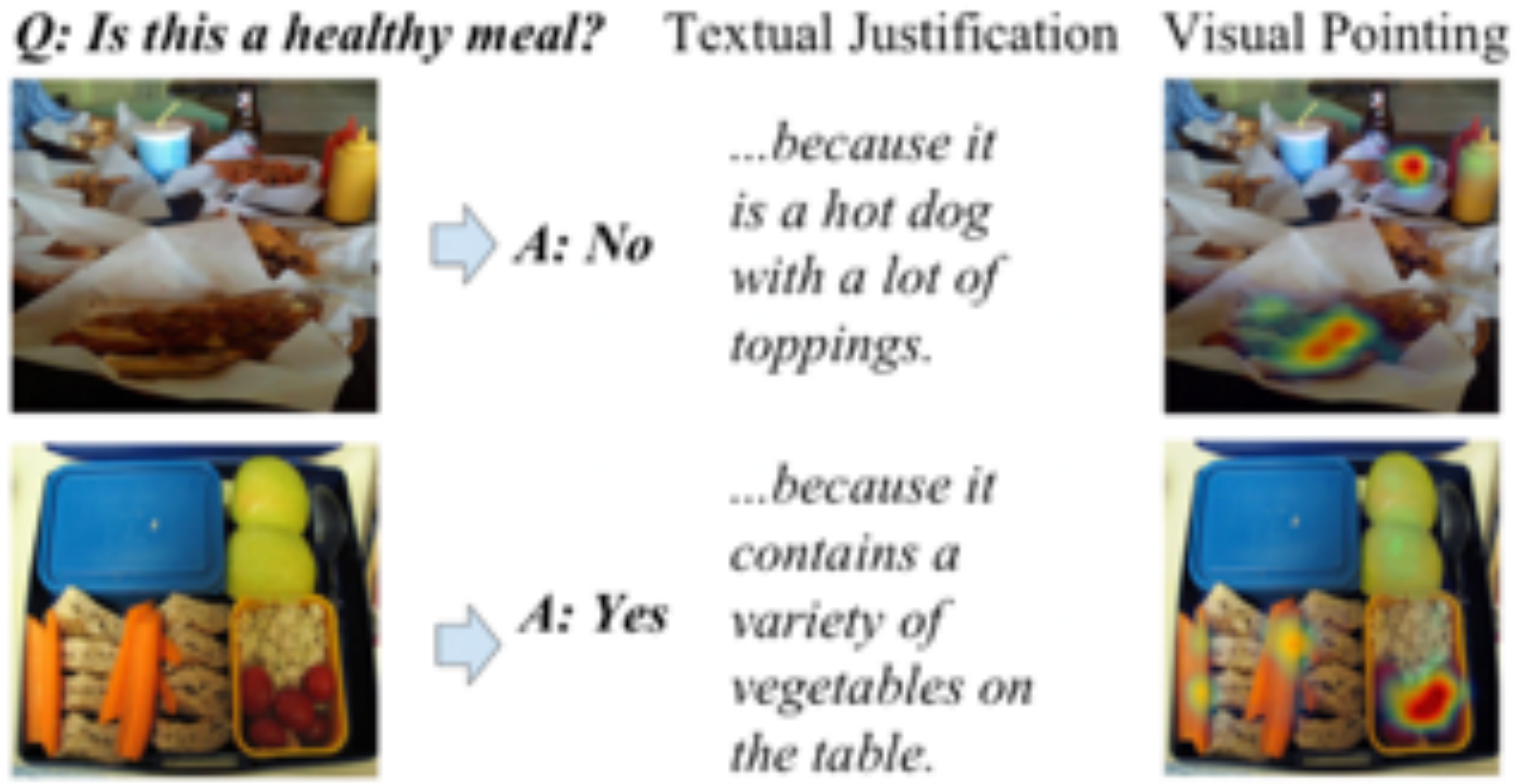


Explain processing

Role of individual units

Explain representation

Attention based



Explanation producing

Taxonomy

	Processing	Representation	Explanation producing
Methods	Proxy Methods Decision Trees Salience Mapping Automatic-rule extraction	Role of layers Role of neurons Role of vectors	Scripted conversations Attention based Disentangled representations

Methods that Explain Processing

DeepRED –
Rule Extraction from Deep Neural Networks*

Jan Ruben Zilke, Eneldo Loza Mencía, and Frederik Janssen

Technische Universität Darmstadt
Knowledge Engineering Group
j.zilke@mail.de, {eneldo,janssen}@ke.tu-darmstadt.de

Extracting Rules from Artificial Neural Networks with Distributed Representations

Sebastian Thrun
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Department of Computer Science III
Römerstr. 164, D-53117 Bonn, Germany
E-mail: thrun@carbon.informatik.uni-bonn.de

"Why Should I Trust You?"
Explaining the Predictions of Any Classifier

Marco Tulio Ribeiro
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Sameer Singh
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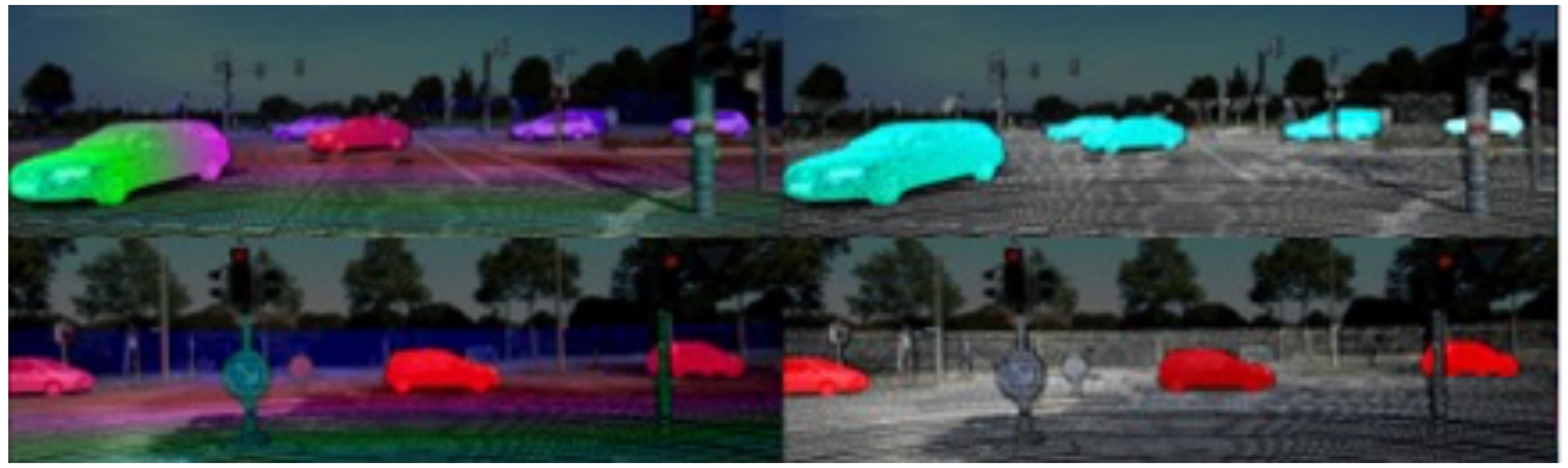
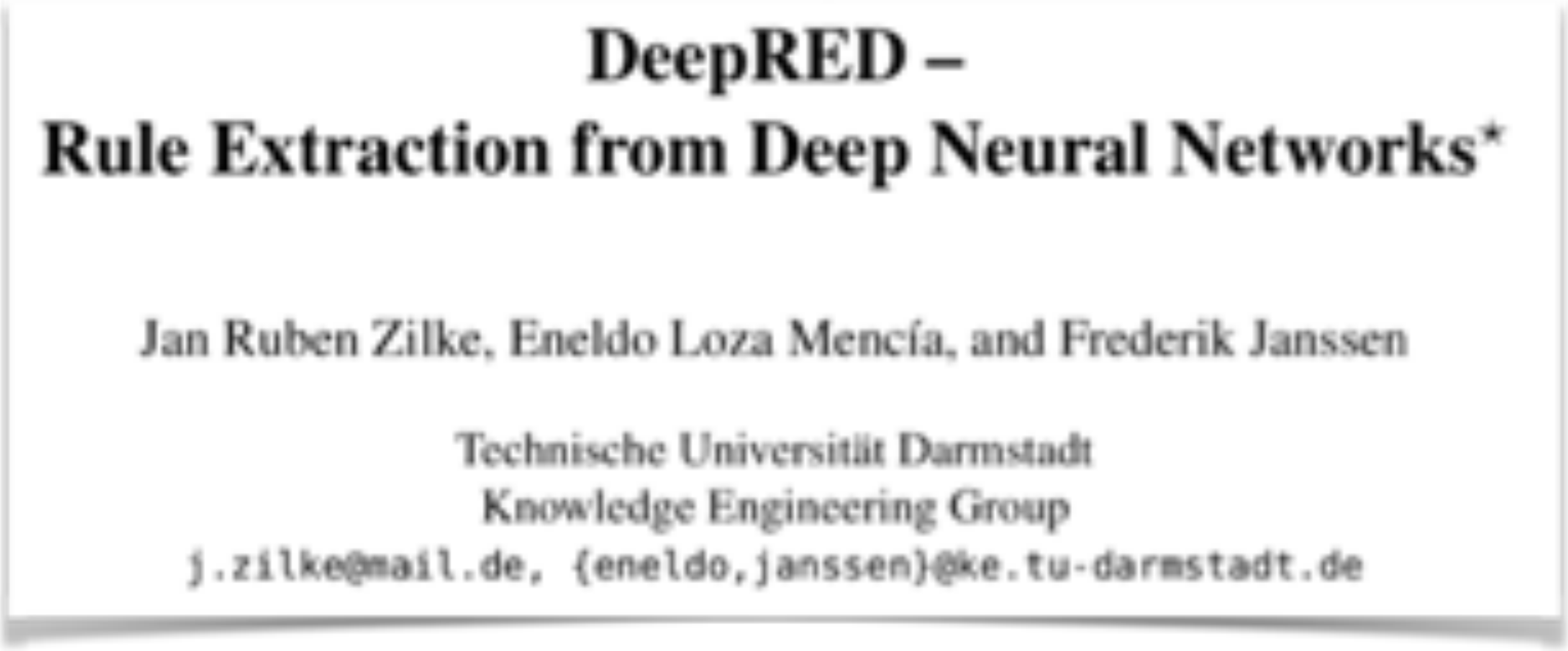
Seattle, WA 98105, USA
guestrin@cs.uw.edu

Examples of Processing Methods



Geiger, Andreas, Philip Lenz, and Raquel Urtasun. "Are we ready for autonomous driving? The kitti vision benchmark suite." *Computer Vision and Pattern Recognition (CVPR), 2012 IEEE Conference on*. IEEE, 2012.



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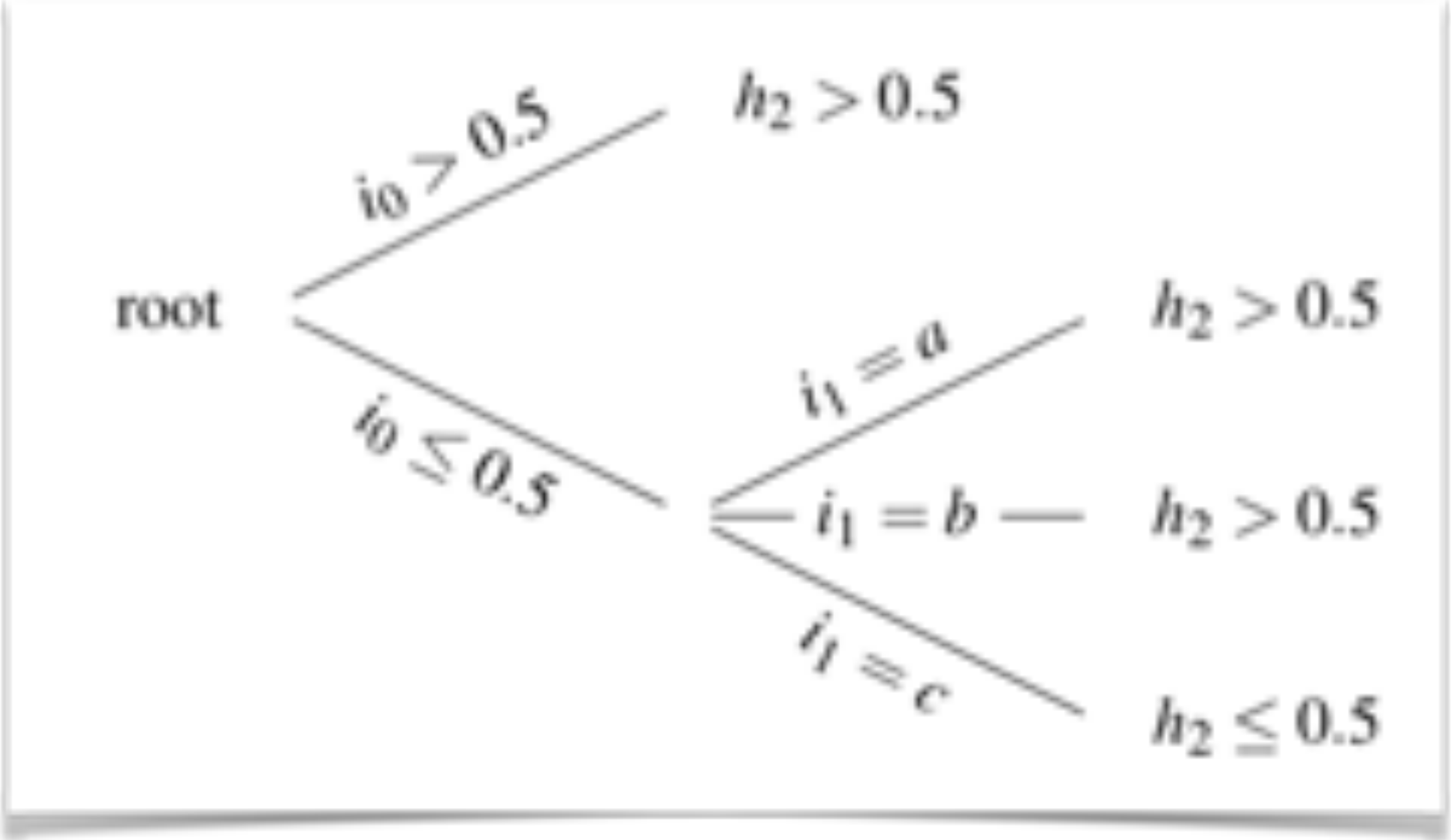

Zilke, Jan Ruben et al. "DeepRED - Rule Extraction from Deep Neural Networks." *DS* (2016).

Taxonomy

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Methods that Explain Representations

**Network Dissection:
Quantifying Interpretability of Deep Visual Representations**

David Bau*, Bolei Zhou*, Aditya Khosla, Aude Oliva, and Antonio Torralba
CSAIL, MIT
{davidbau, bzhou, khosla, oliva, torralba}@csail.mit.edu

**Interpretability Beyond Feature Attribution:
Quantitative Testing with Concept Activation Vectors (TCAV)**

Been Kim   Martin Wattenberg   Justin Gilmer   Carrie Cai   James Wexler
Fernanda Viegas   Rory Sayres

CNN Features off-the-shelf: an Astounding Baseline for Recognition

Ali Sharif Razavian   Hossein Azizpour   Josephine Sullivan   Stefan Carlsson
CVAP, KTH (Royal Institute of Technology)
Stockholm, Sweden
{razavian,azizpour,sullivan,stefanc}@csc.kth.se

Examples of Explained Representations

Network Dissection:
Quantifying Interpretability of Deep Visual Representations

David Bau*, Bolei Zhou*, Aditya Khosla, Aude Oliva, and Antonio Torralba
CSAIL, MIT
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D. Bau, B. Zhou, A. Khosla, A. Oliva, and A. Torralba, "Network dissection: Quantifying interpretability of deep visual representations," in *Computer Vision and Pattern Recognition*, 2017.

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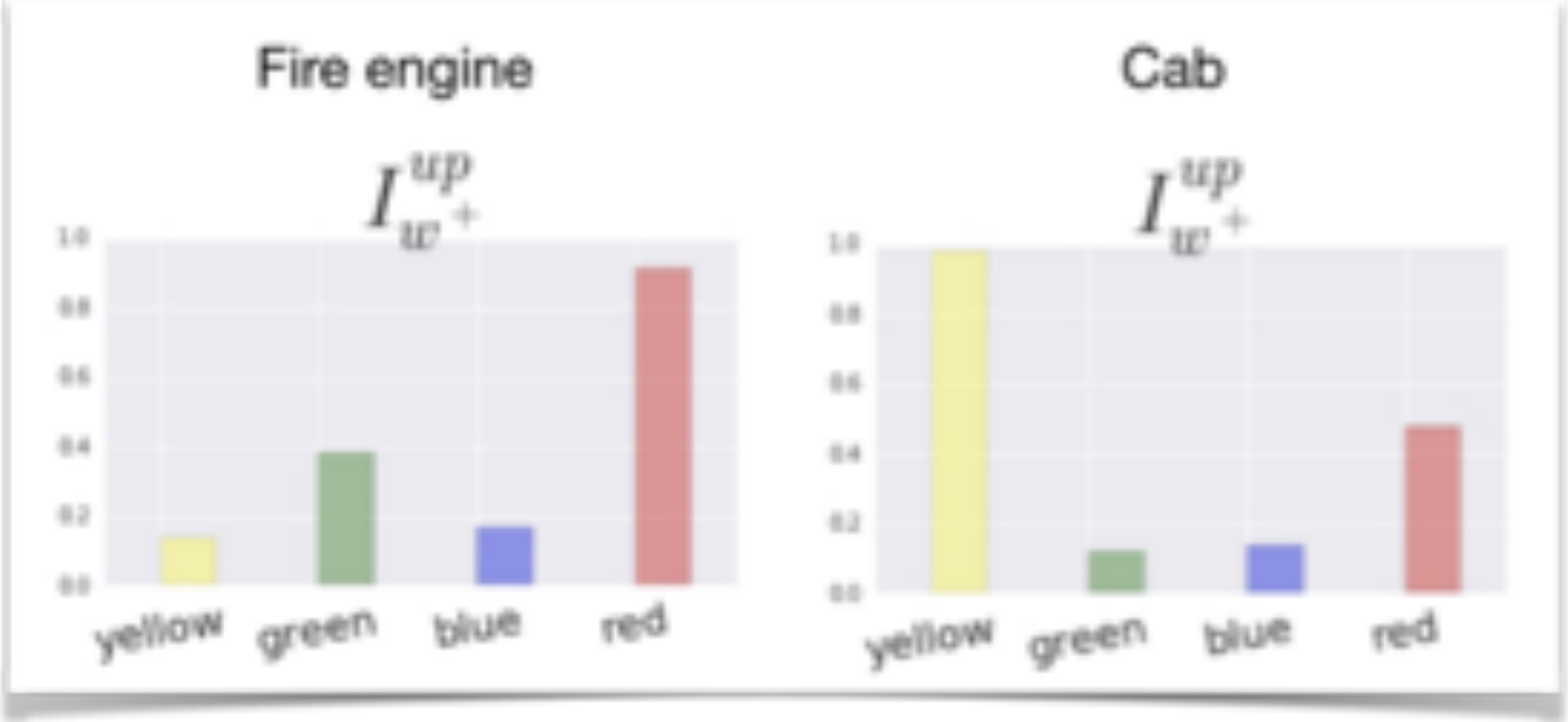

Kim, Been, et al. "Tcav: Relative concept importance testing with linear concept activation vectors." *arXiv preprint arXiv:1711.11279* (2017).

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Methods that Produce Explanations

Multimodal Explanations: Justifying Decisions and Pointing to the Evidence

Dong Huk Park[1], Lisa Anne Hendricks[1], Zeynep Akata[2,3], Anna Rohrbach[1,3],
Bernt Schiele[3], Trevor Darrell[1], and Marcus Rohrbach[4]

[1]EECS, UC Berkeley, [2]University of Amsterdam, [3]MPI for Informatics, [4]Facebook AI Research

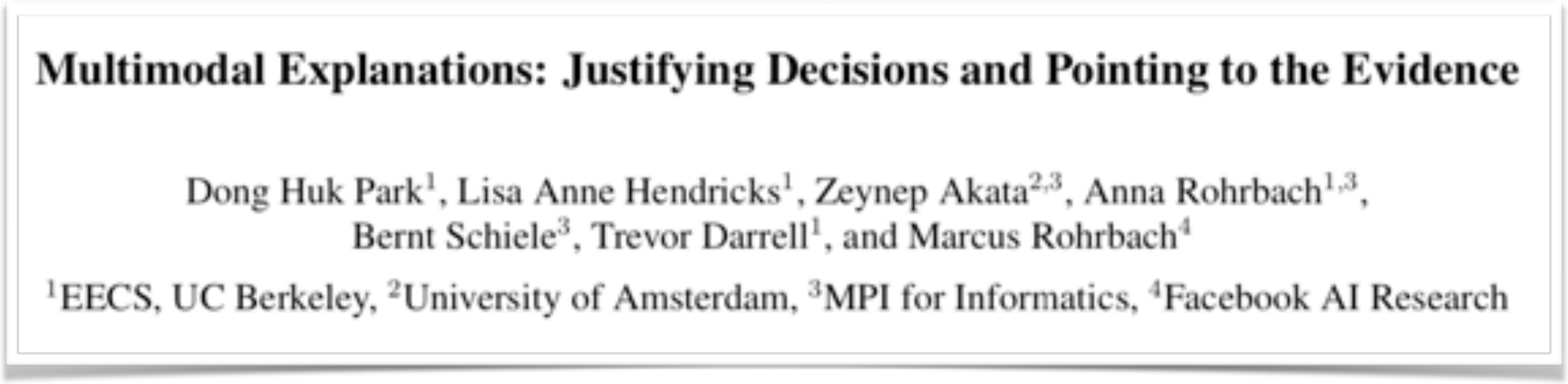
Hierarchical Question-Image Co-Attention for Visual Question Answering

Jiasen Lu*, Jianwei Yang*, Dhruv Batra*†, Devi Parikh*†
* Virginia Tech, † Georgia Institute of Technology
{jiasenlu, jw2yang, dbatra, parikh}@vt.edu

InfoGAN: Interpretable Representation Learning by Information Maximizing Generative Adversarial Nets

Xi Chen†‡, Yan Duan†‡, Rein Houthooft†‡, John Schulman†‡, Ilya Sutskever‡, Pieter Abbeel†‡
† UC Berkeley, Department of Electrical Engineering and Computer Sciences
‡ OpenAI

Examples that Produce Explanations



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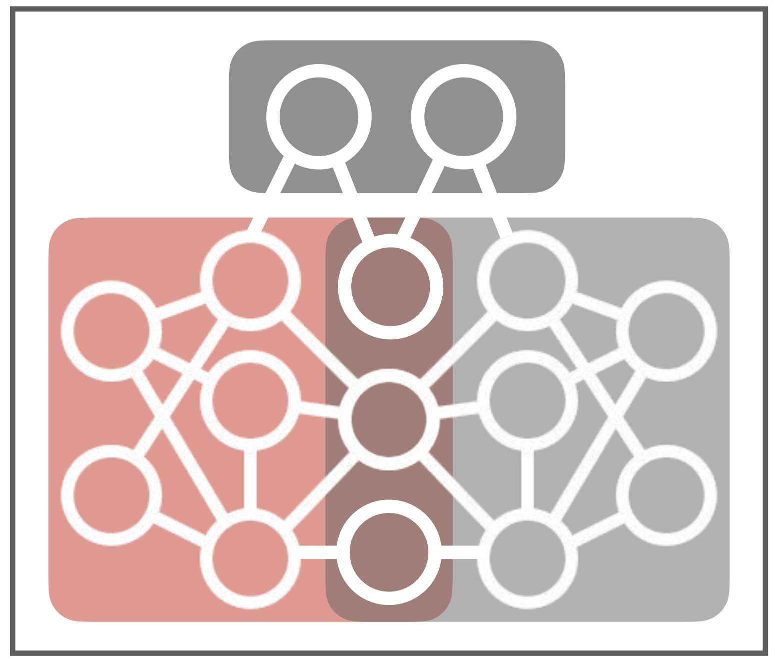
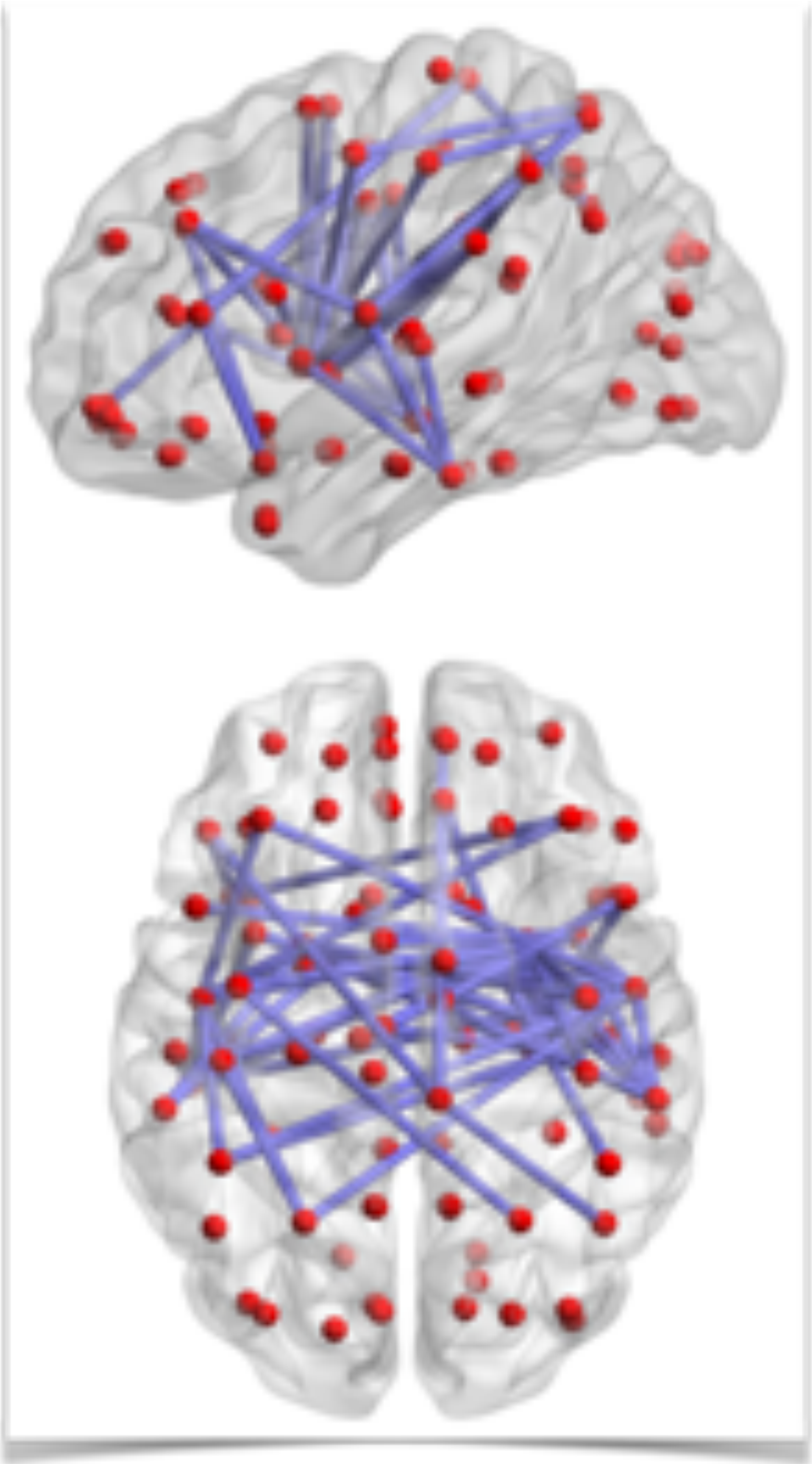
Park, Dong Huk, et al. "Multimodal Explanations: Justifying Decisions and Pointing to the Evidence." *31st IEEE Conference on Computer Vision and Pattern Recognition*. 2018.

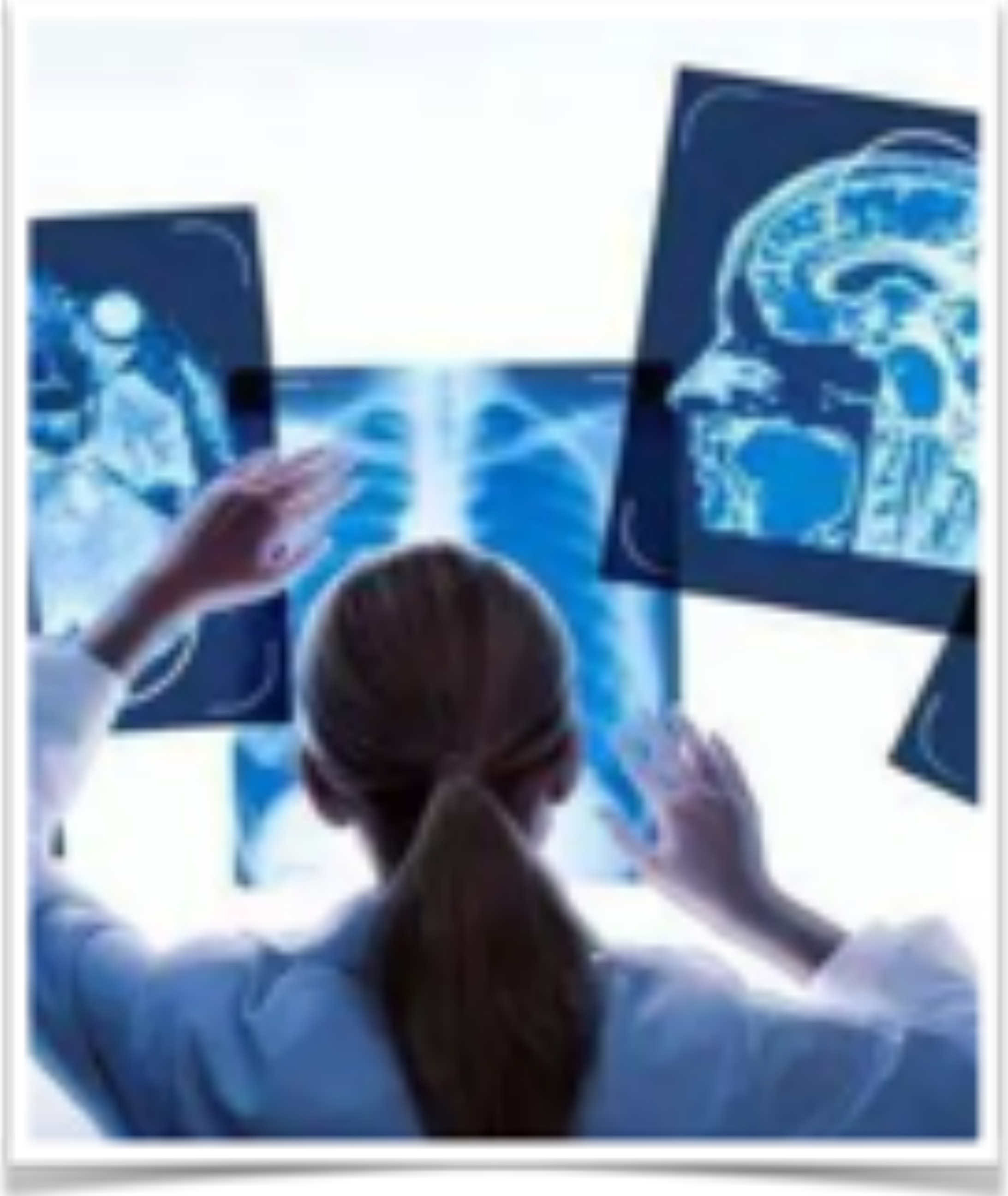


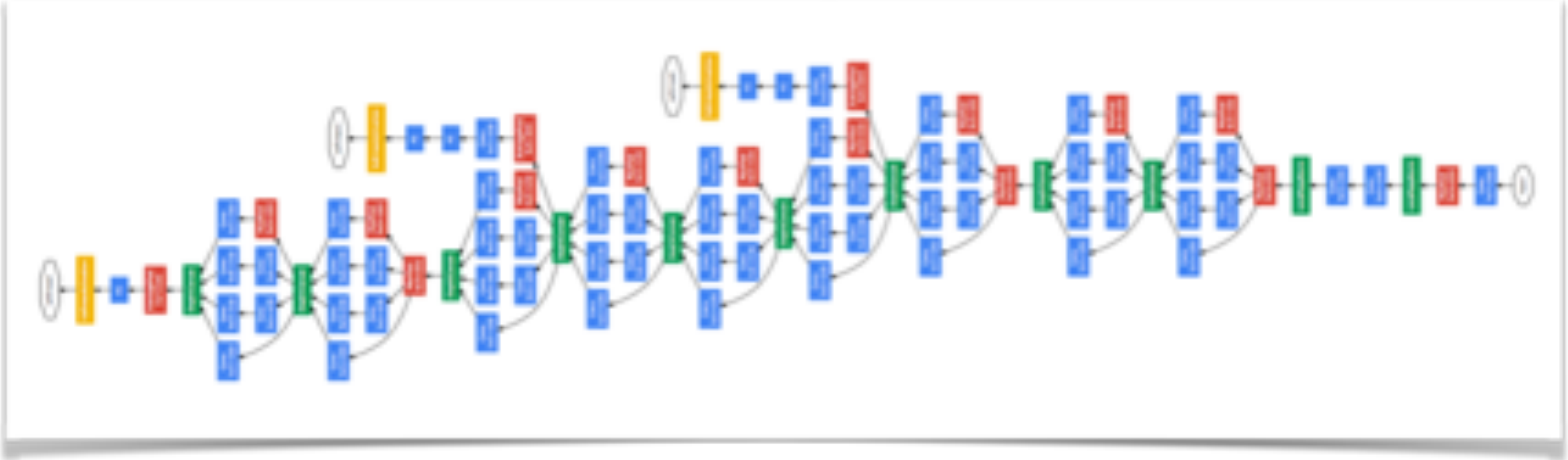
The best option is to veer and slow down. The vehicle is traveling too fast to suddenly stop. The vision system is inconsistent, but the lidar system has provided a reasonable and strong claim to avoid the object moving across the street.

[1] L.H. Gilpin. Explaining possible futures for robust autonomous decision-making. Proceedings of the AAAI Fall Symposium on Anticipatory Thinking, 2019.
[2] L.H. Gilpin et al. Anomaly Detection Through Explanations. Under Review.

A Problem: Insides Matter

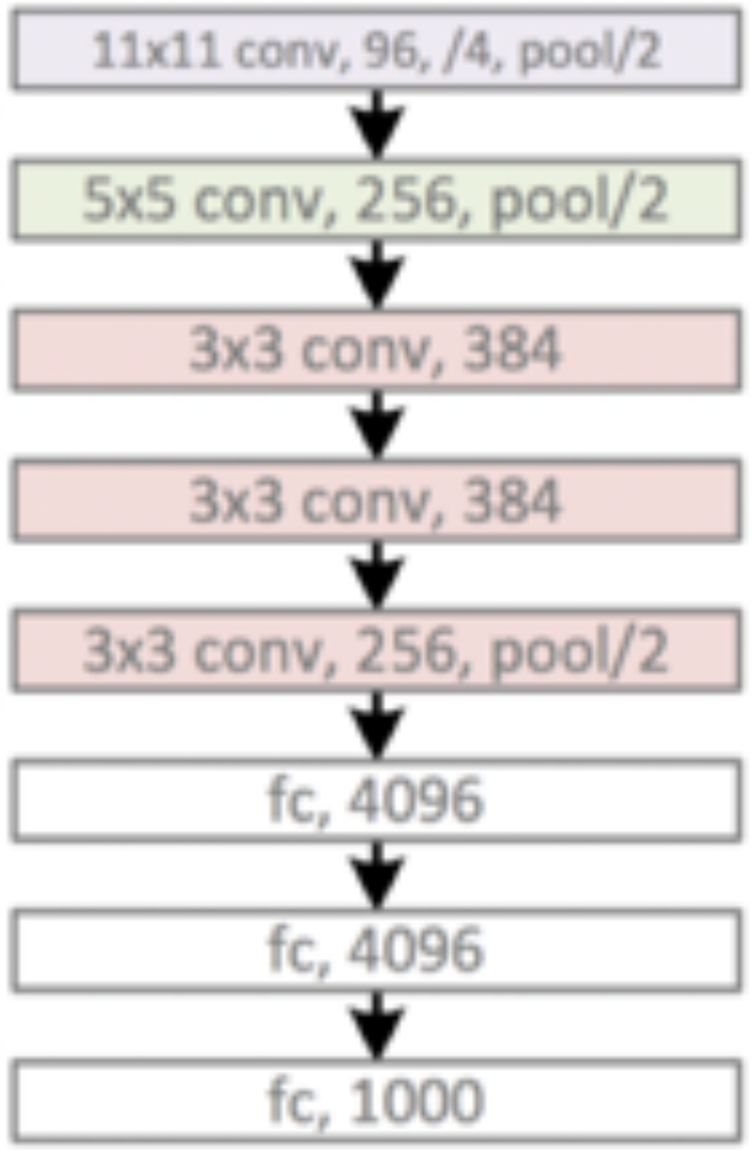




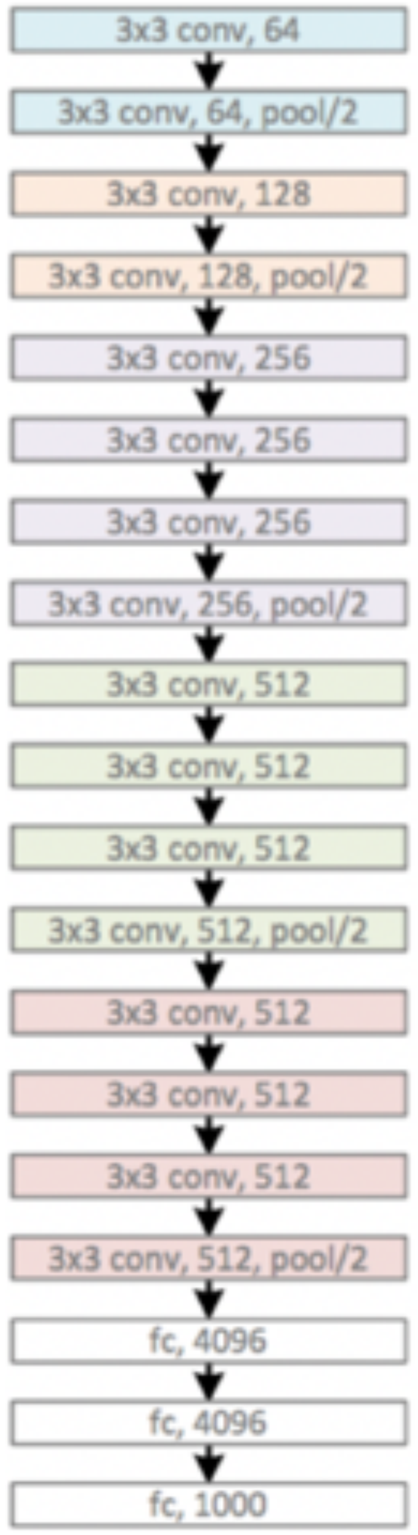


The More Complex (Deeper) The Deeper the Mystery

IMAGENET

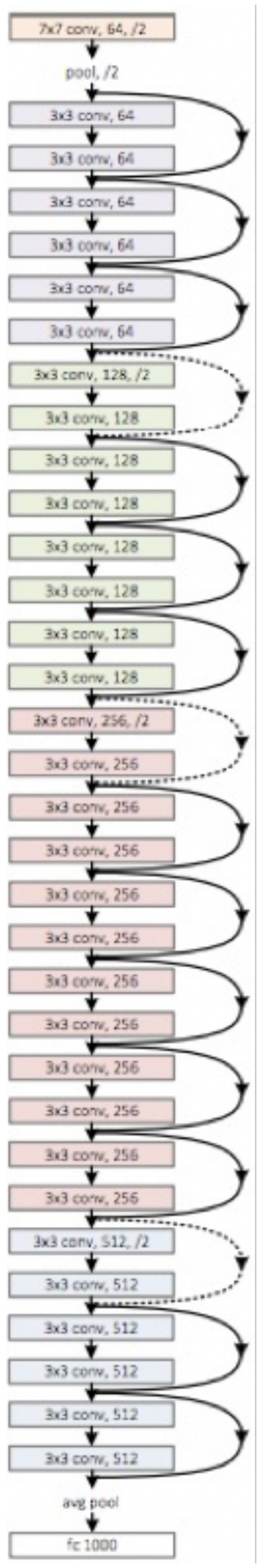


AlexNet (2012)
8 layers; acc 84.7%



VGG (2014)
19 layers; acc 91.5%

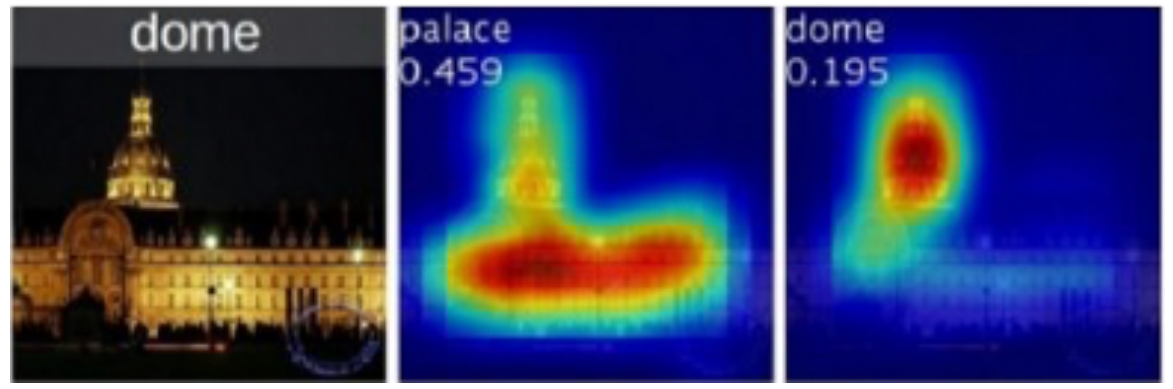
GoogLeNet (2015)
22 layers; acc 92.2%



ResNet (2016)
152 layers; acc 95.6%

What is Being Explained?

Visual cues

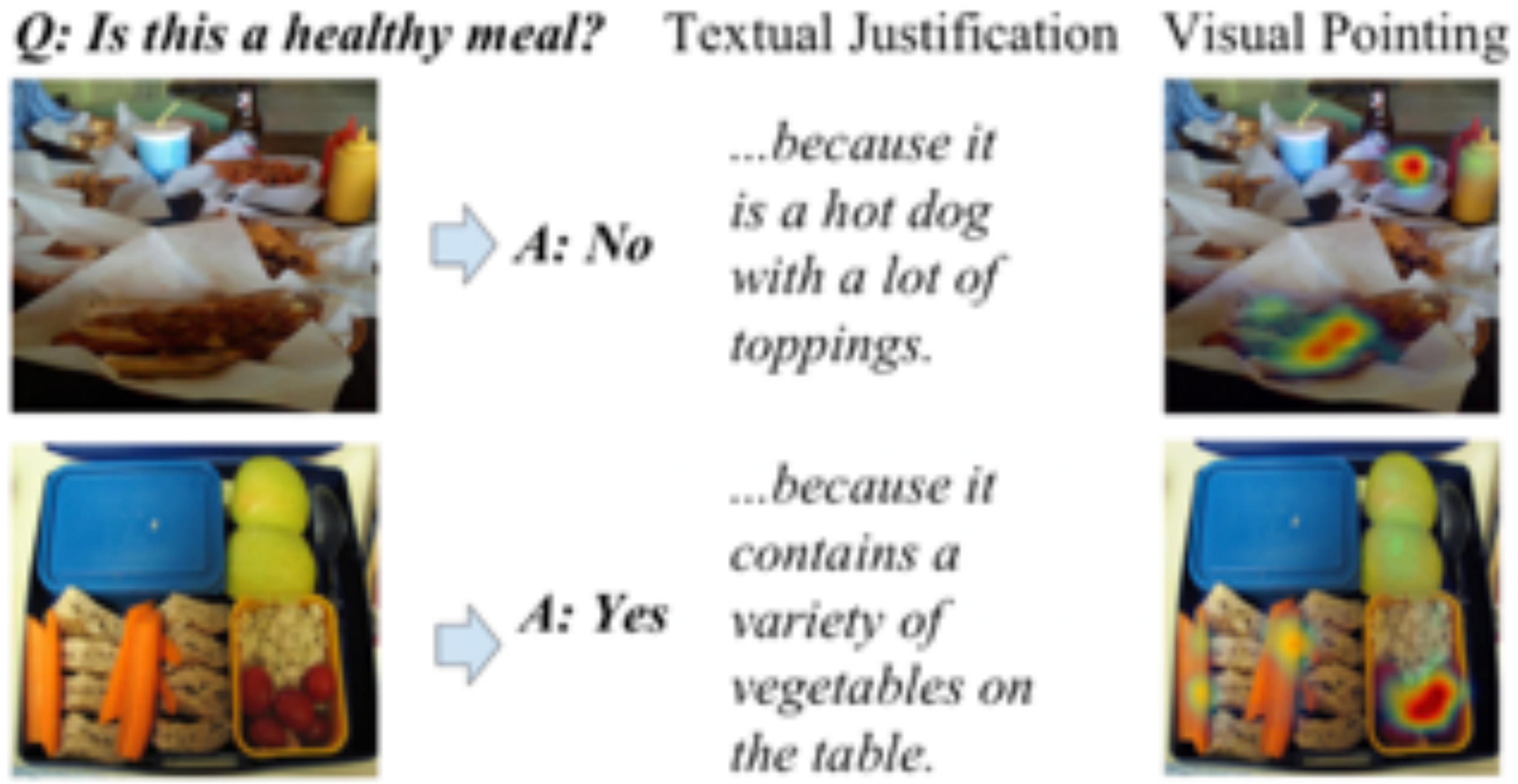


Completeness to model

Role of individual units

Completeness on other tasks

Attention based



Human evaluation

Taxonomy

	Processing	Representation	Explanation producing
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Evaluation	Completeness to model Completeness on a substitute task	Completeness on a substitute task Detect biases	Human evaluation Detect biases

Challenges in Explainability

- Standards and metrics for explanations
    - How to **evaluate** explanations?
- Current metrics of evaluation are “fuzzy”
    - User based evaluations are not *always* appropriate
- Benchmarks for safety-critical and mission-critical tasks.

But How Can Explanations Help?

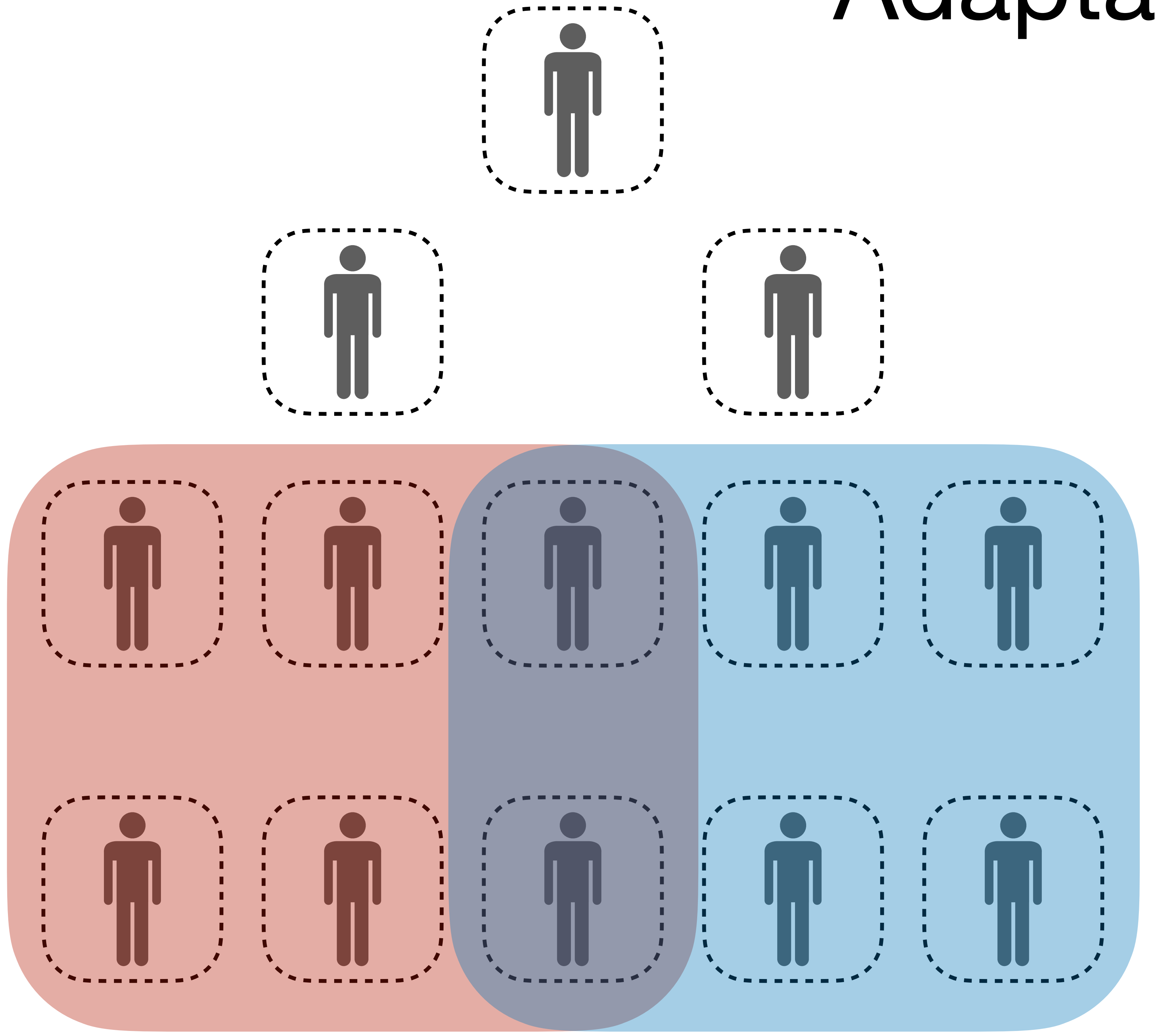
Explaining Explanations: An Approach to Evaluating Interpretability of Machine Learning

Leilani H. Gilpin, David Bau, Ben Z. Yuan, Ayesha Bajwa, Michael Specter and Lalana Kagal
Computer Science and Artificial Intelligence Laboratory
Massachusetts Institute of Technology
Cambridge, MA 02139
{lgilpin, davidbau, bzy, abajwa, specter, lkagal}@ mit.edu

- Ex-post-facto
- Static
- Dynamic
- Self-explaining architectures.

Explanatory Anomaly Detection

Adaptable self-explaining architectures



Local Sanity Checks

Reconcile inconsistencies between explanations.

1. Hierarchy of overlapping self-explaining committees.
2. Continuous interaction and communication.
3. When failure occurs, a story can be made, combining the member's explanations.

[1] L.H. Gilpin. Explaining possible futures for robust autonomous decision-making. Proceedings of the AAAI Fall Symposium on Anticipatory Thinking, 2019.
[2] L.H. Gilpin et al. Anomaly Detection Through Explanations. Under Review.

Explanations can Mitigate Common Problems

Reconcile inconsistencies between explanations.

Reconcile conflicting explanations

Local Sanity Checks

The Trollable Self-Driving Car

Humans are pretty good at guessing what others on the road will do. Driverless cars are not—and that can be exploited.

Reason about new examples.
Utilize commonsense knowledge.

Contributions and Future Work

- A taxonomy and best practices for explanations via completeness and interpretability
  - What [part or parts] is being explain?
- Future directions
  - How can a network explain itself?
  - How to incorporate explainable methods?
  - Is there a provable trade-off between completeness and interpretability?
  - What explanations are best suited for policy?
    - See our follow-up paper: “Explaining explanations to society”