IS4246 Smart Systems and AI Governance

Lecture 4

Agenda

- Review From Last Time
- Explainable AI

Learning Objectives

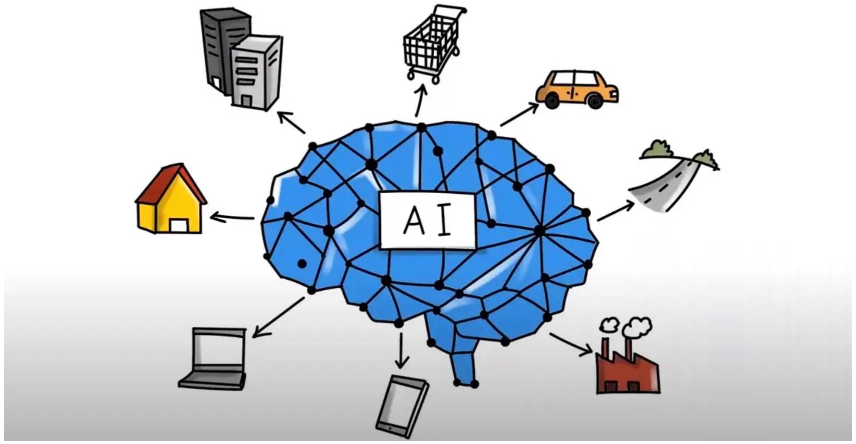
1. Understand the importance of XAI.
2. Explain Interpretability vs Explainability.
3. Understand how to explain black-box model decisions.
4. Appreciate differences between explainability methods.
5. Understand current/potential use cases for explainability in critical applications.

Explainable AI (XAI)

- XAI aims to help humans understand why a machine decision has been reached and whether or not it is trustworthy
- Its goal is to enable and widen acceptance of AI systems by humans
- XAI bridges the gap between machine intelligence and human intelligence

Critical importance of XAI

- Intelligent systems offer great possibility
- XAI raises concern of giving systems too much power
- Explanations of decision-makings processes must be understandable to domain experts
- XAI encourages creating human-like solutions and studying the brain
- User rights must be protected when machines take over decision process



Reasons to Explain

- Explain to justify
- Explain to control
- Explain to improve
- Explain to discover

Explain to justify

Controversies over AI/ML enabled systems yielding biased or discriminatory results

Need for explanations to ensure AI based decisions were not made erroneously

Explanation for a decision = need for reasons or justifications

Need for explanations to ensure compliance with legislation (e.g. GDPR)

Explain to control

- Need to understand more about system behavior
- Greater visibility over unknown vulnerabilities and flaws
- Rapidly identify and correct errors in low criticality situations (debugging)

Explain to Improve

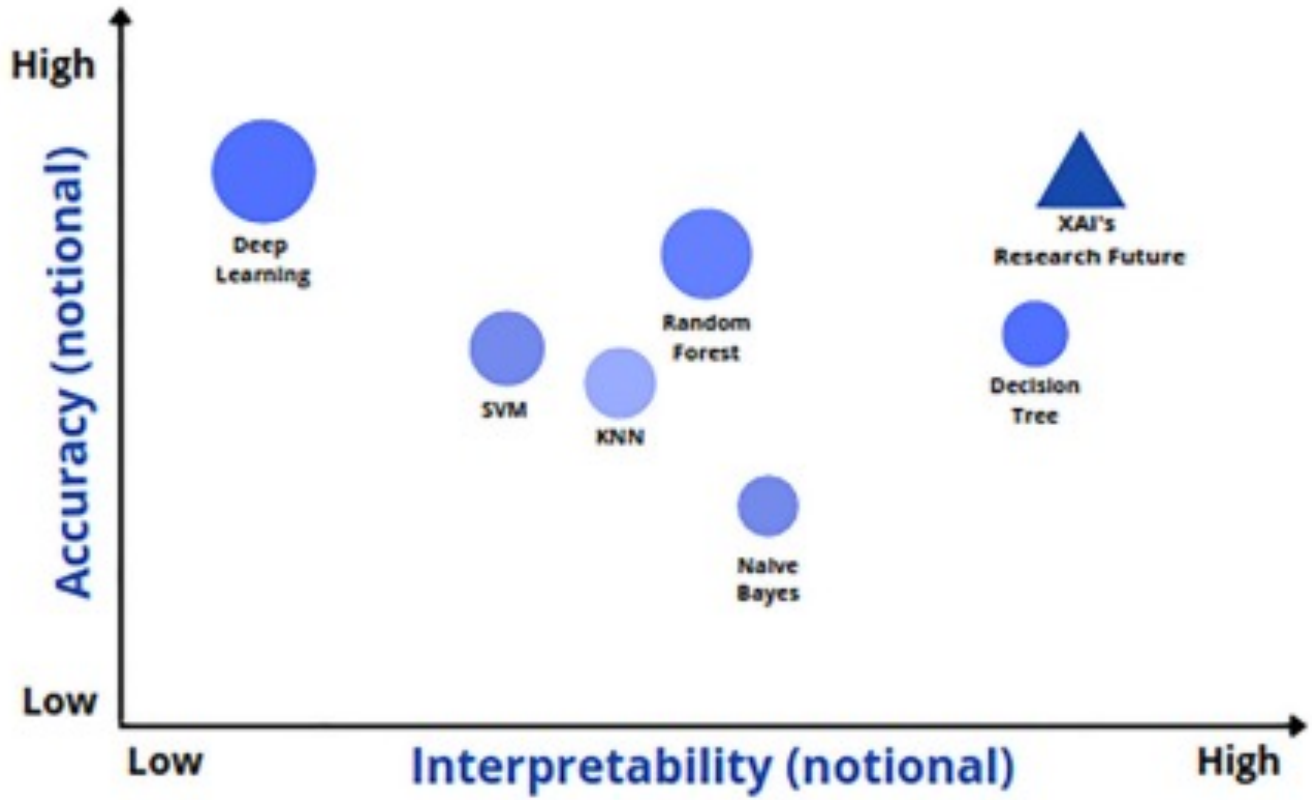
- Need to be able to explain and understand the model for it to be more easily improved
- Knowing why the system produced specific outputs will know how to make it smarter

Explain to Discover

Asking for explanations to learn new facts, to gather information and thus to gain knowledge

XAI models to teach us about new and hidden laws in science

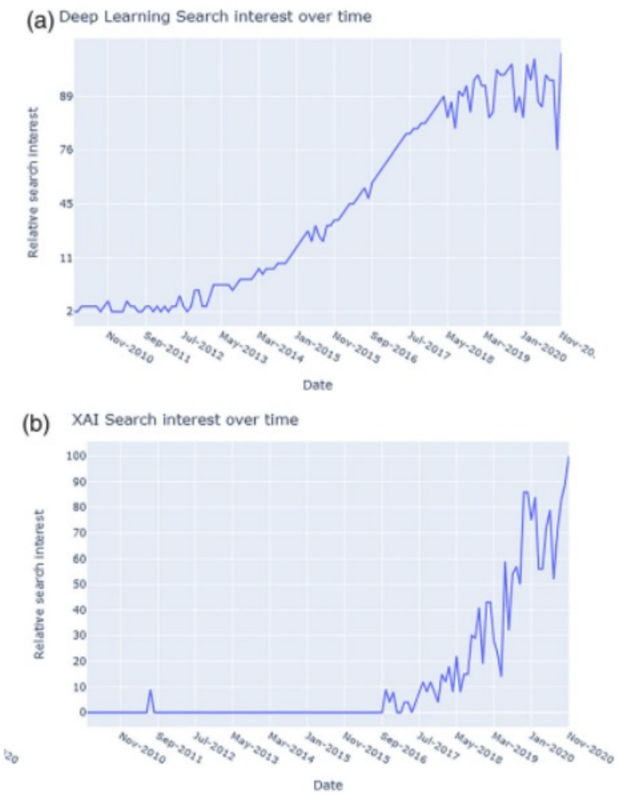
Trade-offs between Accuracy and Interpretability?



Accuracy vs. interpretability for different machine learning models

Historical Significance

- Early forms of AI & ML were interpretable & self-explanatory
- Increase in data complexity led to a focus on accuracy, forgetting explainability
- Recently, explainability has regained importance, necessary for acceptance by society & regulatory authorities
- Still an open research area for SVMs and Deep Learning, Neural Networks



Transparency, Interpretability and Explainability

- **Transparent**: the *model's* potential to be understandable, *opposite to "black-box"*
- **Interpretable**: capacity to *provide interpretations* understandable by humans
- **Explainable**: provides explanations as an interface between humans and an AI system. Must be both accurate and comprehensible

Principles to Strive For

- **Explanation**: An AI system must supply evidence, support; or reasoning for each decision made by the system.

- **Meaningful**: The explanation provided by the AI system must be understandable by, and meaningful to, its users. As different groups of users may have different necessities and experiences, the explanation provided by the AI system must be fine-tuned to meet the various characteristics and needs of each group.

- **Accuracy**: The explanation provided by the AI system must reflect accurately the system's processes.

- **Knowledge limits**: AI systems must identify cases that they were not designed to operate in and, therefore, their answers may not be reliable.

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Four Principles of Explainable Artificial Intelligence

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Additional Goals of Explainable Systems

- Causal
- Counterfactual
- Social
- Selective
- Transparent
- Semantic
- Interactive

Causal Explanations

- Knowing what relationship there is between input and output, or between input features
- Causal explanations are largely lacking in the machine learning literature
- How to measure the causal understanding of an explanation (causability)
- Measuring the causal understanding of an explanation of a machine statement has to be based on a causal model

Counterfactuals

- Empirical evidence indicates that humans psychologically prefer counterfactual or contrastive explanations
- People asking why event P happened, instead of some event Q
- Issues related to the diversity and proximity of counterfactuals arise in designing counterfactual explanations

Social

- Interactive transfer of knowledge tailored for the recipient's background and level of expertise
- Explanations involving one or more explainers and explainees engaging in information transfer
- Conversational or argumentative processes can enhance user's inspection of explanations and increase trust in the system

Selective Explanations

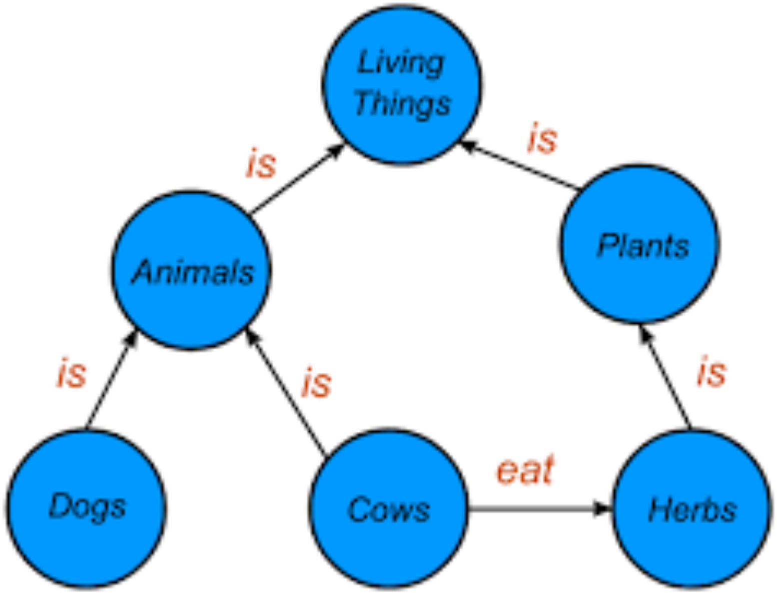
- Explanations do not always need to be complex representations of the real world
- Informational content of explanations must be selected according to user's background and needs
- Explanations can be tailored to doctor's level of technicality or lay user's need for simplicity

Transparency

- Explanations should help in understanding the underlying logic and identify wrong system behaviour
- Trade-off between transparency and privacy must be found when generating explanations
- Differentially private model should be used to generate local and global explanations

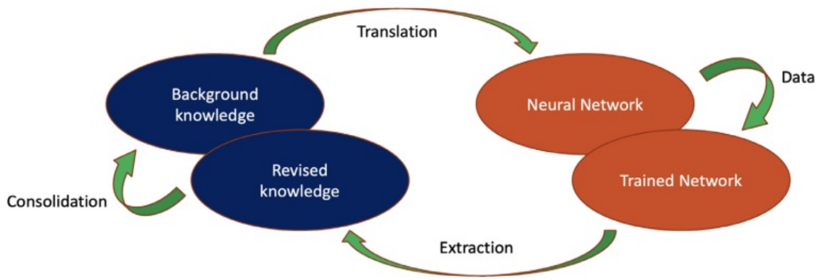
Semantic

- Symbolic grounding by means of ontologies, conceptual networks, or knowledge graphs
- Formal representation and reasoning for knowledge manipulation
- Manner in which to provide personalized explanations for different stakeholders



Interactive Explanations

- Explanations should be interactive and allow explainee to revise and consolidate knowledge Background knowledge can be used for meaningful semantics of explanations
- Background knowledge injected back to improve model performance



Taxonomy of approaches

Model types:	Explanation methods:
• Transparent • Opaque	• Model-agnostic • Model-specific • Explanation by simplification • Explanation by feature relevance • Visual explanation • Local explanation

Transparent Models

- kNN, decision trees, rule-based learning, and Bayesian networks
- Transparent decisions, but transparency in itself doesn't guarantee explainability

Model-Agnostic XAI Approaches

- Designed to be general
- Relate input of a model to its outputs without depending on the intrinsic architecture

Model-Specific XAI Approaches

- Bring transparency to a particular type of model by taking advantage of its features

Explanation by Simplification

- Alternate model such as a linear model or decision tree to explain a more complex model

Explanation by Feature Relevance

- Evaluate a feature based on expected marginal contribution to the model's decision after considering all combinations

Visual Explanation

- Data visualization approaches to interpret the prediction or decision over the input data

Local Explanations

- Approximate the model in a narrow area around a specific instance
- Explain how the model operates when encountering similar inputs

Opaque Models

- Random forest, neural networks, and SVMs
- High accuracy, but not transparent

Overview of Taxonomy

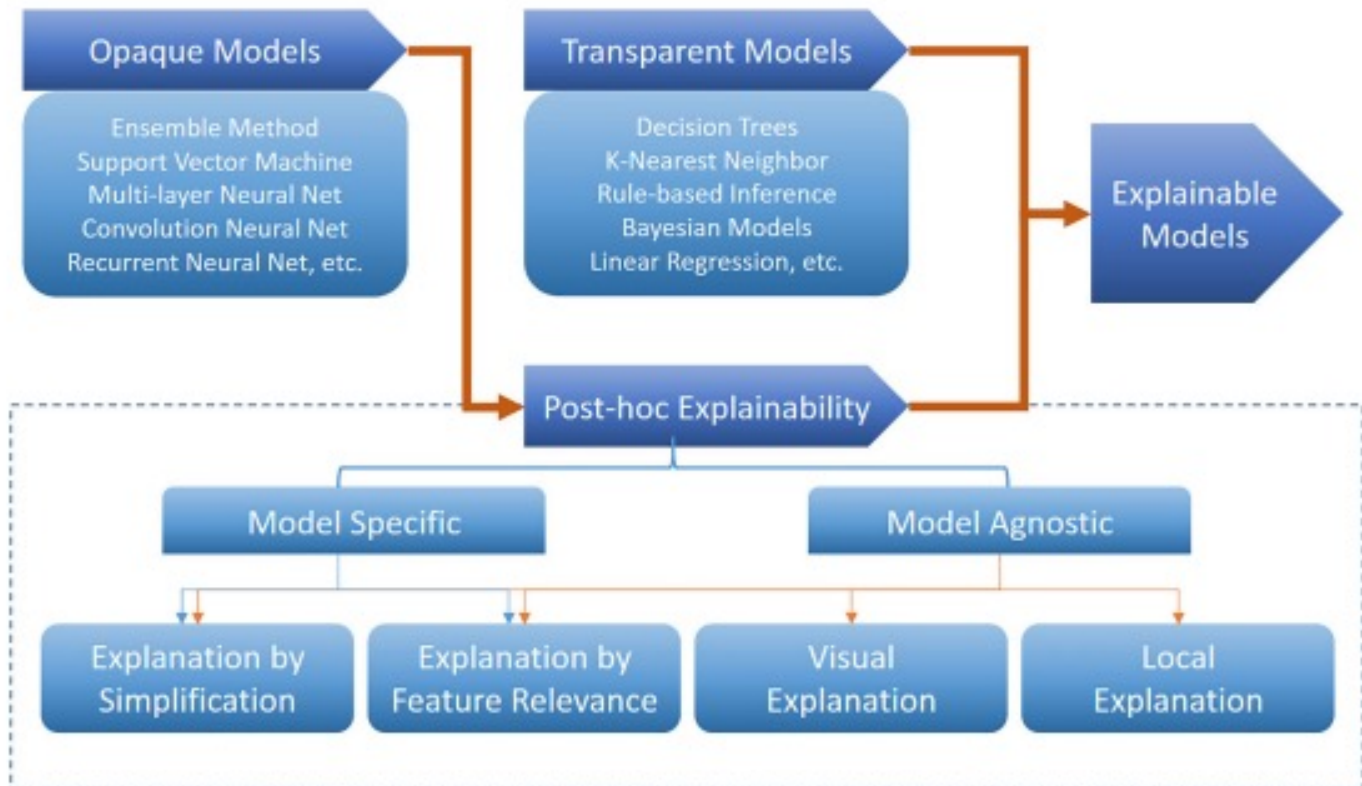


FIGURE 3 The high-level ontology of explainable artificial intelligence approaches

State of the Art

Widely Used Methods

Features-oriented methods (e.g. SHAP)

Class activation maps for CNNs

Global methods (GAMs)

Concept Models

Surrogate Models

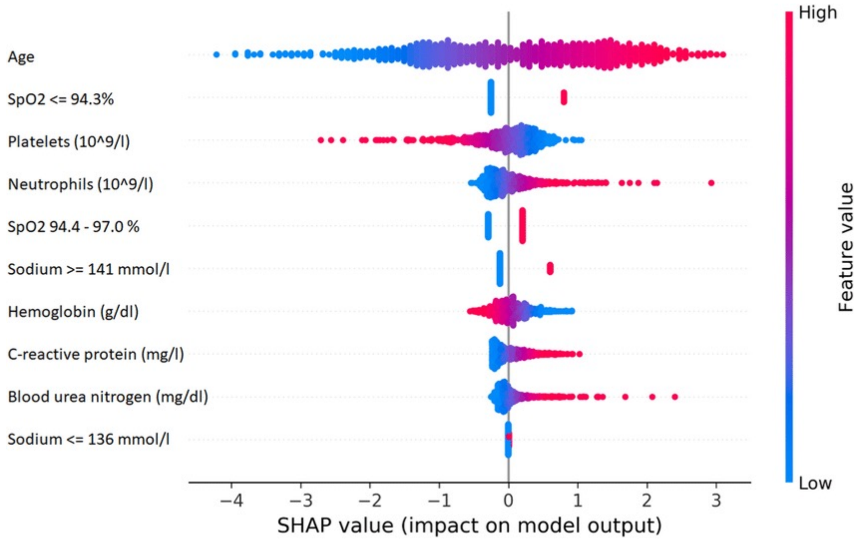
Local Explanations (e.g., LIME)

Local Pixel-Based

Human-Centric Methods

Features-oriented methods (e.g. SHAP)

- SHapley Additive exPlanation (SHAP) is a method to explain the contribution of the features to a prediction
- SHAP is based on the concepts of game theory and the Shapley Value which assigns an individual contribution to each factor in the model

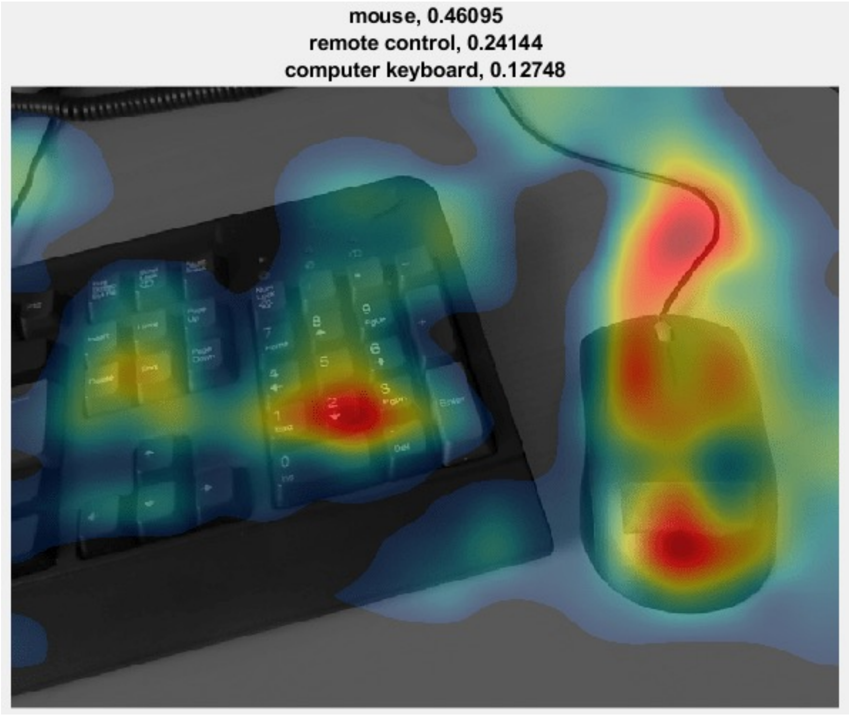


Features-oriented methods (e.g. SHAP)

- SHAP deconstructs the ML model into individual features and then determines the contribution of each of those features to a given output • SHAP can work with any machine learning model and is model-agnostic
- It works by calculating the importance of each feature by comparing it to a "reference" value, which is often the average output of the model
- SHAP is designed to be able to work with both linear and non-linear models

Class activation maps (CAMs) specific to CNNs

- CAMs represent the per-class weighted linear sum of visual patterns
- Applied to final convolutional feature map prior to output layer
- Highlight areas in input image most influential over CNN decisions
- Cannot be applied to pre-trained networks
- Map scaling may lead to loss of spatial info



Global Methods

Examples: Craven & Shavlik (1995), Frosst & Hinton (2017), Odense & Garcez (2017), Zhou, Jiang& Chen (2003), Lou et al. (2012, 2013)

Goal: Generate general representations of black-box models and the features it has been trained on

Strategies: Extract decision trees, decision rules and feature importance vectors

Surrogate Models: LIME

Local Interpretable Model-Agnostic Explanations (LIME)

A model-agnostic technique to create explanations of ML models by training surrogate models on a set of perturbed instances of the original data.

Image classification involves perturbing superpixels in an image

Local model is not always informative or reliable at a human level if parameters are chosen based on heuristics

Use Cases

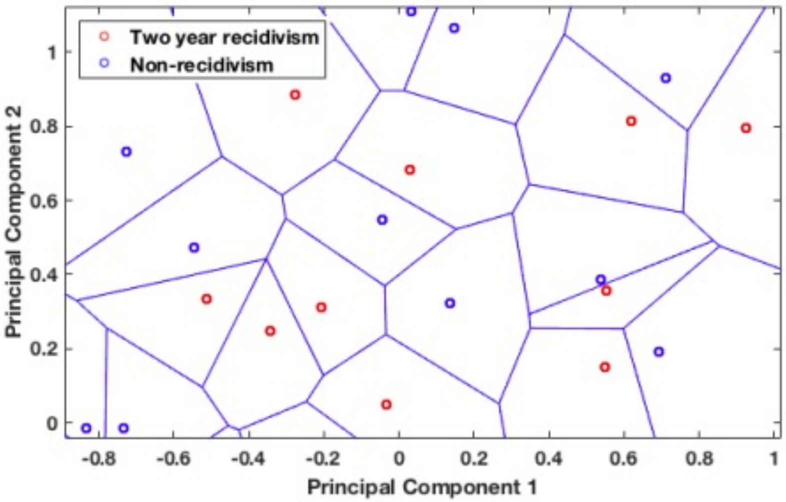
- Medical
- Criminal Justice
- Autonomous Vehicles

Medical AI Applications

- Growing demand during COVID-19 pandemic • To be trustworthy, transparent, interpretable, and explainable
- Example: Employing DL to Identify COVID-19 via CT scans
- Outperforms GoogleNet, Resnet and VGG-16
- Explanable Architecture for Decision Visualization
- Expandable to include more classes

Criminal Justice

- In some countries, automated algorithms are used to predict criminal behavior
- Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) is a widely used criminal risk assessment tool
- There is potential for racial bias to be introduced into predictive models



Autonomous Systems

- XAI and Autonomous Systems
  – Self-driving vehicles - Crash of an Autonomous car owned by Uber (Stilgoe, 2020) -
- Approaches
  – Prototype-based approaches used for understanding visual scene (Soares et al., 2019)
  – Can provide explainable rules

Thank You!