XAI : Explainable Artificial Intelligence

Turning Black Box into Glass Box

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Spring 2021

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XAI

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Let’s classify Huskies and Wolves

Introduction

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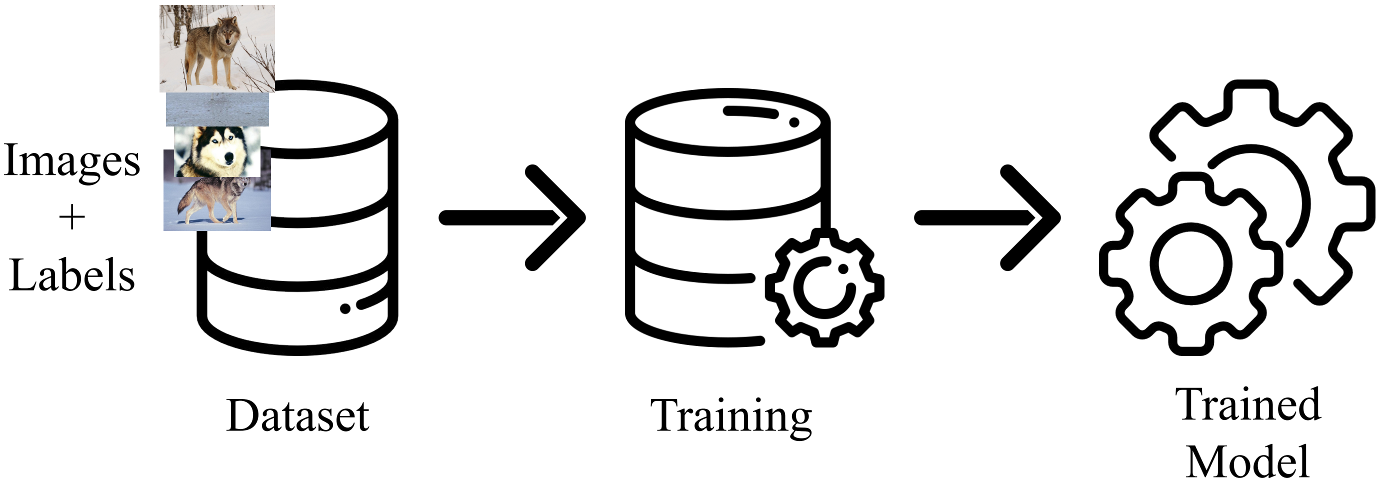
Let's classify Huskies and Wolves

Classify Huskies and Wolves

Differences?

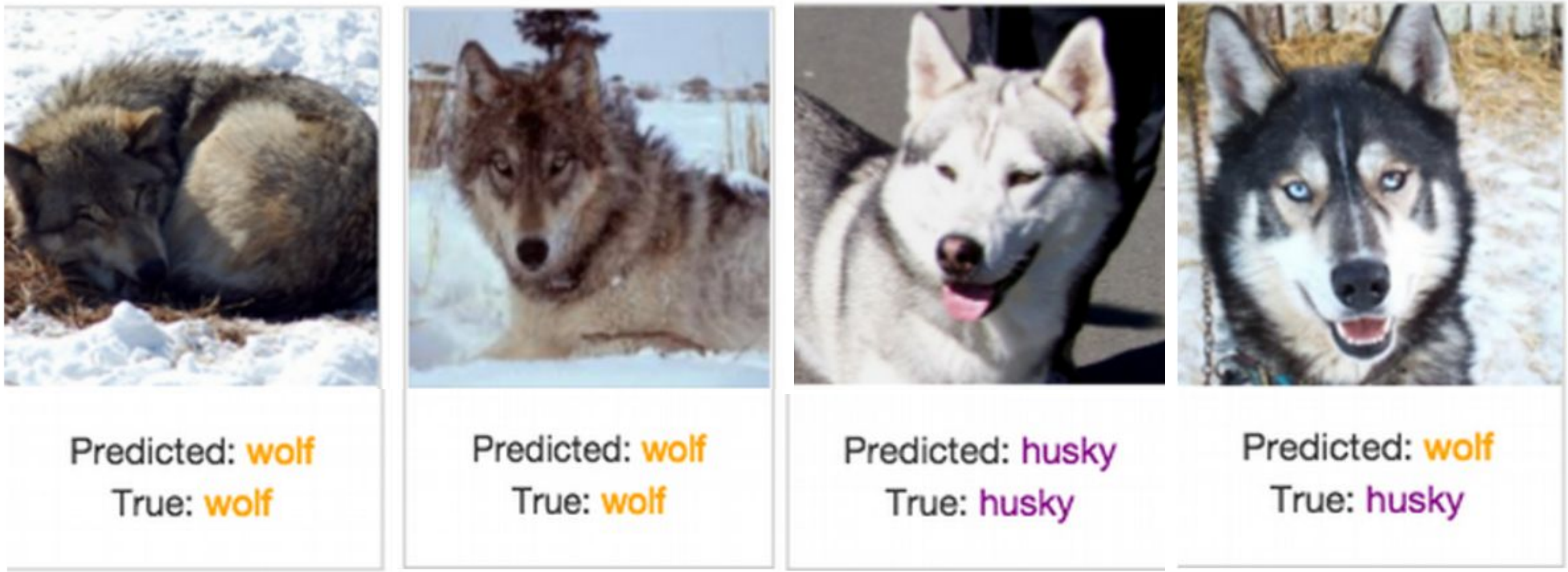
Classify Huskies and Wolves

Building a Classification Model



Test The Model

Which is a Husky and which is a Wolf ?



Test The Model

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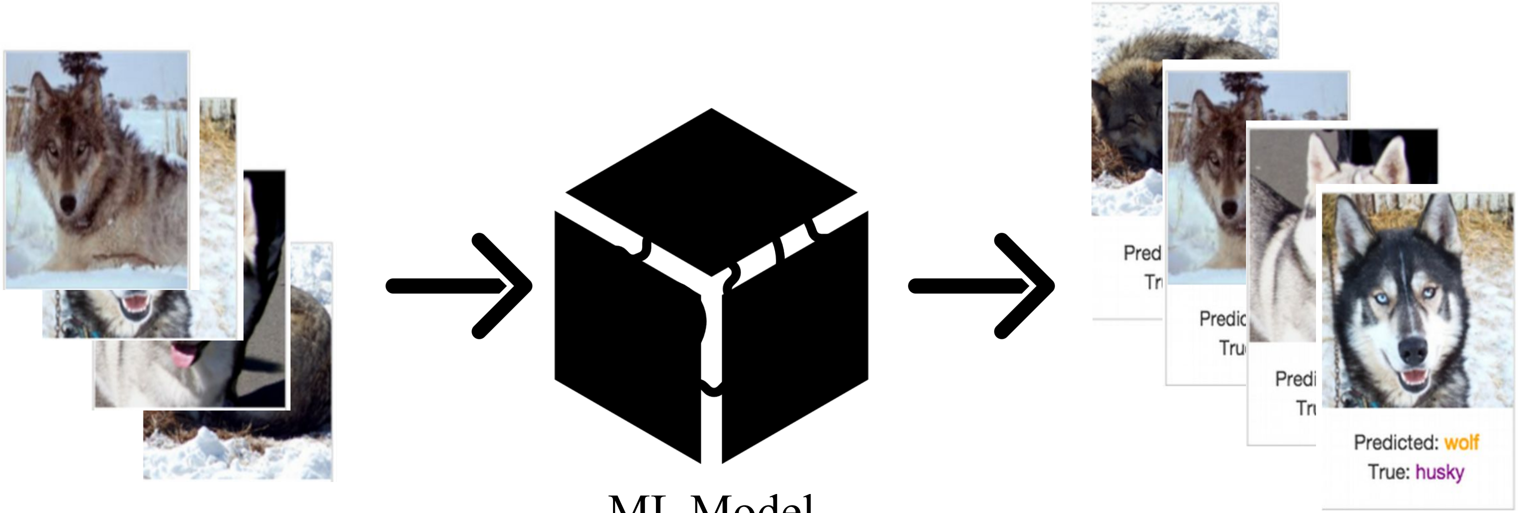
How does the model reach its decisions?



Input

ML Model

Output

How Does The Model Reach Its Decisions?

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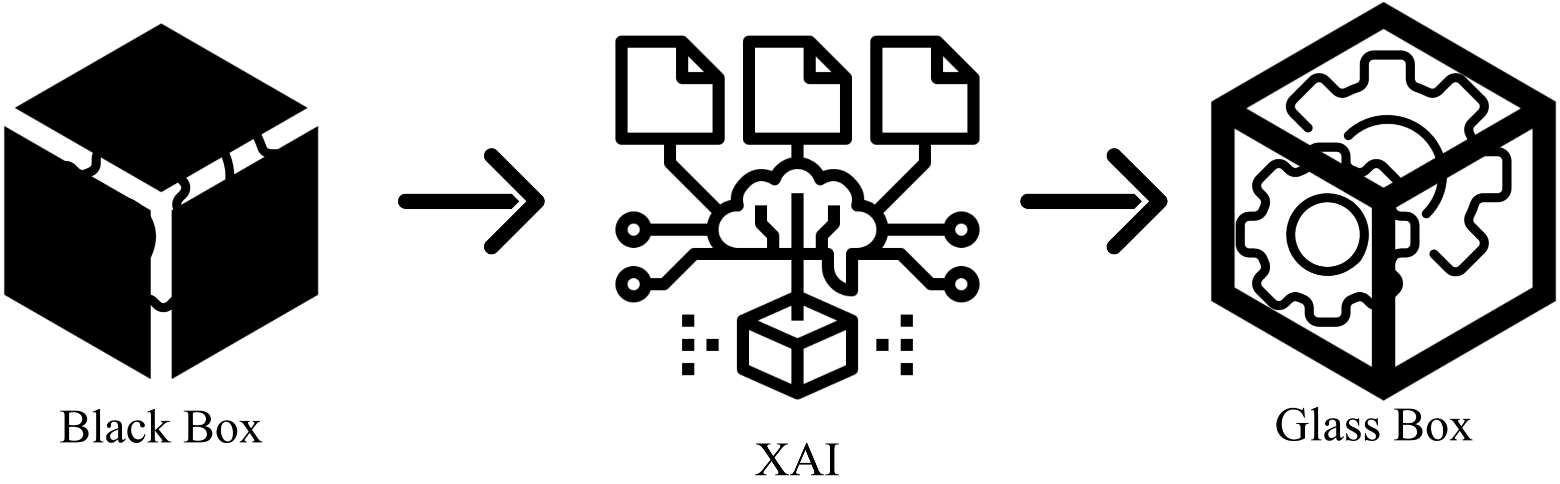

Definition

Explainable AI (XAI) has developed as a subfield of AI, focused on exposing complex AI models to humans in a systematic and interpretable manner.

An explanation is the answer to a why-question (Miller 2017).

- Why did you reach the decision?
- Why is there a 95% accuracy?
- What is the reason behind it?

Categories & Methods

Two Main Categories

Intrinsic Interpretable Models

These methods are intrinsically interpretable ML models by their own structures.

Post-Hoc Explanation

In contrast to the interpretable methods, we need some standalone algorithms to explain the BB ML/DL methods

Intrinsic Interpretable Methods

- Logistic/ Linear Regression
- Decision Trees
- K-Nearest Neighbors
- Rule-base Learners
- Bayesian Models

Post-Hoc Explanation

	Model-Specific	Model-Agnostic
Local	Use attention mechanisms to show how the model selectively focuses on features in high-dimensional input for an instance	Develop interpretable surrogate models with local fidelity in the vicinity of an instance
Global	Enforce interpretability constraints into the structure and learning mechanisms of deep learning models	Develop interpretable global surrogate models based on input-output associations predicted by a black-box model

Post-Hoc Explanation Methods

	Model-Specific	Model-Agnostic
Local	• Attention-based Models	• LIME • SHAP • Anchor
Global	• Intrinsically or Inherently Interpretable Models	• Global Surrogate Models • PDP • ICE

LIME

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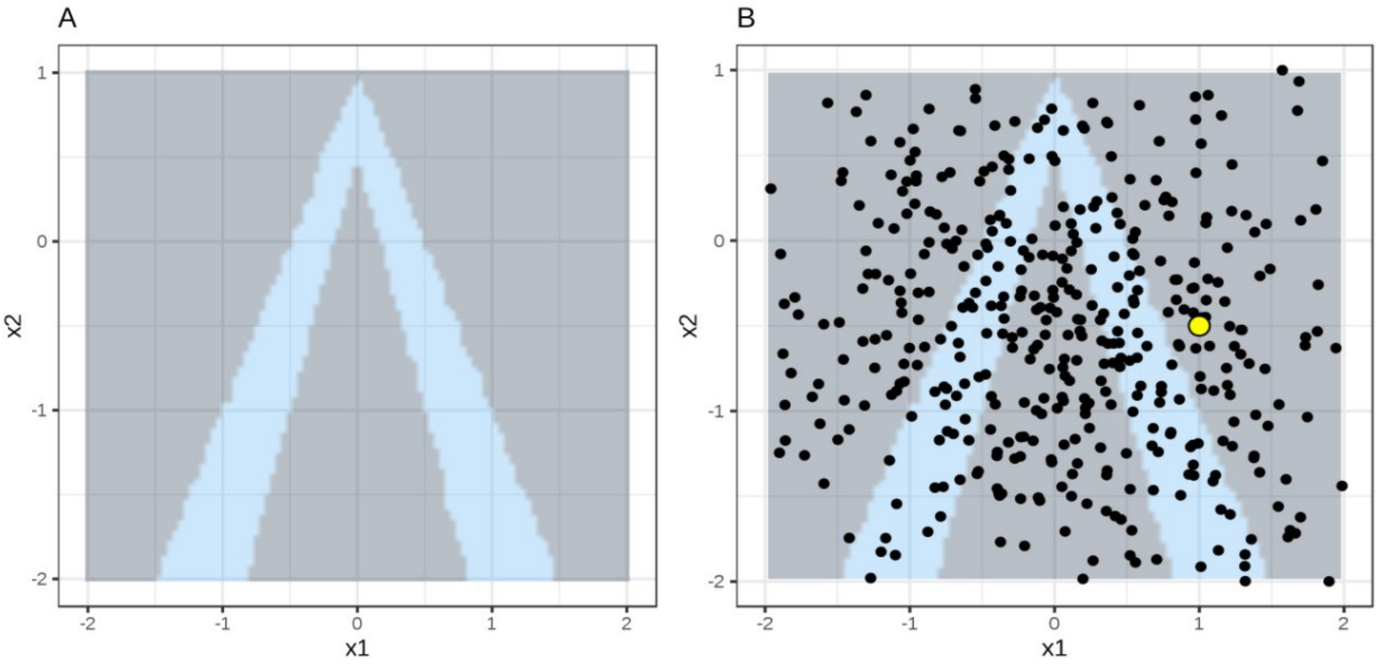
Local Interpretable Model-Agnostic Explanations



LIME

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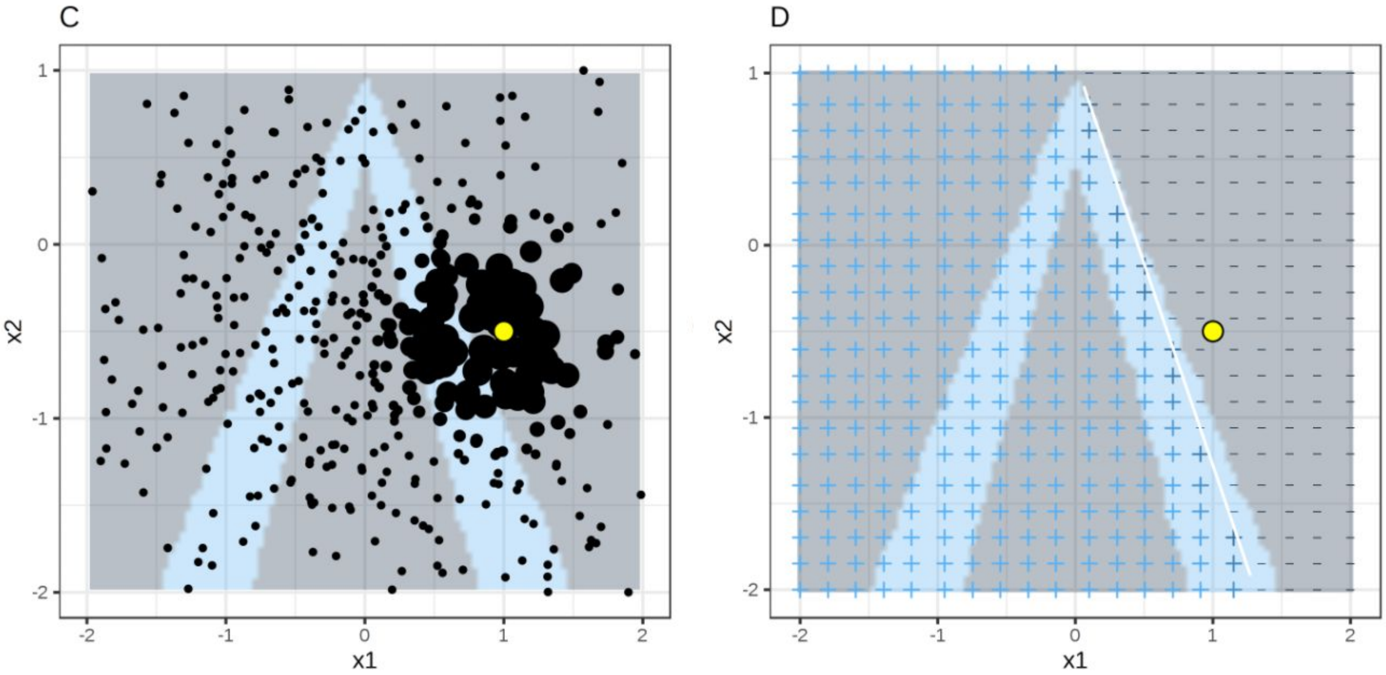
Local Interpretable Model-Agnostic Explanations



LIME

Local Interpretable Model-Agnostic Explanations

LIME algorithm for tabular data. A) Random forest predictions given features x1 and x2. Predicted classes: 1 (dark) or 0 (light). B) Instance of interest (big dot) and data sampled from a normal distribution (small dots). C) Assign higher weight to points near the instance of interest. D) Signs of the grid show the classifications of the locally learned model from the weighted samples. The white line marks the decision boundary (P(class=1) = 0.5).

LIME

Local Interpretable Model-Agnostic Explanations

Our test Instance

Complex Model

Model Complexity

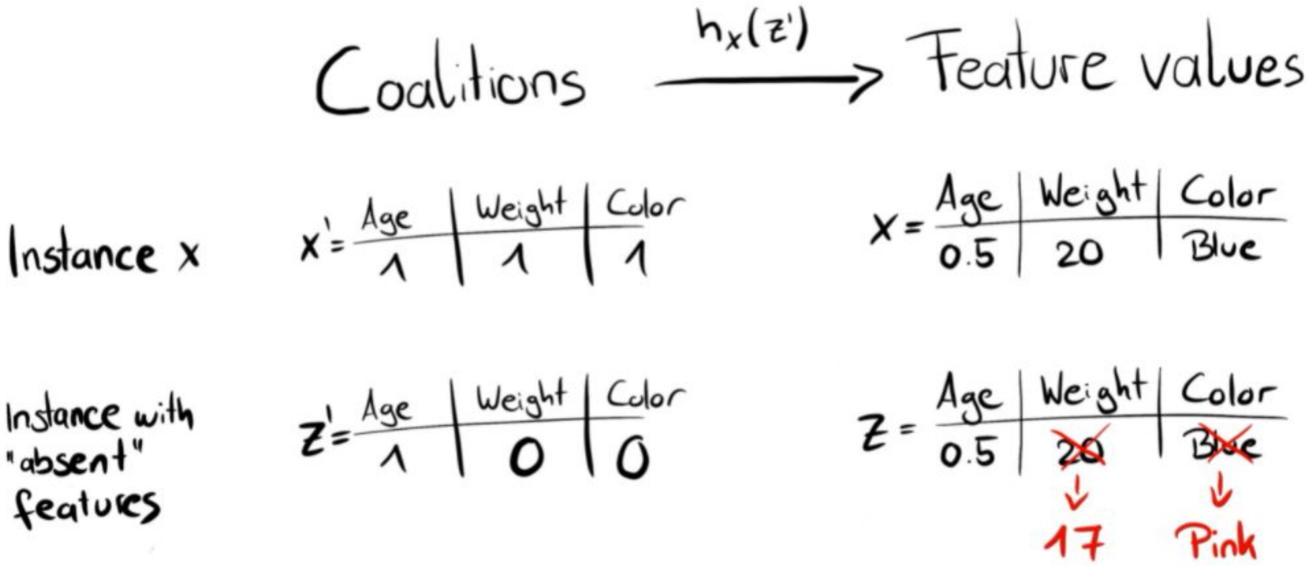
$$\text{explanation}(x) = \arg\min_{g \in G} L(f, g, \pi_x) + \Omega(g)$$

g is a model from intrinsic interpretable family models G

Proximity Measure

SHAP

SHapley Additive exPlanation



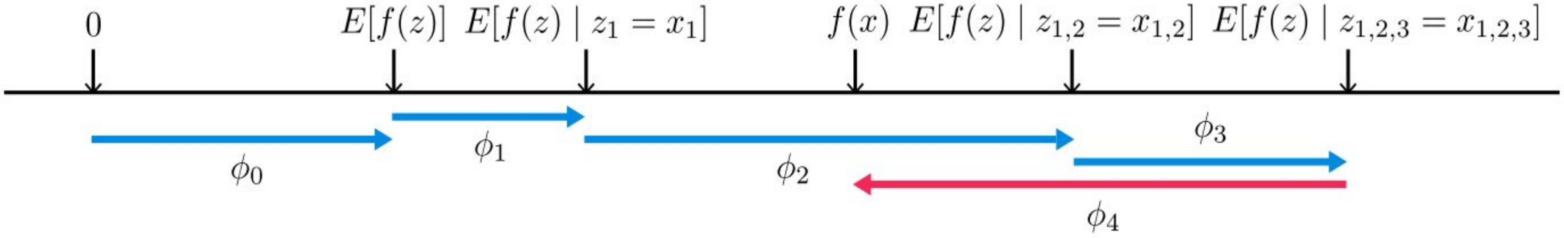
SHAP

SHapley Additive exPlanation

Function hx maps a coalition to a valid instance. For present features (1), hx maps to the feature values of x. For absent features (0),hx maps to the values of a randomly sampled data instance.

In the coalition vector, an entry of 1 means that the corresponding feature value is "present" and 0 that it is "absent".

SHapley Additive exPlanation



SHAP

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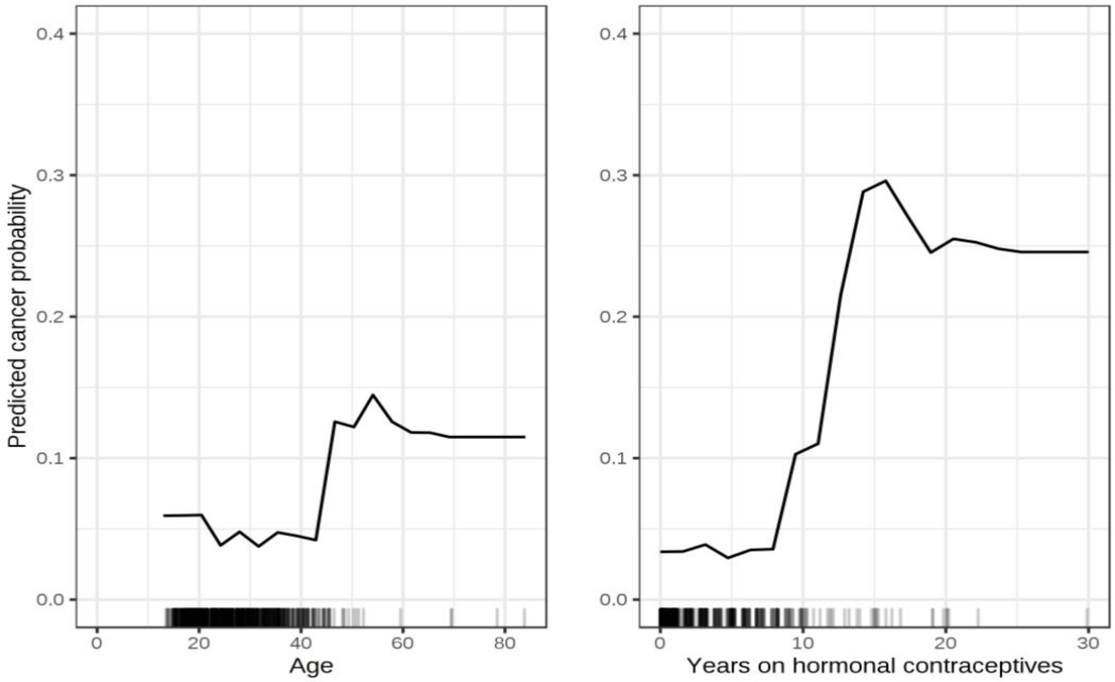
SHapley Additive exPlanation

$$\phi_i(f, x) = \sum_{z' \subseteq x'} \frac{|z'|!(M - |z'| - 1)!}{M!} [f_x(z') - f_x(z' \setminus i)]$$

PDP

Partial Dependence Plot



PDP

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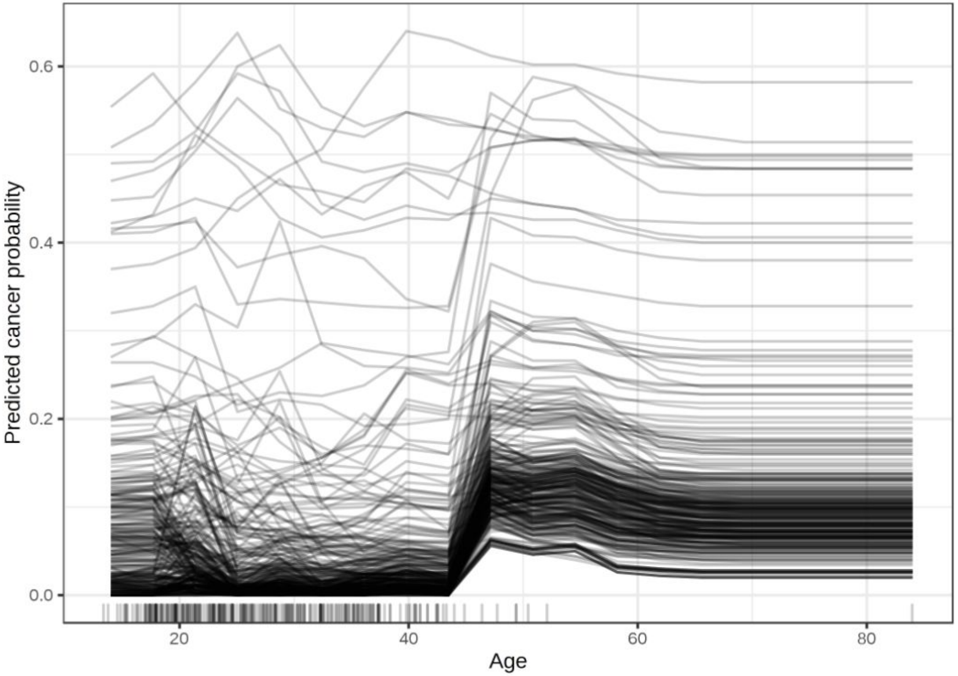
Partial Dependence Plot

PDPs of cancer probability based on age and years with hormonal contraceptives. For age, the PDP shows that the probability is low until 40 and increases after. The more years on hormonal contraceptives the higher the predicted cancer risk, especially after 10 years. For both features not many data points with large values were available, so the PD estimates are less reliable in those regions.

ICE

Individual Conditional Expectation



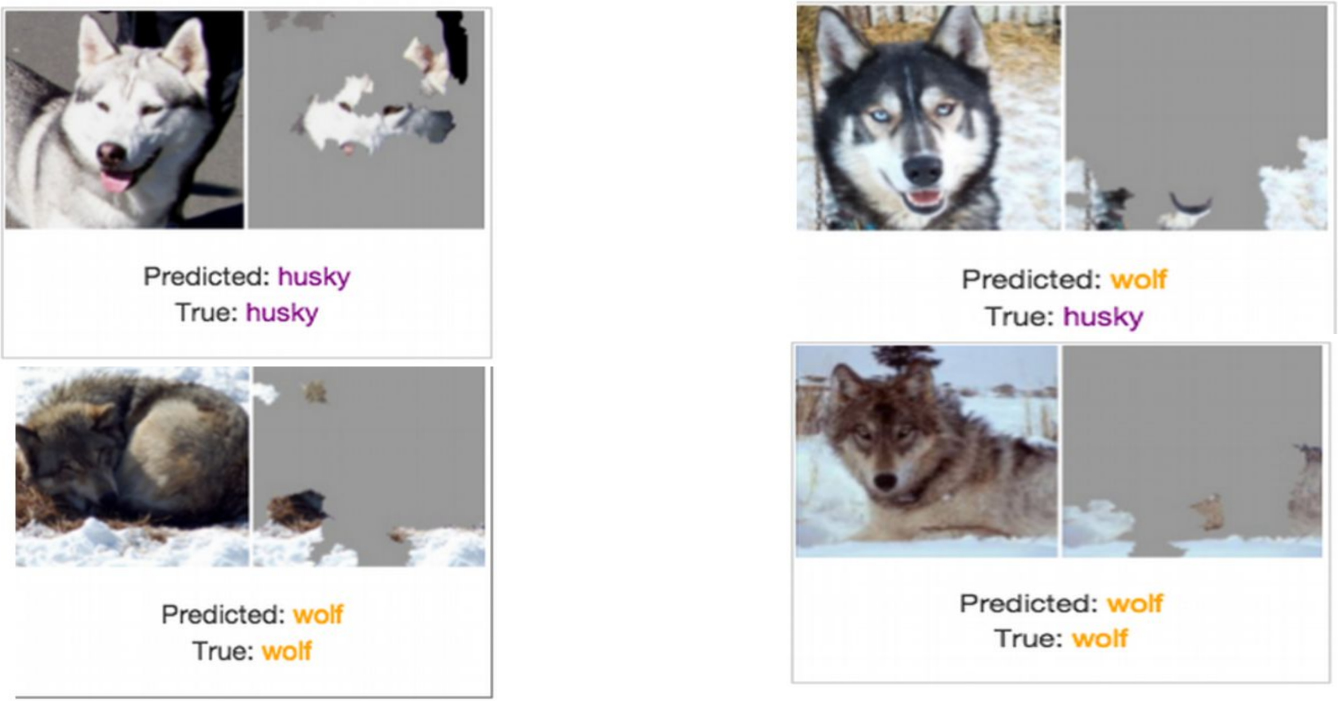
ICE

Individual Conditional Expectation

ICE plot of cervical cancer probability by age. Each line represents one woman. For most women there is an increase in predicted cancer probability with increasing age. For some women with a predicted cancer probability above 0.4, the prediction does not change much at higher age.

Importance

Let’s get back into the husky and wolf classification example



Importance

Do you trust the model?

When should I trust the model?

Who is responsible for the decisions?

Critical Situations

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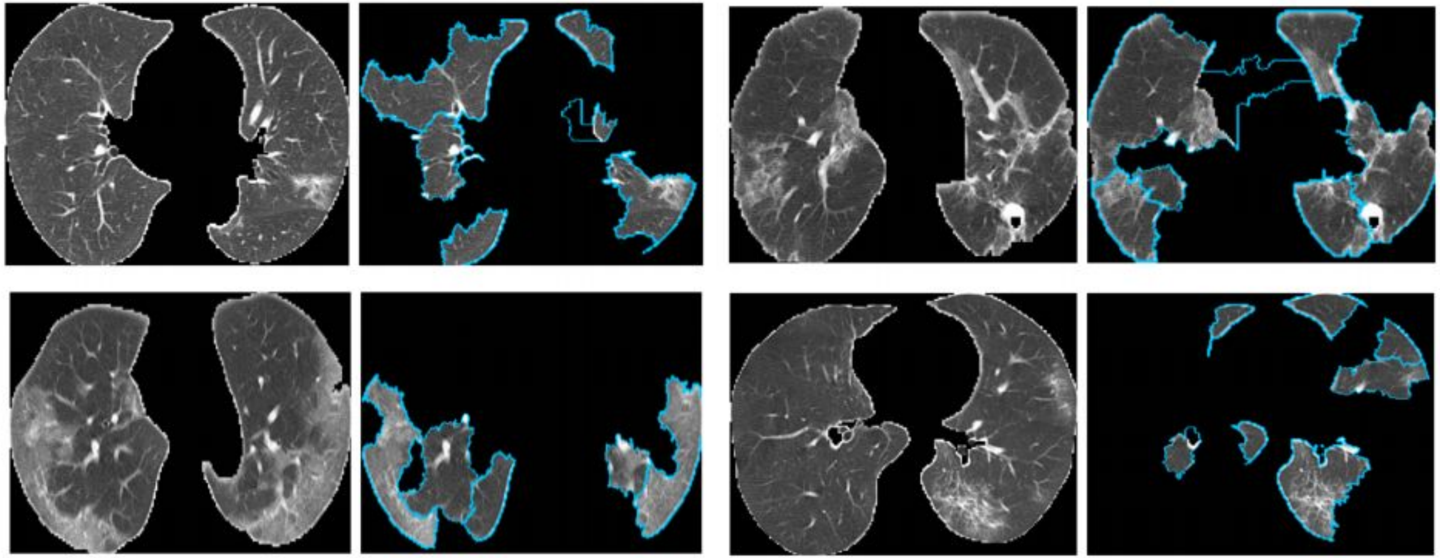
Medical Diagnosis

Covid-19 Detection Through Chest X-Ray



Critical Situations

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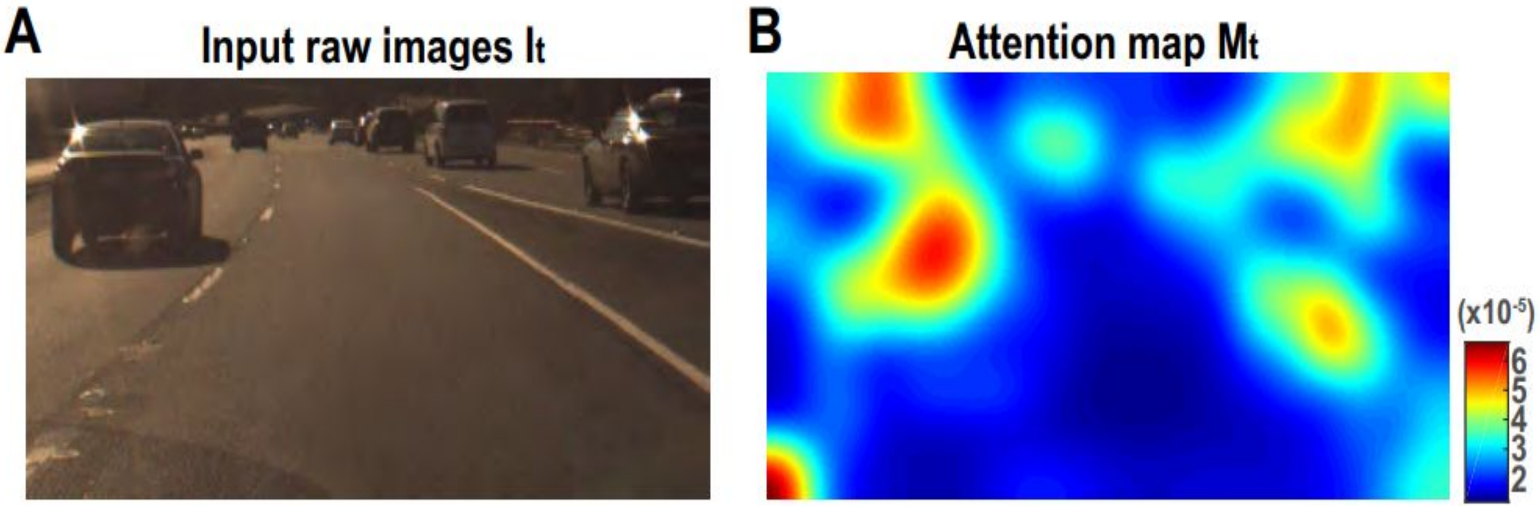
Autonomous Driving

Object Detection



Importance

Improvement of The System

The first step towards improving an AI system is to understand it’s weaknesses.

Learning from The System

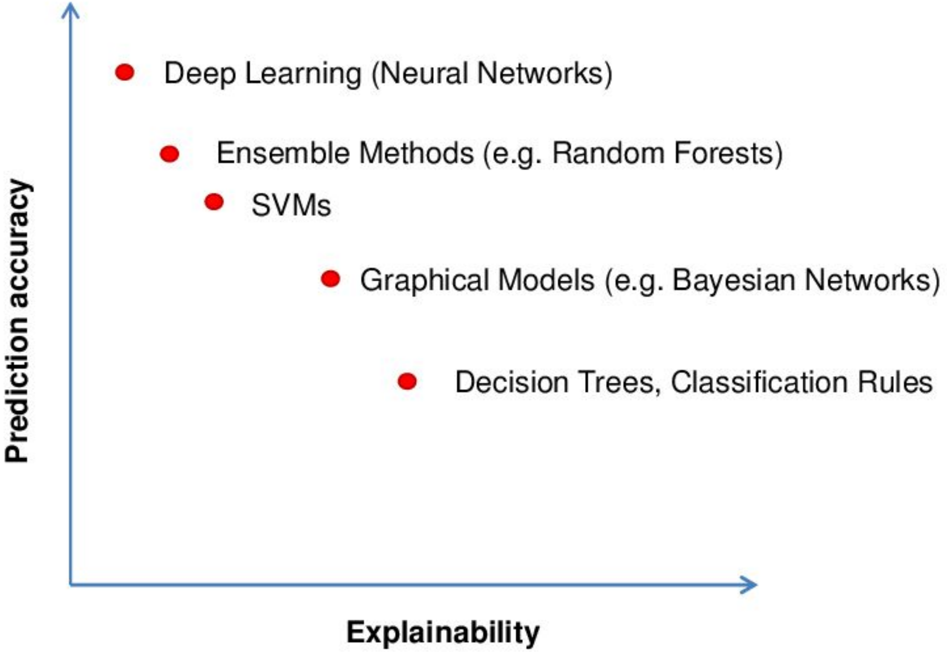
Extract knowledge from the vast amount of data and crealation between them

Compliance to Legislation

legal aspects have recently received increased attention.

Challenges

Performance vs. Explainability



Challenges

Evaluation

Are all models in all defined-to-be-interpretable model classes equally interpretable?

HUMAN-LIKE EXPLANATIONS

Future Works

Ethical AI

Responsible AI

AGI

References

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Introduction

Categories & Methods

Importance

Challenges & Future Works

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THANKS!

Do you have any questions?

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