



Trustworthy AI: Explainability

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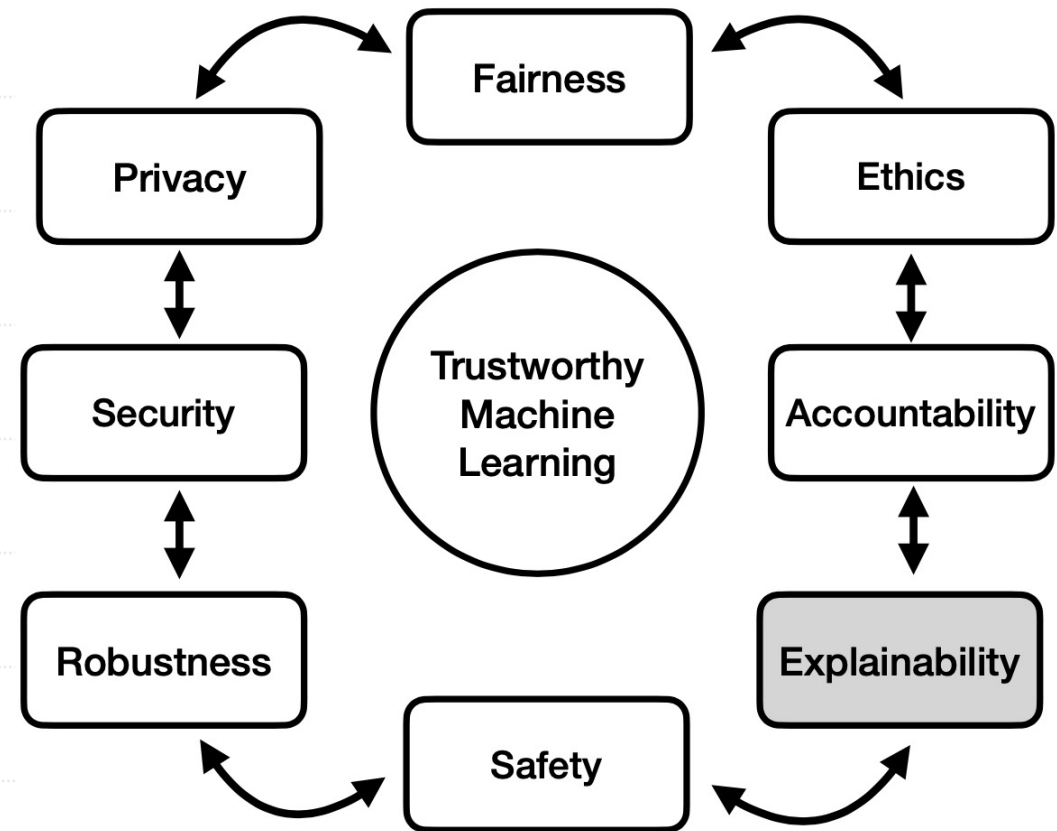


Overview

- Defining Explainability
- Model Understanding
 - Examples
 - Benefits
- Approaches to Model Understanding
 - Interpretable Models
 - Post-hoc Explainability
 - Local Explanations
 - Global Explanations

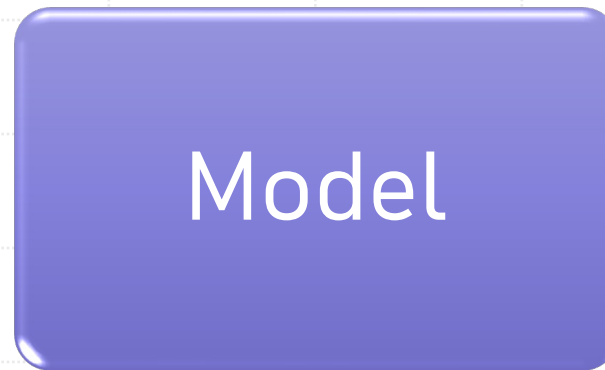
Explainable Artificial Intelligence (XAI)

- Explainability of an AI model describes the extent to which human-users can comprehend and trust the results and output created by the model.



Overview of Predictive Modeling Process

Input
(Data)



Output
(Prediction)

Explainable AI requires model understanding.

Example: Why Model Understanding?

Input



Predictive
Model



Prediction = Siberian Husky



Example: Why Model Understanding?

Input



Model Understanding



Predictive
Model



Prediction = Siberian Husky

This model is
relying on incorrect
features to make
this prediction!! Let
me fix the model



Example: Why Model Understanding?

Input



Model understanding facilitates debugging.

This model is incorrect
make
on!! Let
model

Predictive
Model



Prediction = Siberian Husky



Example: Why Model Understanding?

Defendant Details



Predictive
Model



Prediction = Risky to Release

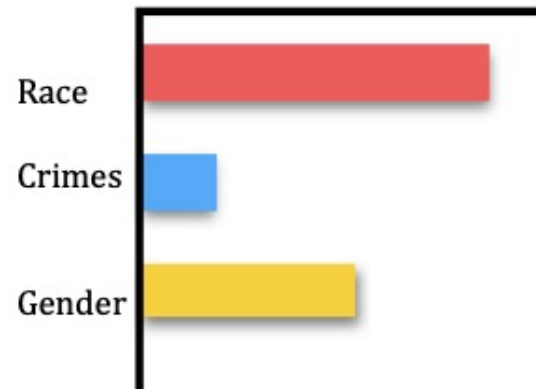


Example: Why Model Understanding?

Defendant Details



Model Understanding



Predictive
Model



Prediction = Risky to Release

This prediction is
biased. Race and
gender are being
used to make the
prediction!!



Example: Why Model Understanding?



Example: Why Model Understanding?

Loan Applicant Details



Predictive
Model



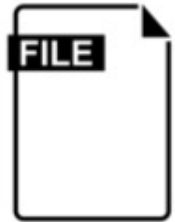
Prediction = Denied Loan



Loan Applicant

Example: Why Model Understanding?

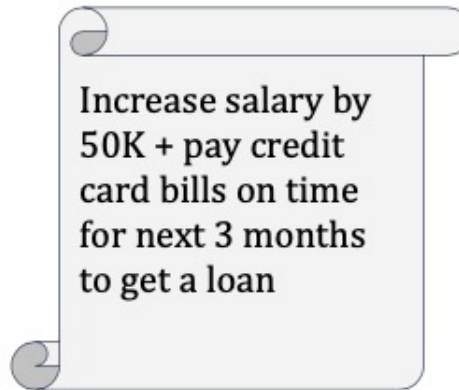
Loan Applicant Details



Predictive
Model



Model Understanding



Prediction = Denied Loan



Loan Applicant

I have some means
for recourse. Let me
go and work on my
promotion and pay
my bills on time.

Example: Why Model Understanding?

Loan Applicant Details

FILE

Model understanding helps provide recourse to individuals who are adversely affected by model predictions.

I have some means

Let me
in my
pay
ne.

to get a loan

Predictive
Model

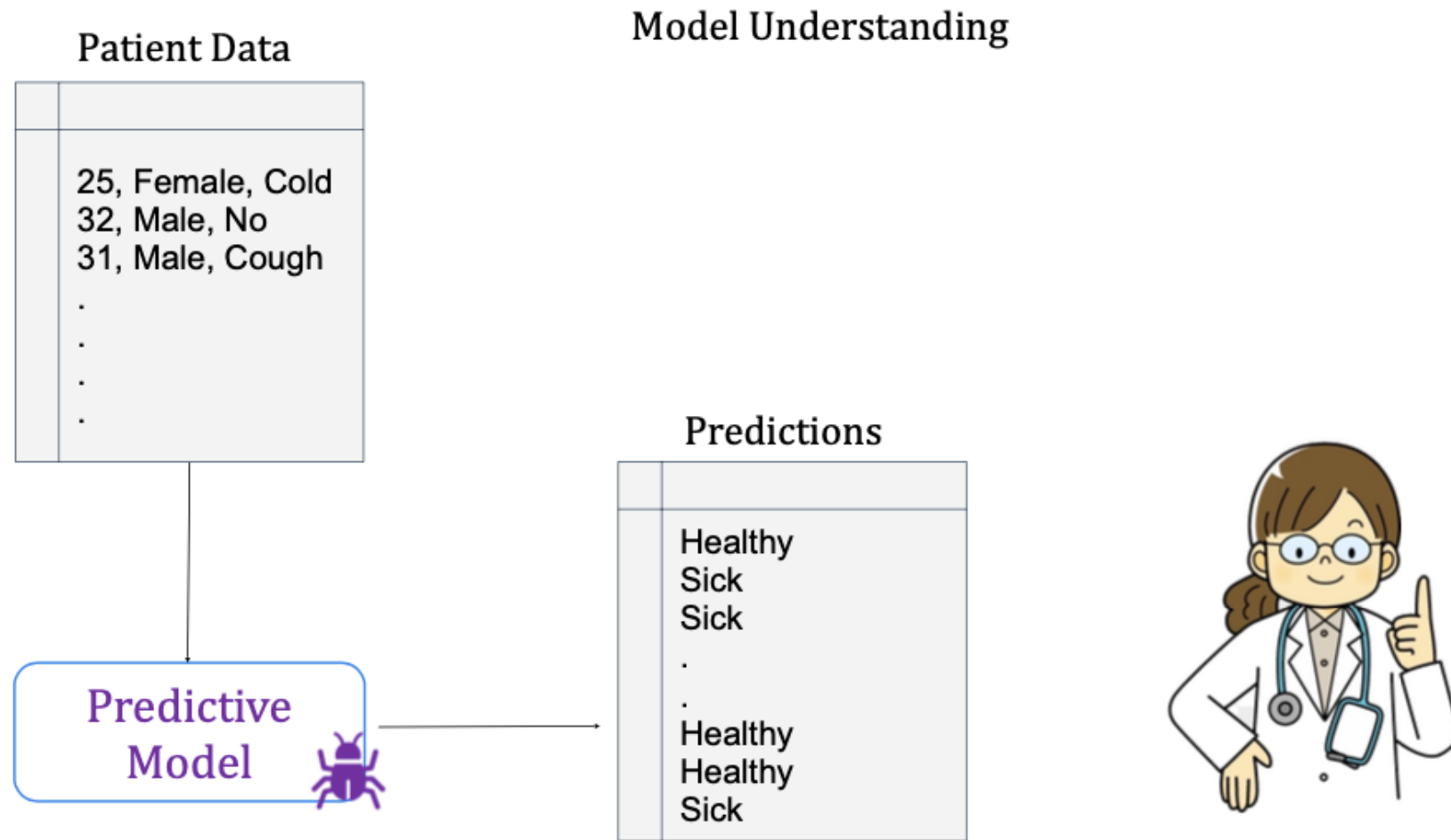


Prediction = Denied Loan

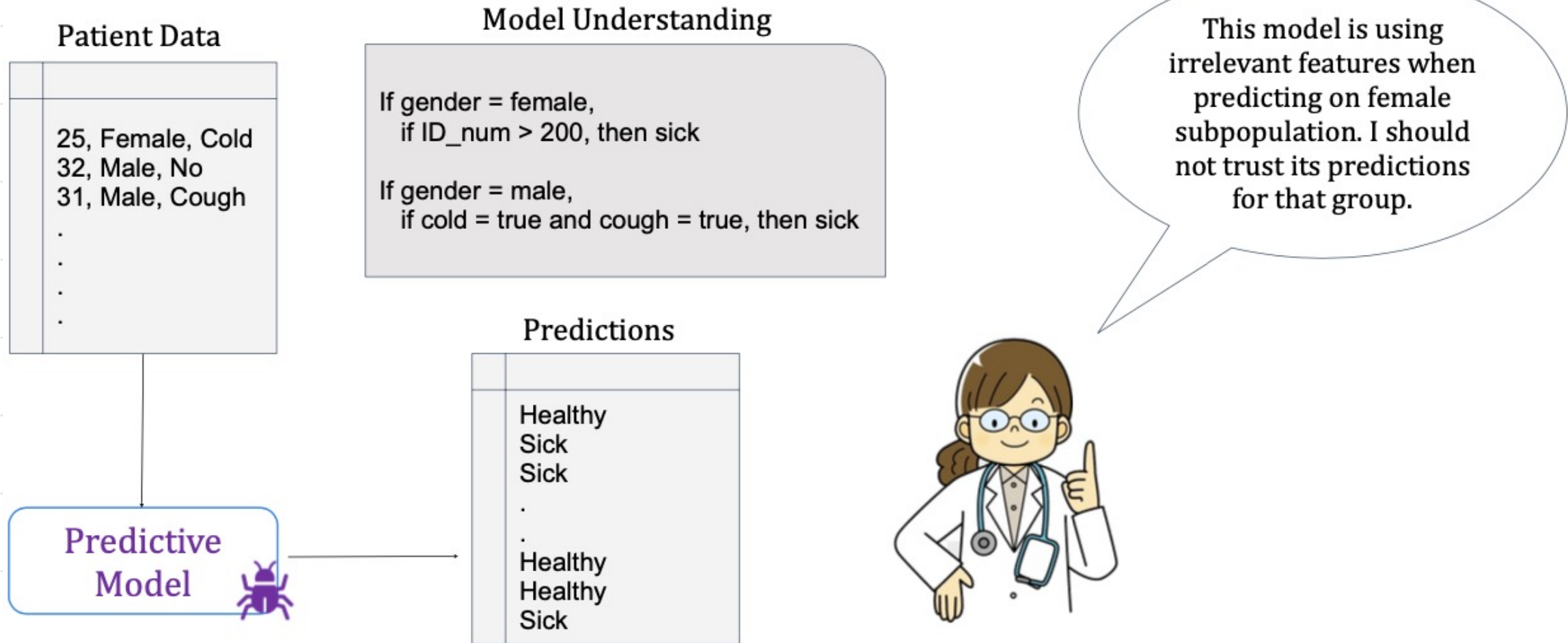


Loan Applicant

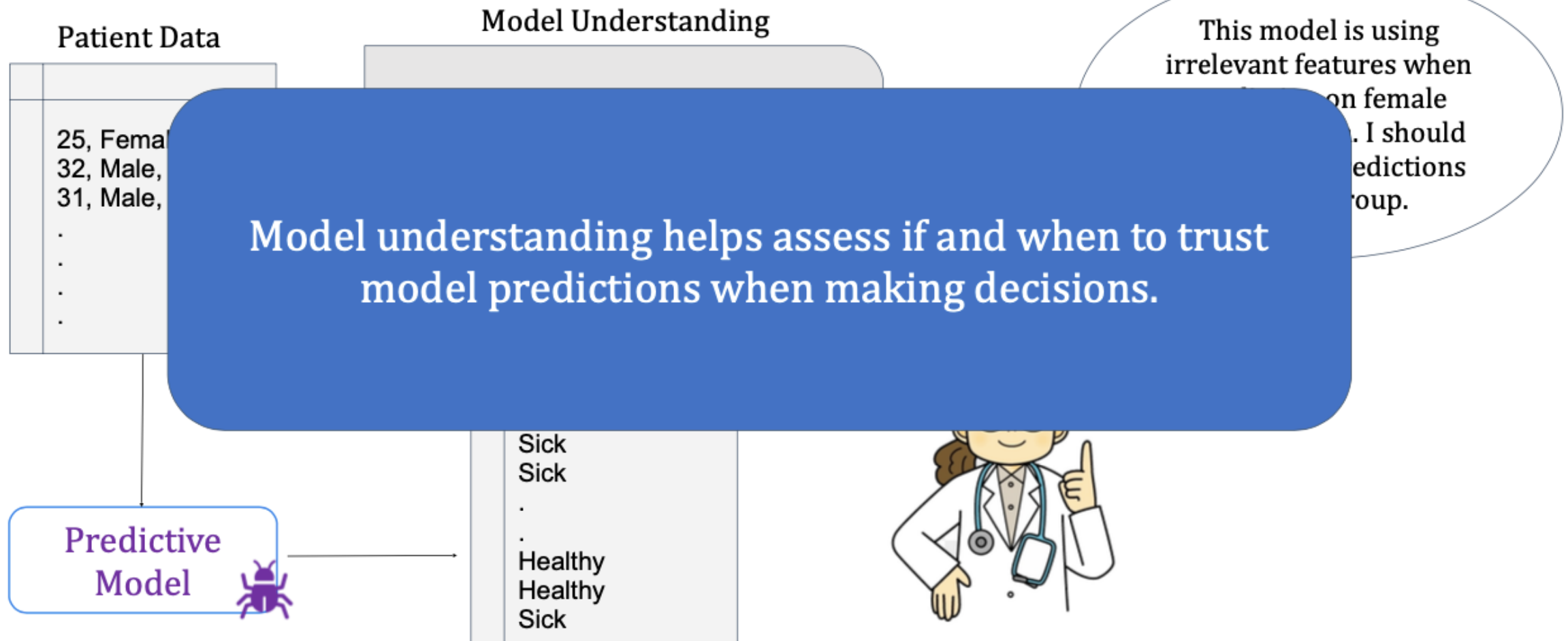
Example: Why Model Understanding?



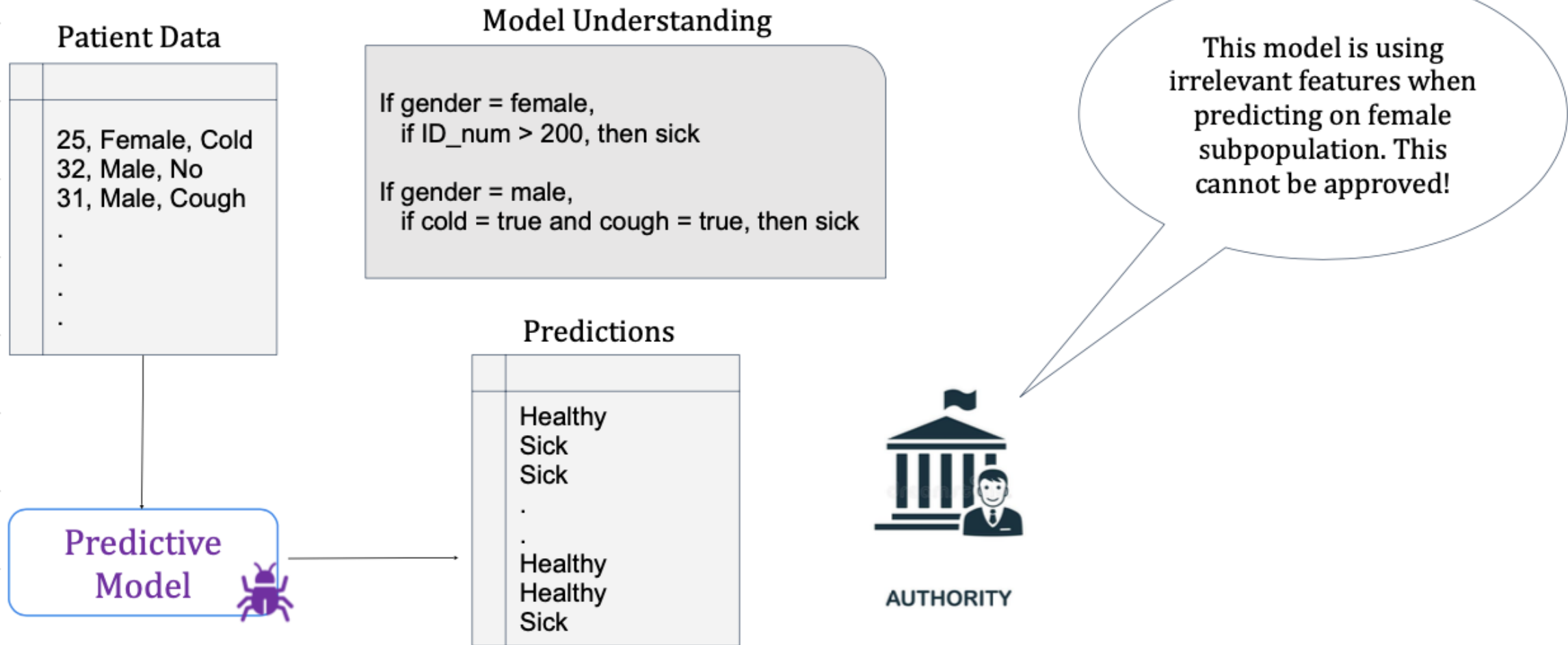
Example: Why Model Understanding?



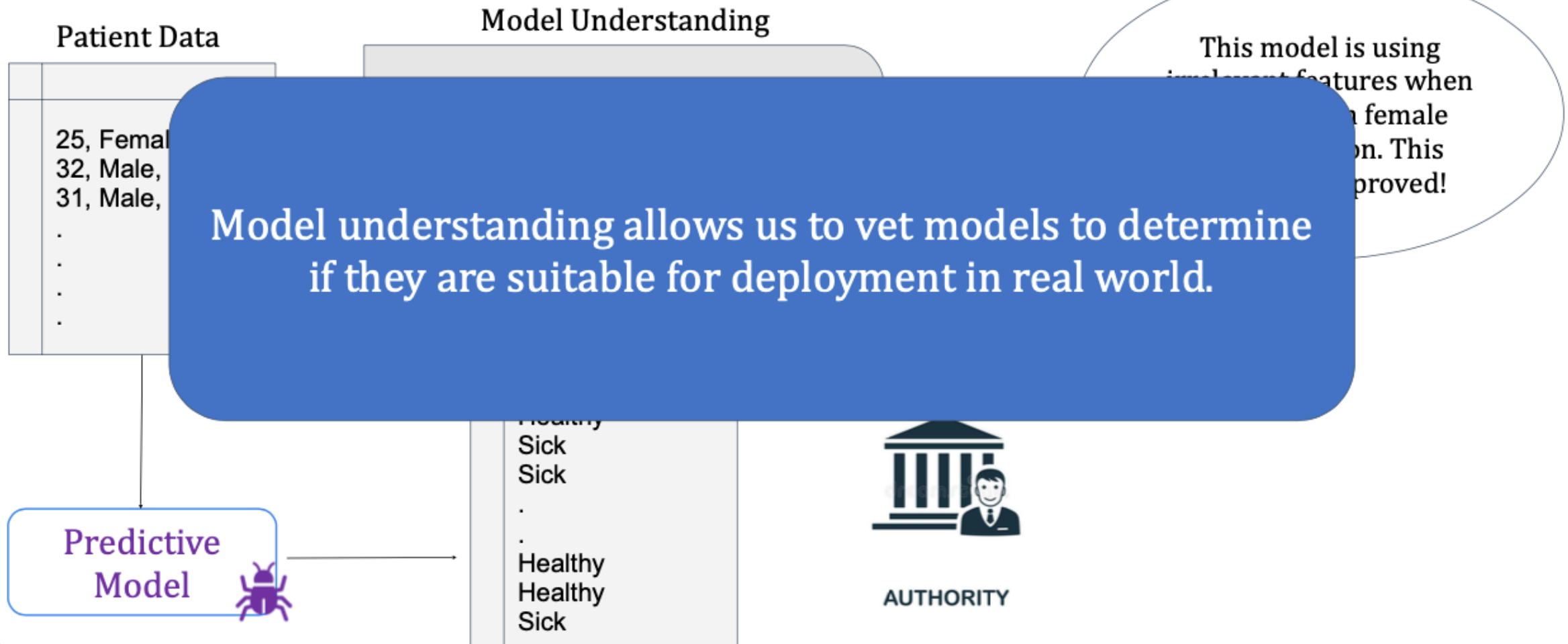
Example: Why Model Understanding?



Example: Why Model Understanding?



Example: Why Model Understanding?



Summary: Benefits of Model Understanding



Debugging



Bias Detection



Recourse



Assess Trustworthiness of Predictions



Vet Models for Deployment

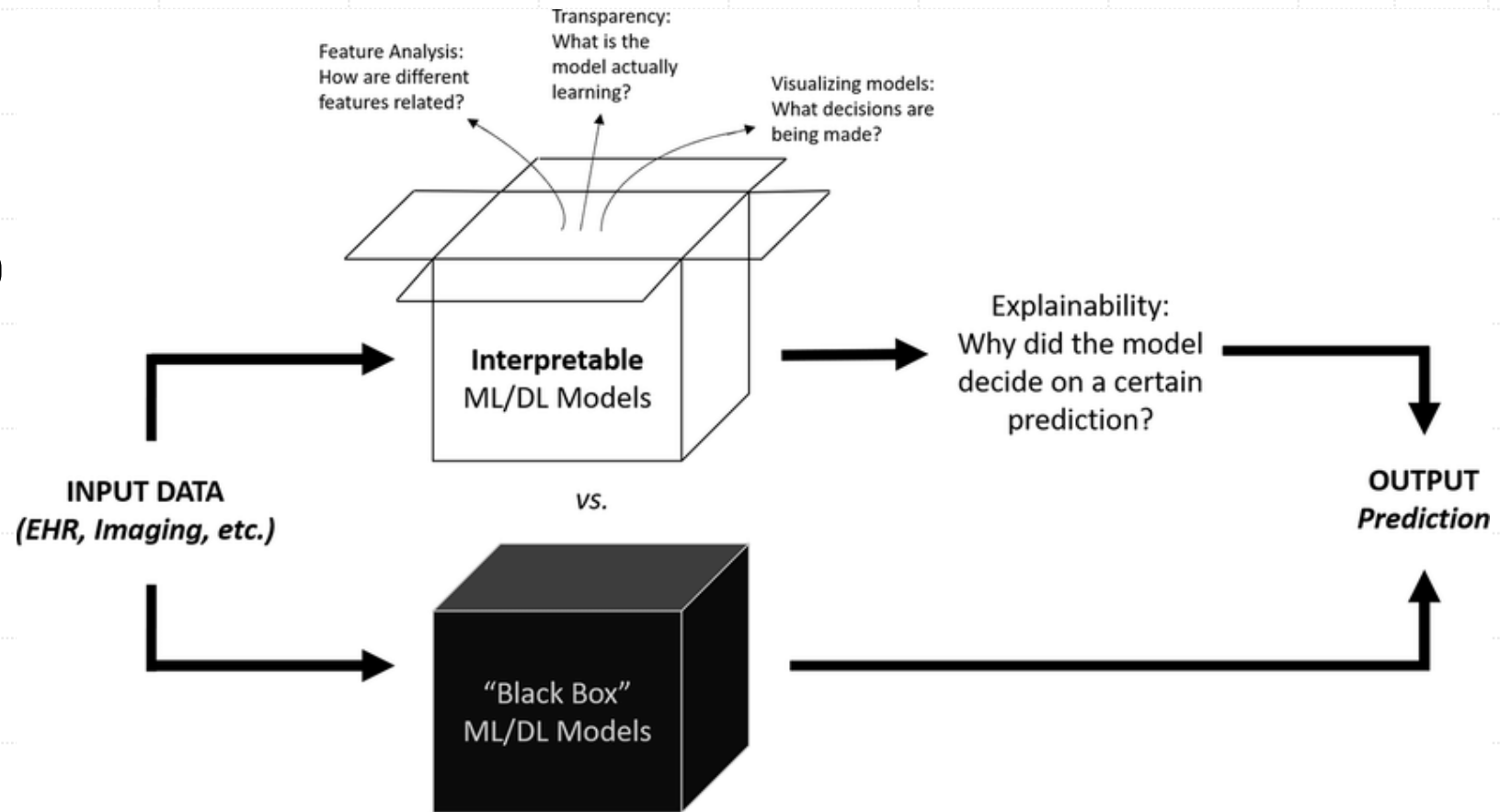
Achieving Model Understanding

Approach #1:

Build inherently interpretable (white box) models.

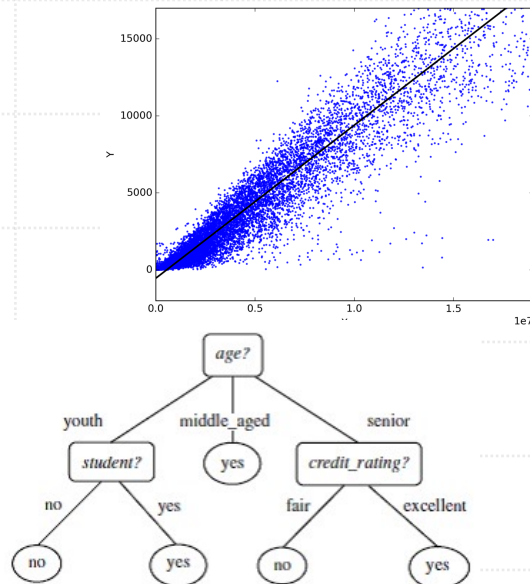
Approach #2:

Explain pre-built (black-box) models in a post-hoc manner.



Inherently Interpretable Models

- These models are interpretable by design. Understanding of the model is clear before receiving results.



The HEART Score for Chest Pain Patients in the ED		
History	• Highly Suspicious	• 2 points
	• Moderately Suspicious	• 1 point
	• Slightly or Non-Suspicious	• 0 points
ECG	• Significant ST-Depression	• 2 points
	• Nonspecific Repolarization	• 1 point
	• Normal	• 0 points
Age	• ≥ 65 years	• 2 points
	• $> 45 - < 65$ years	• 1 point
	• ≤ 45 years	• 0 points
Risk Factors	• ≥ 3 Risk Factors or History of CAD	• 2 points
	• 1 or 2 Risk Factors	• 1 point
	• No Risk Factors	• 0 points
Troponin	• $\geq 3 \times$ Normal Limit	• 2 points
	• $> 1 - < 3 \times$ Normal Limit	• 1 point
	• \leq Normal Limit	• 0 points
Risk Factors: DM, current or recent (< 1 month) smoker, HTN, HLP, family history of CAD, & obesity		
Score 0 – 3: 2.5% MACE over next 6 weeks \rightarrow Discharge Home		
Score 4 – 6: 20.3% MACE over next 6 weeks \rightarrow Admit for Clinical Observation		
Score 7 – 10: 72.7% MACE over next 6 weeks \rightarrow Early Invasive Strategies		

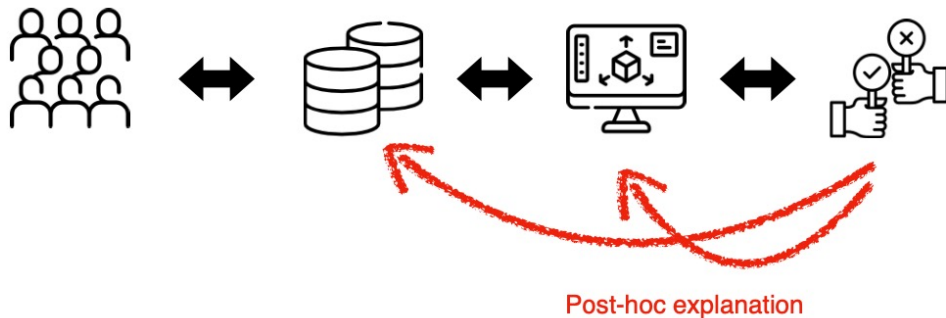
Examples

- Linear Models
- Shallow Decision Tree
- Rule Based Models
- Risk Scores

Post-hoc Explainability

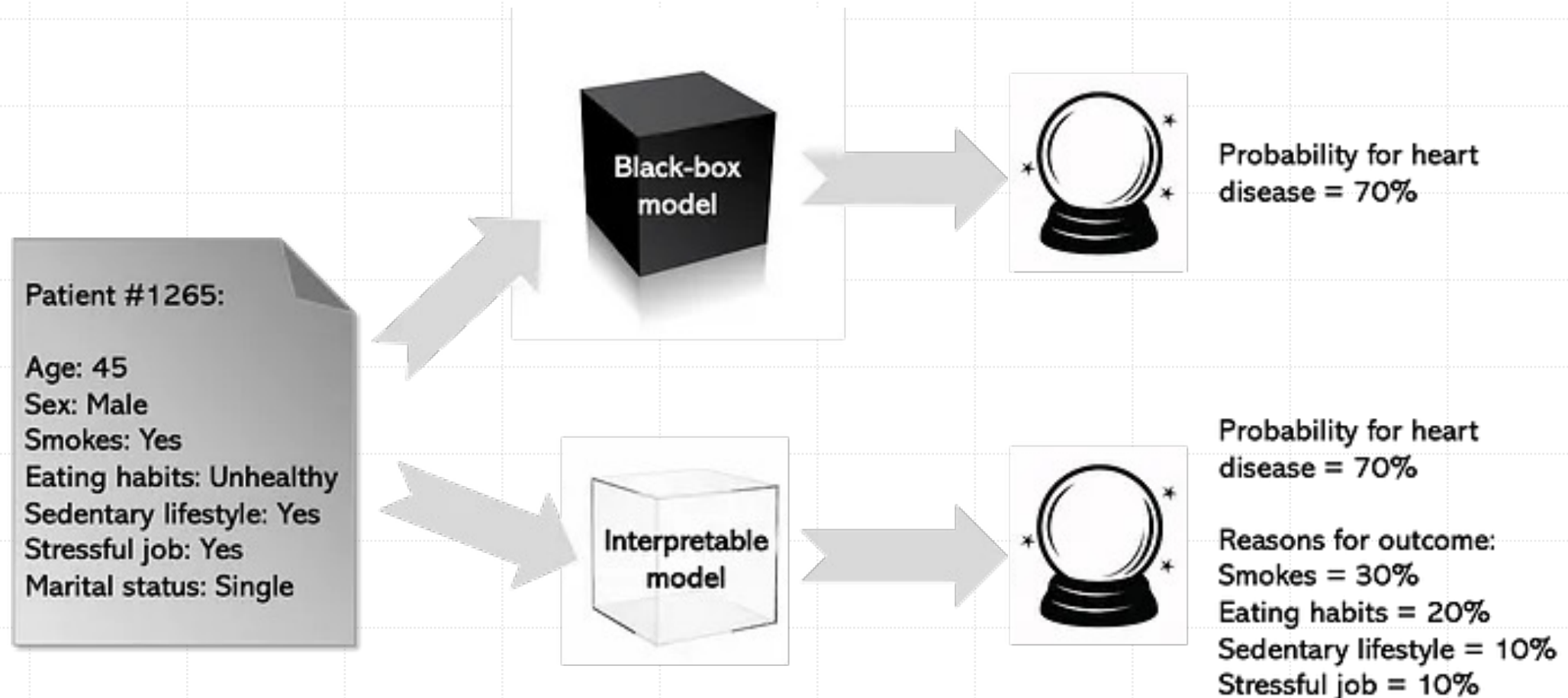


Building an inherently interpretable model is not always possible and we are left with a black box. In that case, models can be interpreted post-hoc.



Post-hoc explanation occurs after execution of the model.

White Box vs. Black Box Example





Approaches for Post-hoc Explainability

Local Explanations

Local explanations focus on the data and provide explanations for individual outcomes. Therefore, they provide trust for model outcomes.

Global Explanations

Global explanations focus on the model and provide an understanding of the decision process. Therefore, they provide a sense of understanding to how the model works.



Thank You

Please send us your questions at:

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