Explainable Artificial Intelligence

Introduction

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- Becoming increasingly important

Better Go/Chess Player

More “Realistic” Text Generation

ChatGPT

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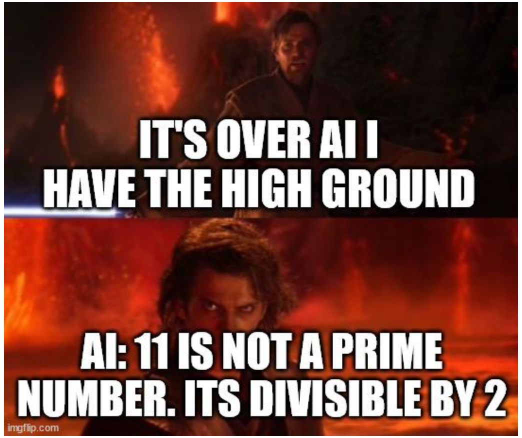
Equal to Humans at Drawing Hands

Unfortunately

- Deployment in critical fields faces an uphill battle



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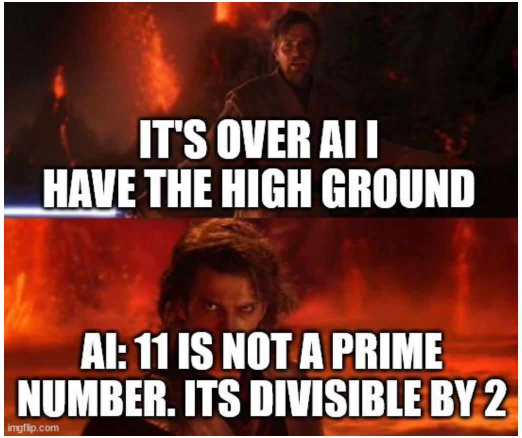

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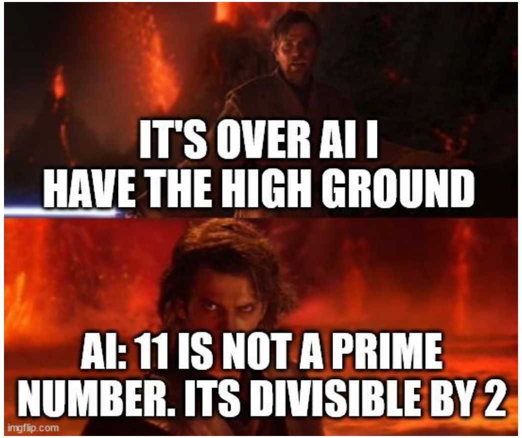

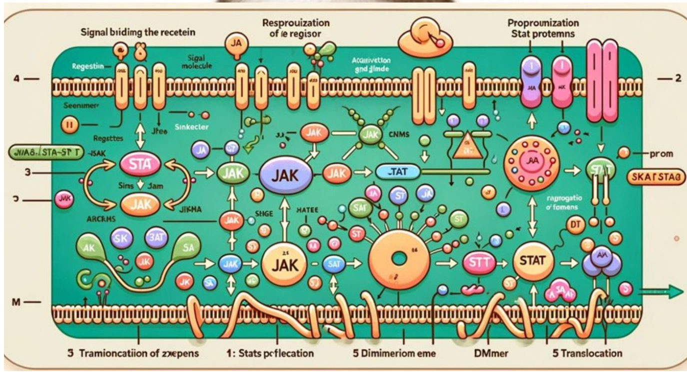

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RETRACTED: Cellular functions of spermatogonial stem cells in relation to JAK/STAT signaling pathway Retracted

Thus

- There is need in understanding decisions made by AI

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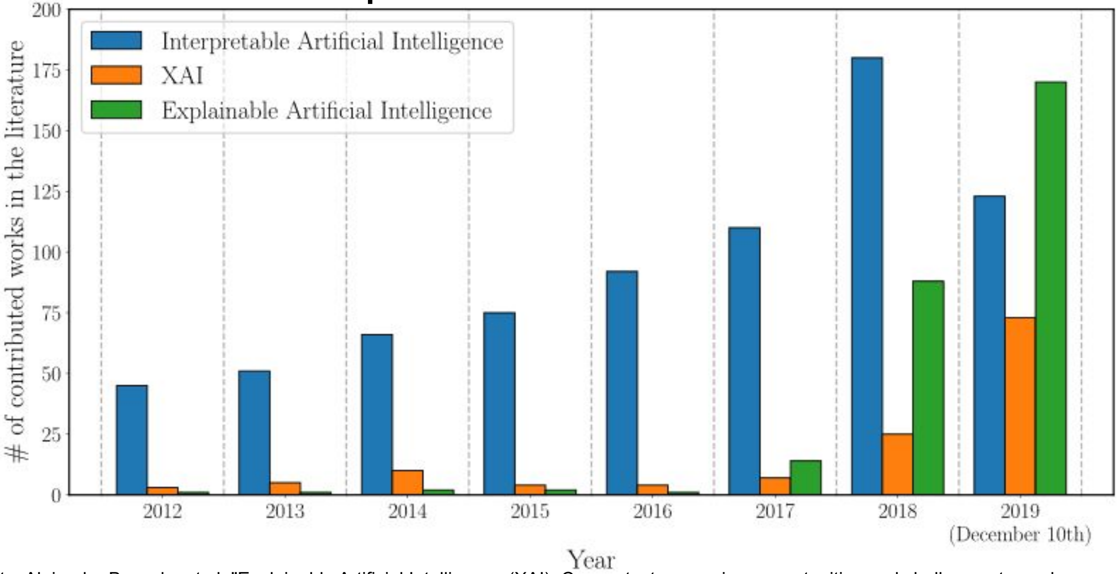
- There is need in understanding decisions made by AI
- The first AI systems were interpretable
- The current age of AI is dominated by opaque decision processes

Explainable Research Growth

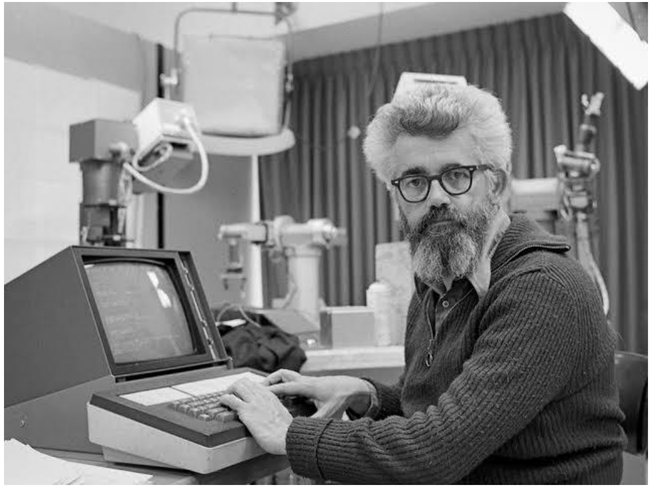


Arrieta, Alejandro Barredo, et al. "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI." *Information fusion* 58 (2020): 82-115.

History Lesson

- AI dates back to the 1950's

John McCarthy



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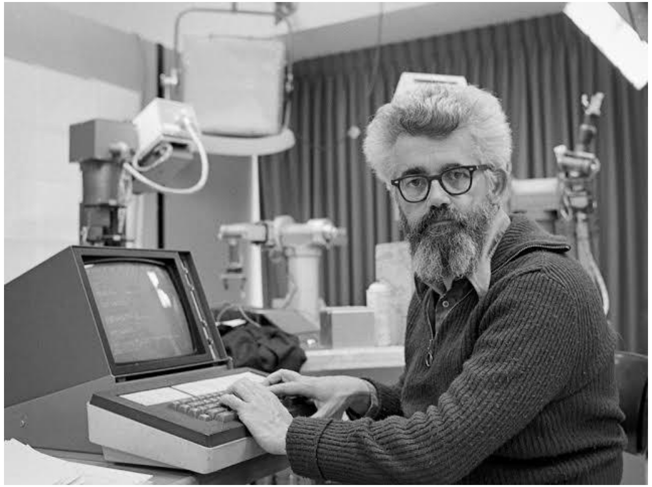
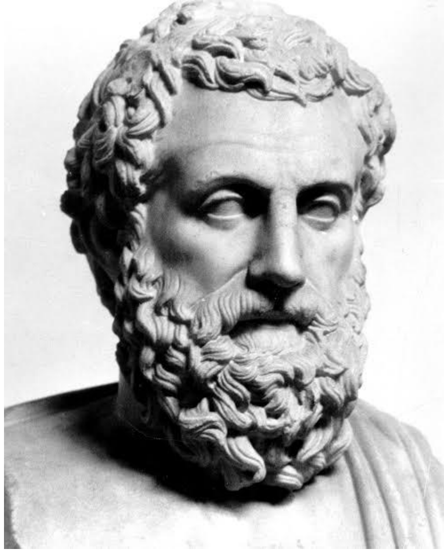


Aristotle



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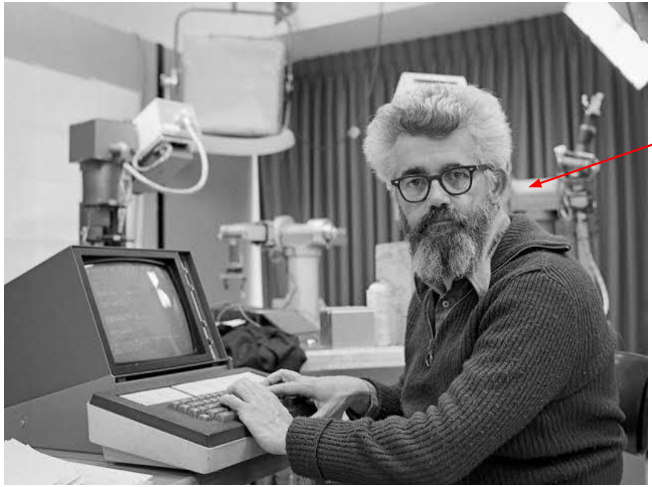
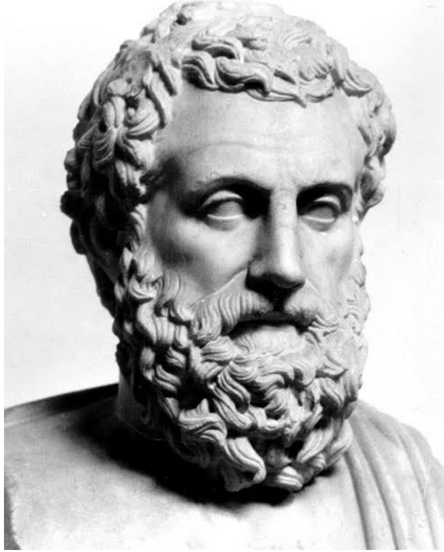


Old school cool

Aristotle



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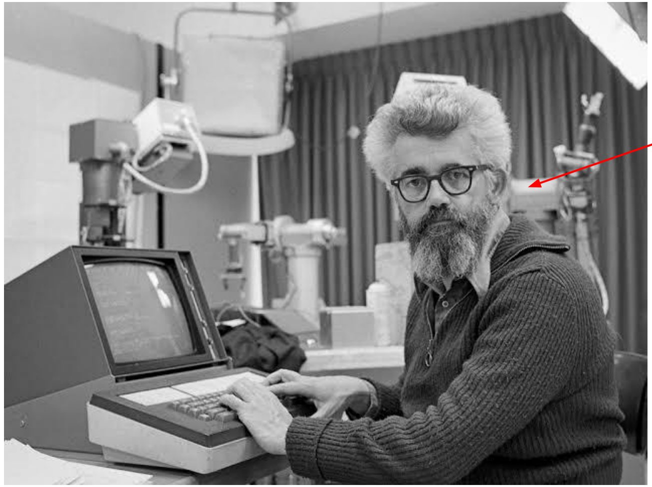
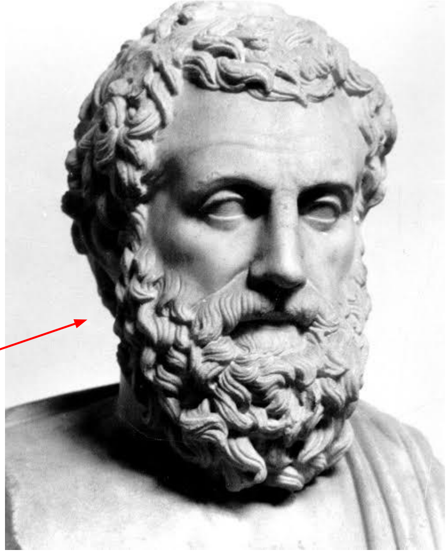


Old school cool

Literally immortalized into stone

Aristotle



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- The "Golden Age" of AI 1956-1974
- Micro-Worlds by Marvin Minsky

"The question of whether a computer can think is no more interesting than the question of whether a submarine can swim."

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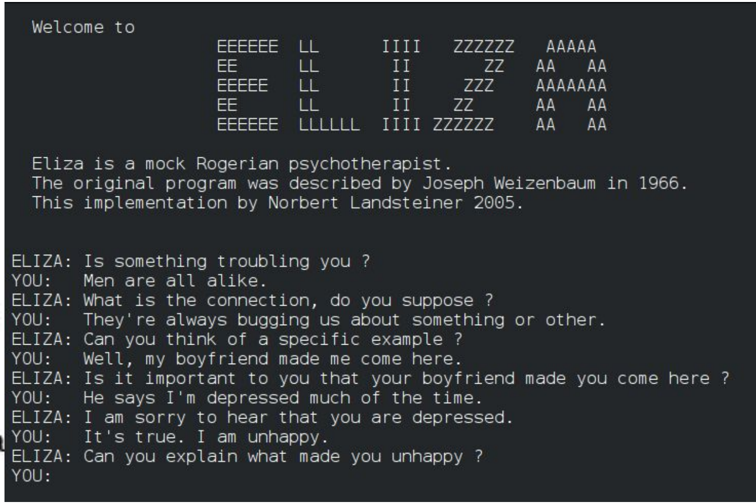
- John McCarthy’s development of Lisp
- The first chatbot ELIZA
- Lots of research funded by DARPA



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- What were some examples of “white-box” AI algorithms?

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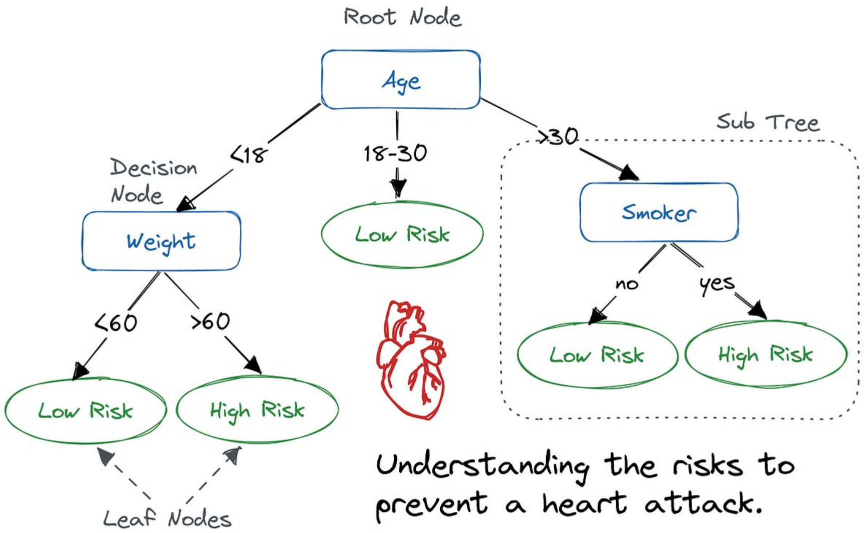
- Rule-based algorithms
- Linear decision
- Clustering



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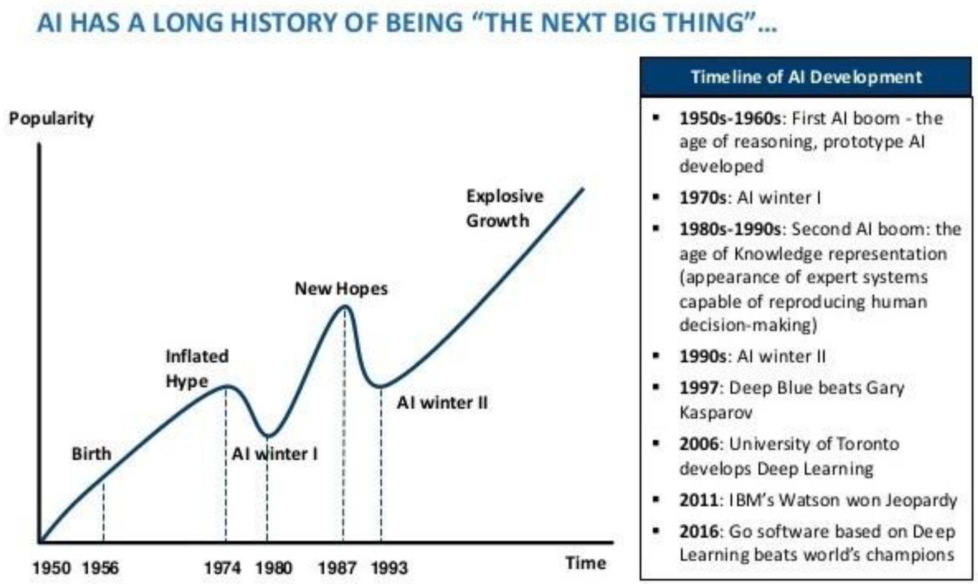

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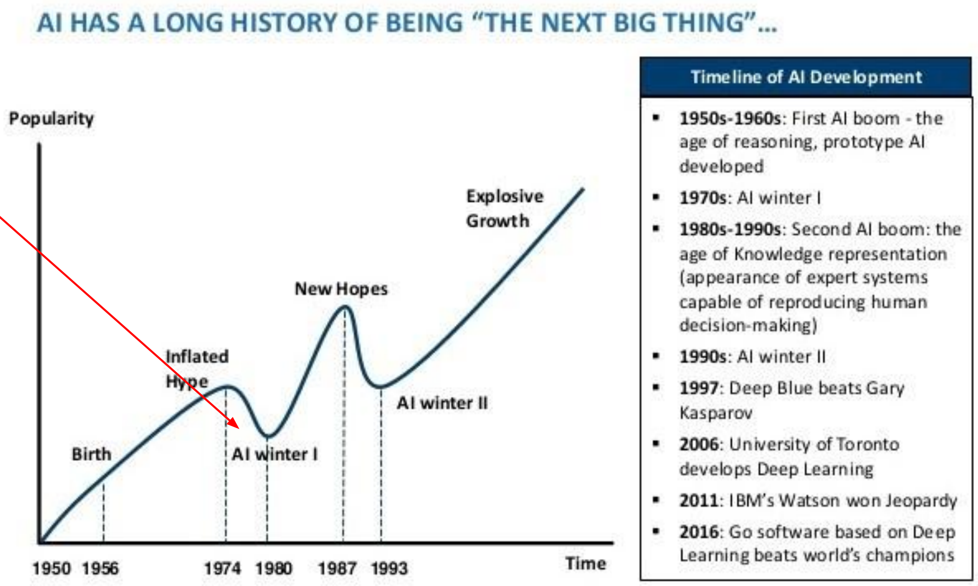

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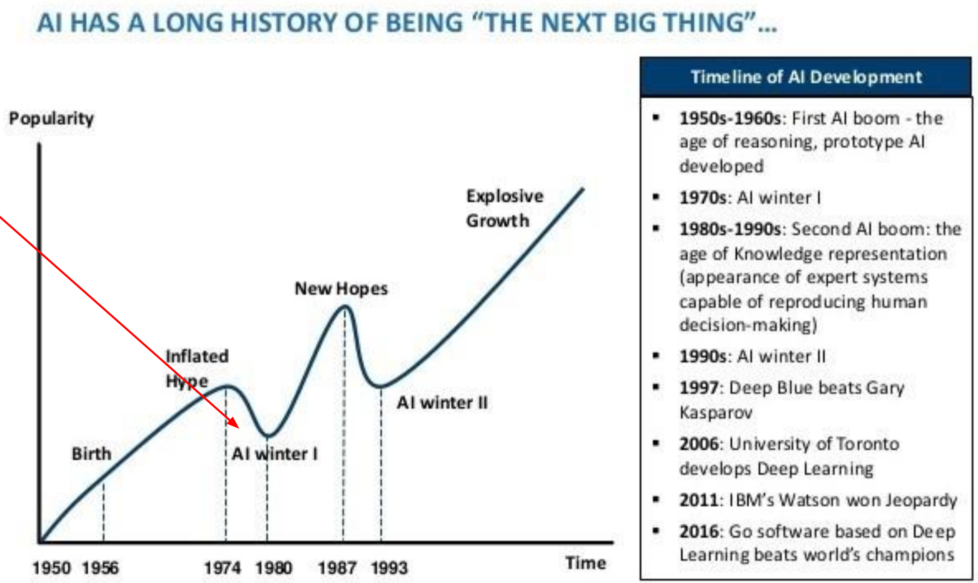
- Why?



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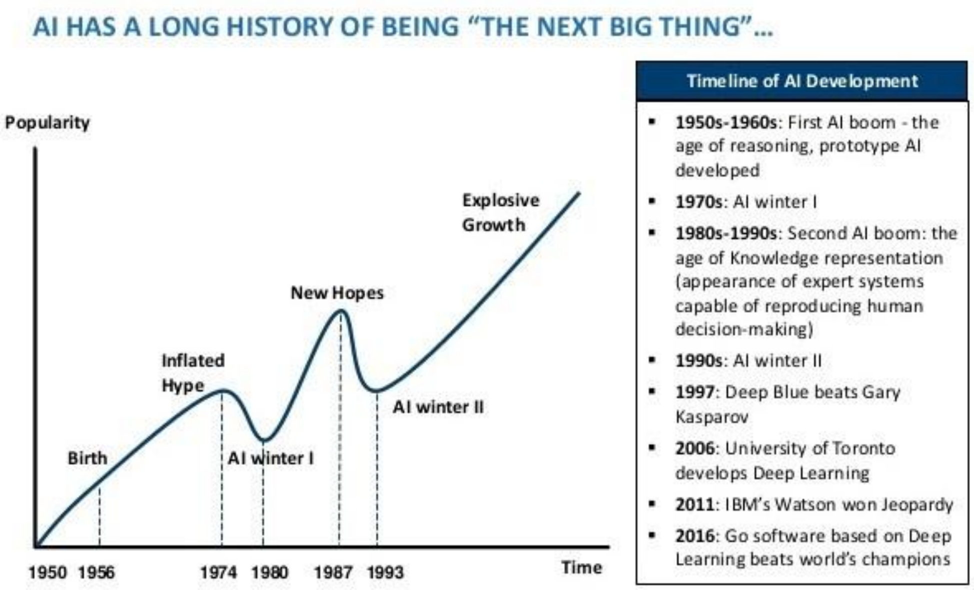

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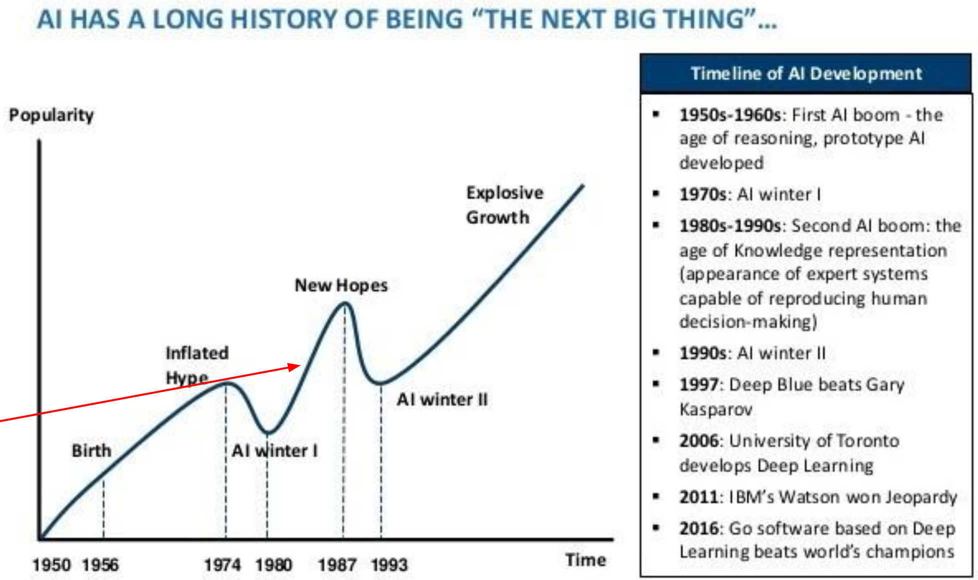

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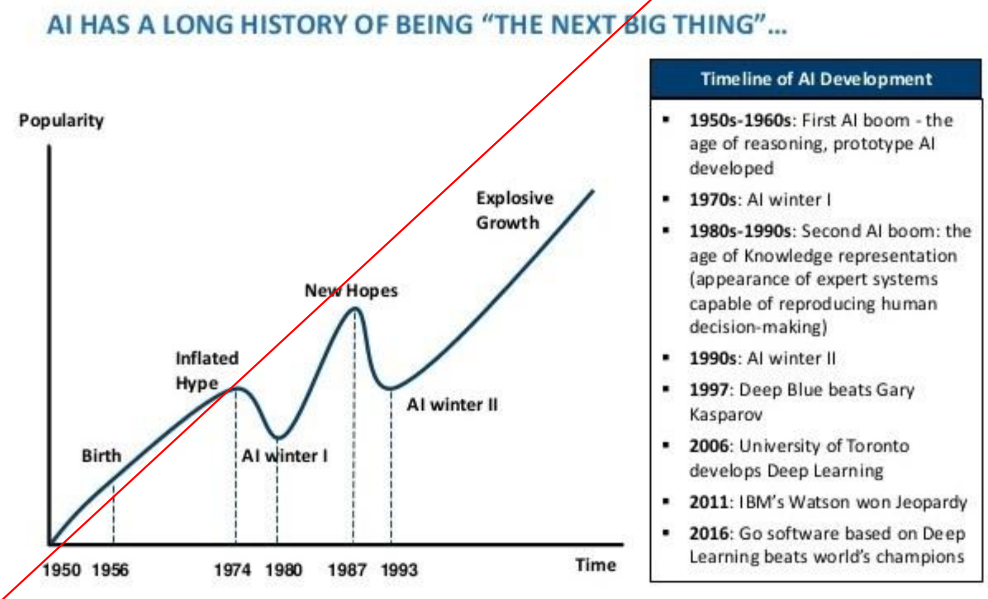
- Moore’s law and Neural networks



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  - Pre generated responses about domain specific decisions

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- Systems can be **improved** by **understanding** them

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- Increase in demand for “**ethical AI**”
- Need to understand trade off of **transparency** to **performance**
- Systems can be **improved** by **understanding** them
  - This is the idea that researchers ignore/miss

Important Terminology

- **Understandability** – characteristic of a model to make a human understand its function (how the model works) without the need for explaining its internal structure or algorithmic processes

Arrieta, Alejandro Barredo, et al. "Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI." *Information fusion* 58 (2020): 82-115.

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  Transparency – A model is considered to be transparent if by itself it is understandable
  - I believe that the usability and transpareness of an AI system is the most crucial concept in XAI
  - Understandability is also important

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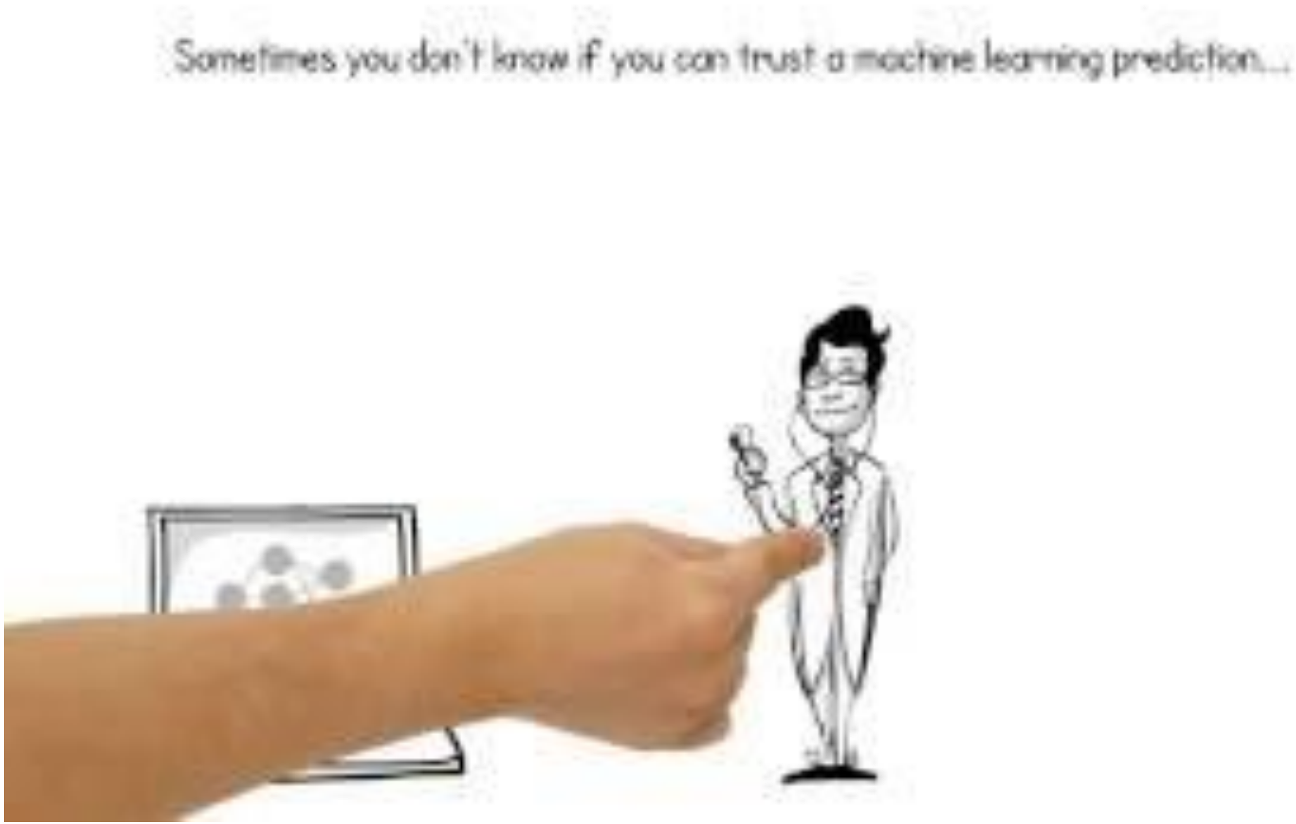
- **Global Explanation** – provides understanding of a model's overall behavior across the entire dataset

Local Interpretable Model-agnostic Explanations (LIME)



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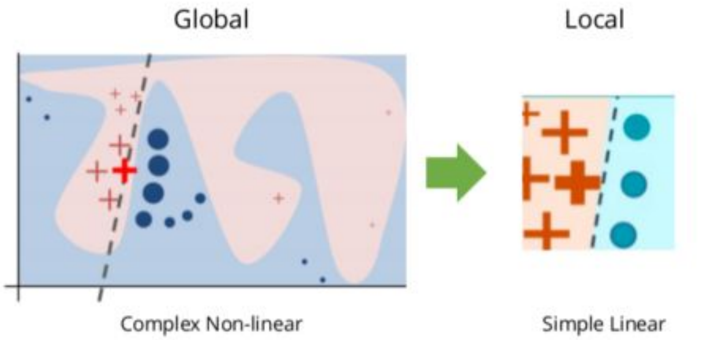

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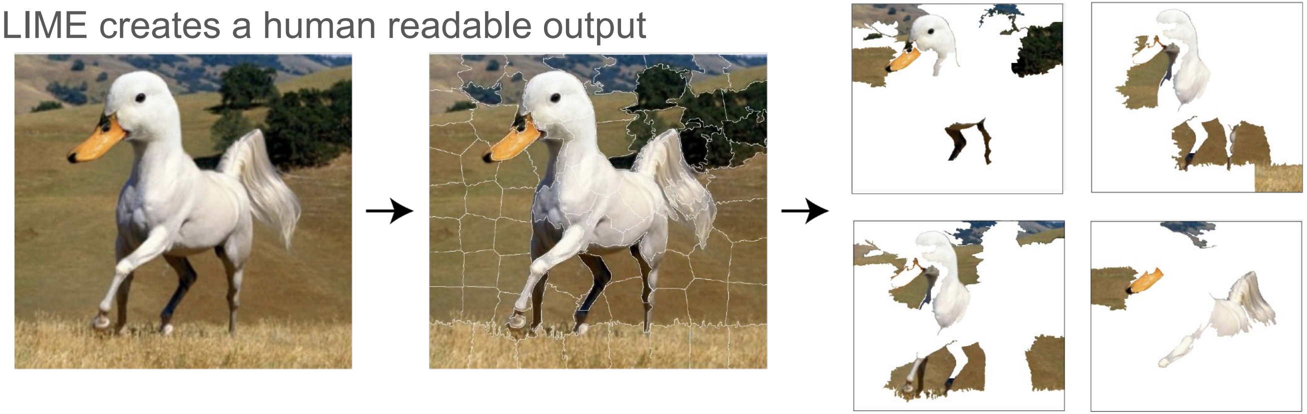
  - LIME creates a human readable output



Label: standard poodle
Probability: 0.18
Explanation Fit: 0.37

Label: goose
Probability: 0.15
Explanation Fit: 0.55

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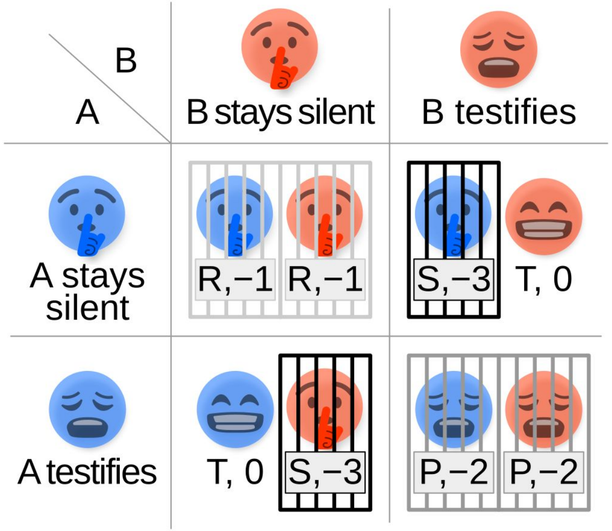
- Famous example of cooperative game-theory
- Prisoner's Dilemma
  - Two rational agents
  - Can either cooperate or stay silent
  - Dilemma is that the payoff is higher if the agents cooperate



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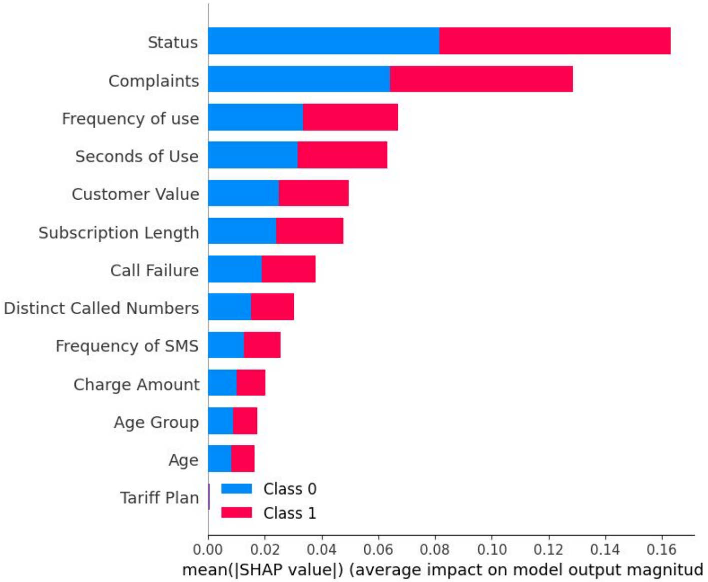
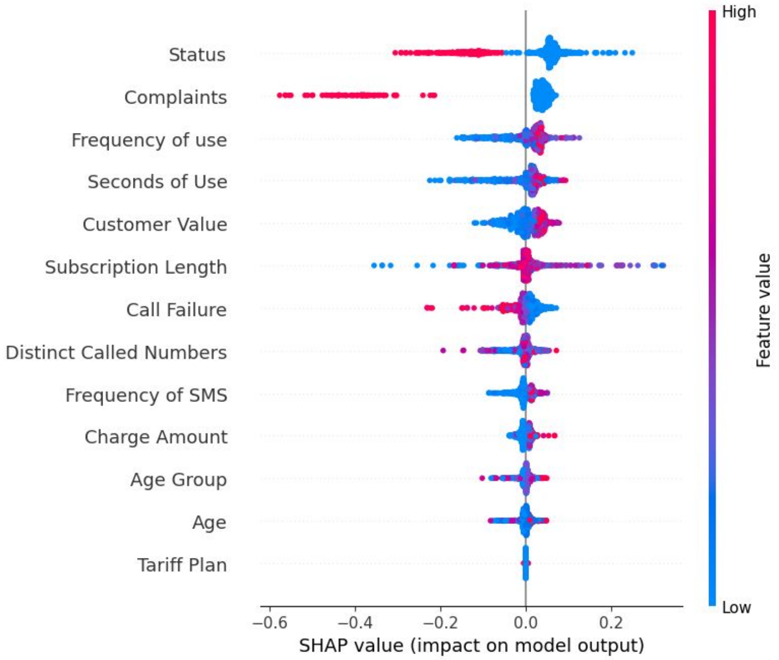
  - Compute the marginal contributions of the selected feature
  - Using the marginal contributions, calculate the additive shapley value

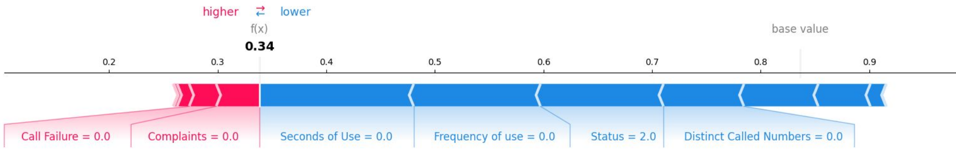


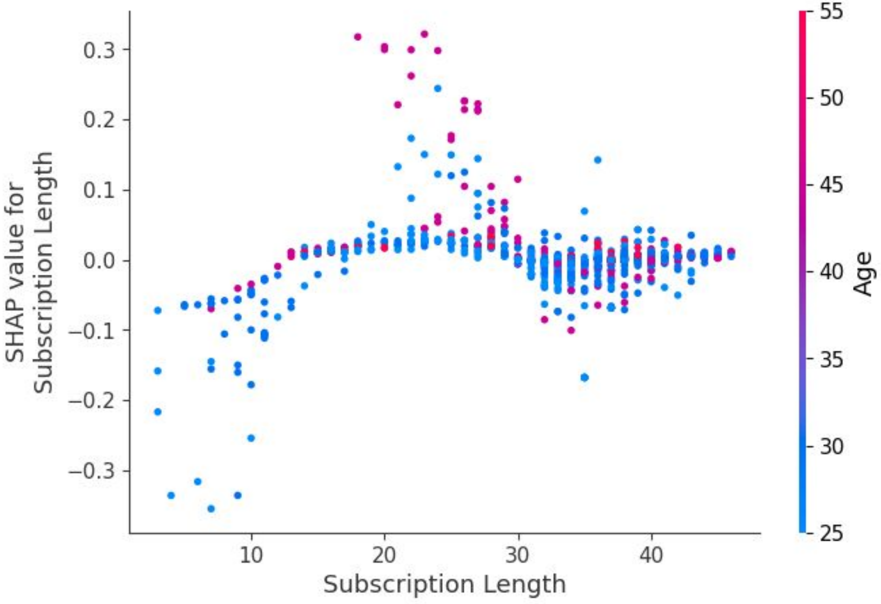
Summary Plot



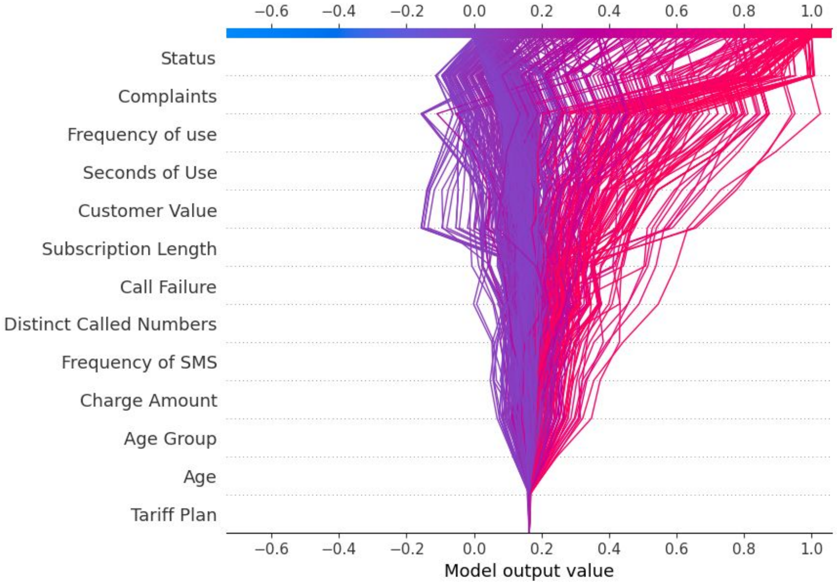
Other Summary Plot

Force Plot





Dependence Plot For Subscription Length



Decision Plot

Layer-wise Relevance Propagation (LRP)

- LRP creates local explanations specifically for neural networks
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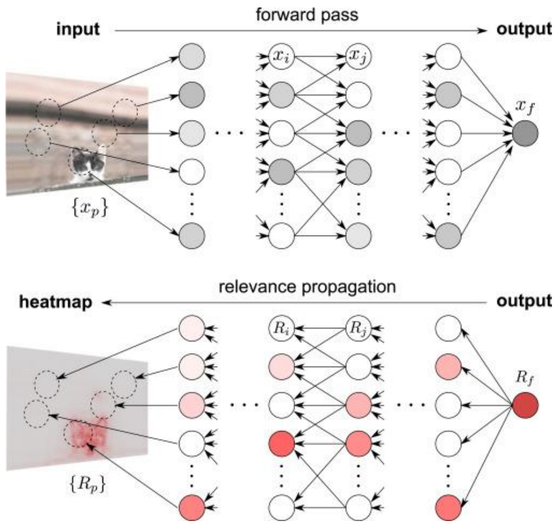

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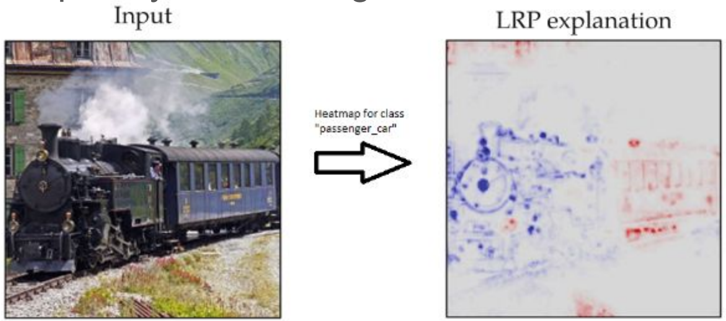
  - Propagate back to input layer and assign relevance scores



Quick Review

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- Game-theory/Feature based explanations (SHAP)
- Decomposition based (LRP)

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- Python packages
  - LIME (pip install lime)
  - SHAP (pip install shap)
  - LRP (no simple pip install, there are other implementations it seems)
  - ELI5 (pip install eli5)
  - Interpret (pip install interpret) – appears to be an explanation suite
  - OmniXAI (pip install omnixai) – appears to be an explanation suite

The Counterfactual

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  - “Explanation describes the smallest change to the feature values that changes the prediction to a predefined output”
- Becoming more common in the literature (especially with the rise of LLMs)

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- General Algorithm:
  - Select a sample to be explained and the desired label to change to (y’)

The Counterfactual

- Local explanation centered around flipping the label
  - “Explanation describes the smallest change to the feature values that changes the prediction to a predefined output”
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        - -> $L(x, x', y', \lambda) = \lambda \cdot (\hat{f}(x') - y')^2 + d(x, x')$

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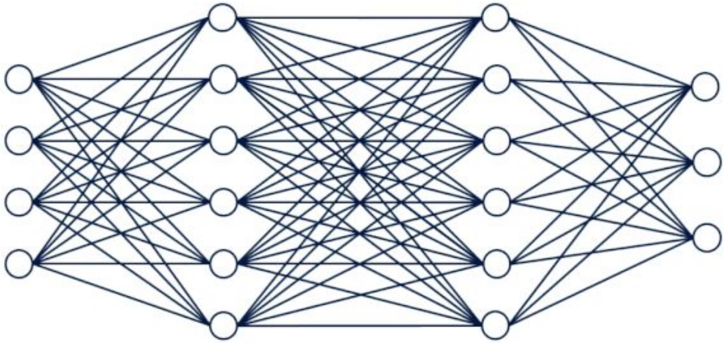
    - -> $L(x, x', y', \lambda) = \lambda \cdot (\hat{f}(x') - y')^2 + d(x, x')$
    - $(\hat{f}(x') - y')^2$ – quadratic distance between counterfactual and desired output
    - $d(x, x')$ – distance between original and counterfactual samples
    - λ – affects explanations. Higher values prefers predictions close to y'. Lower values prefer counterfactuals x' more similar to x

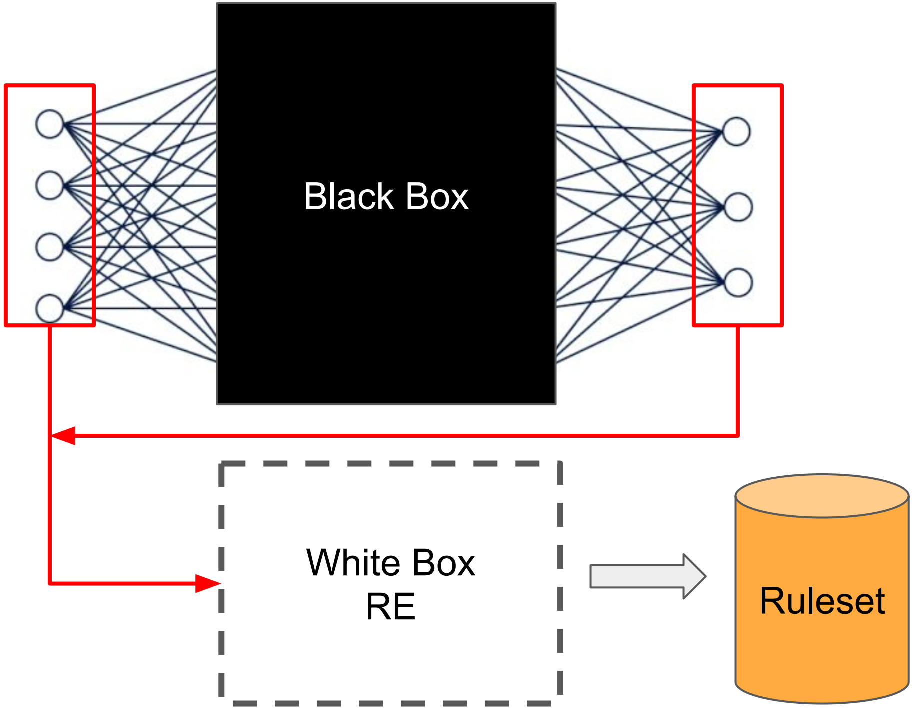
Rule Extraction

- Types
  - Pedagogical
  - Decompositional
  - Eclectic



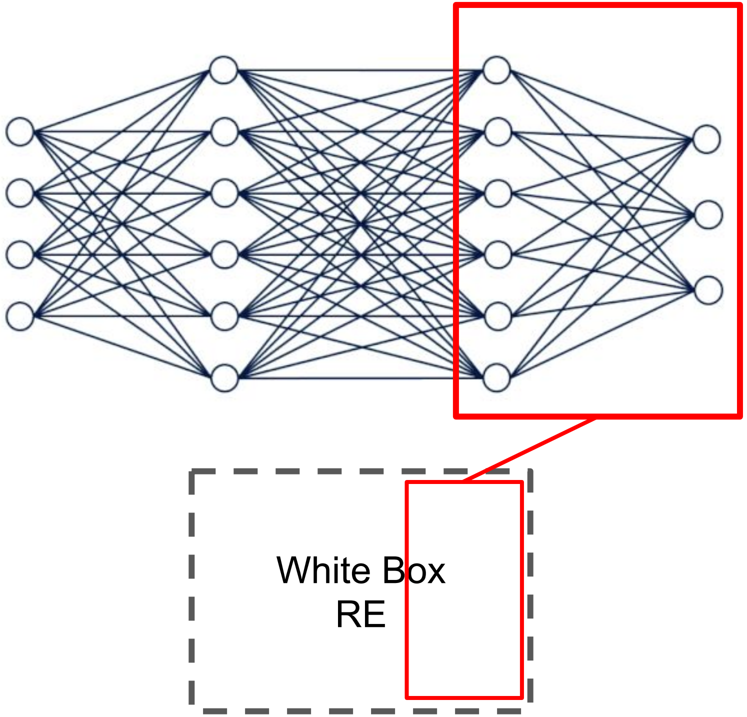
Rule Extraction

- **Pedagogical**
  - Inputs and outputs
  - Train a decision tree
  - **Maintains the black box**
  - Trustworthy?



Rule Extraction

- **Decompositional**
  - Uses weights
  - Trains a decision tree per layer
  - **Opens the black box**
  - Expensive, but trustworthy



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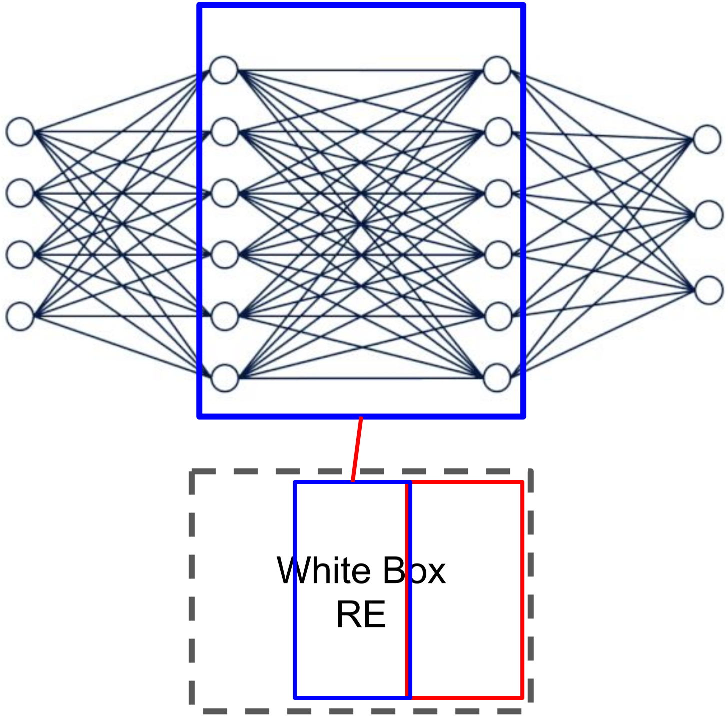

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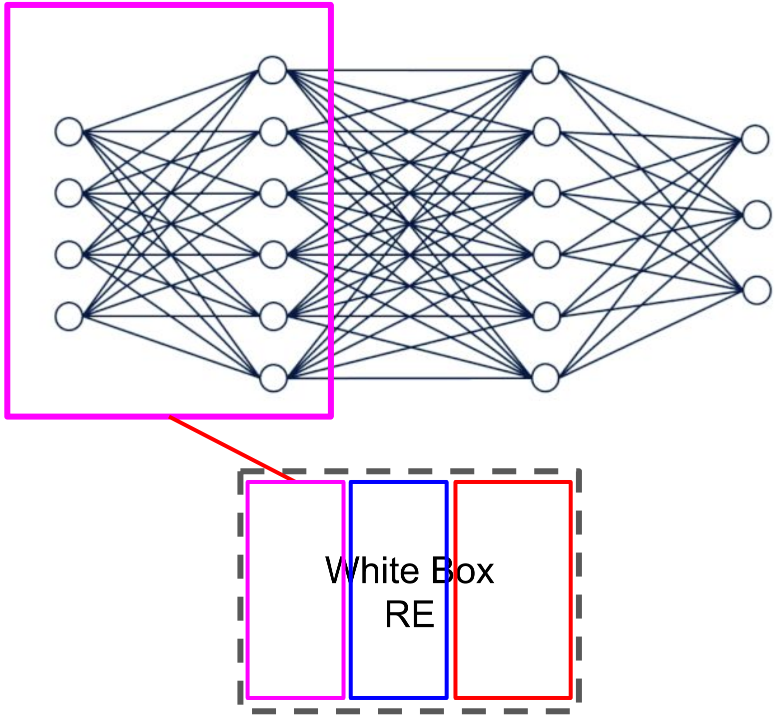

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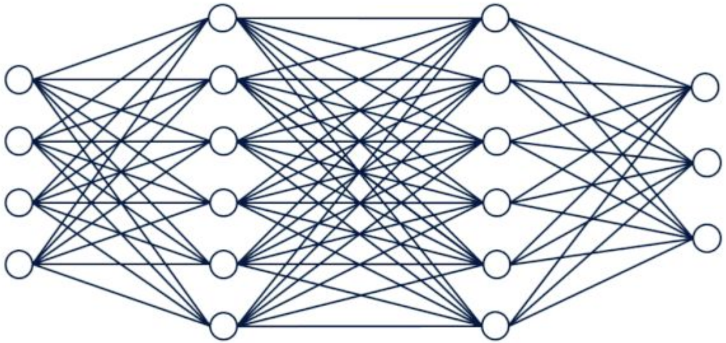
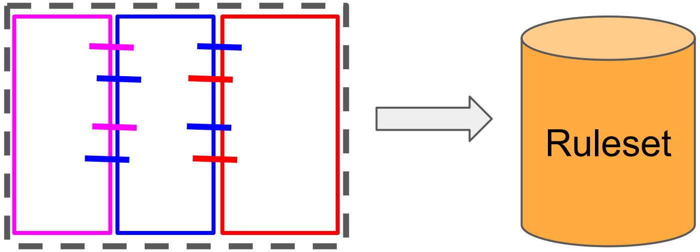
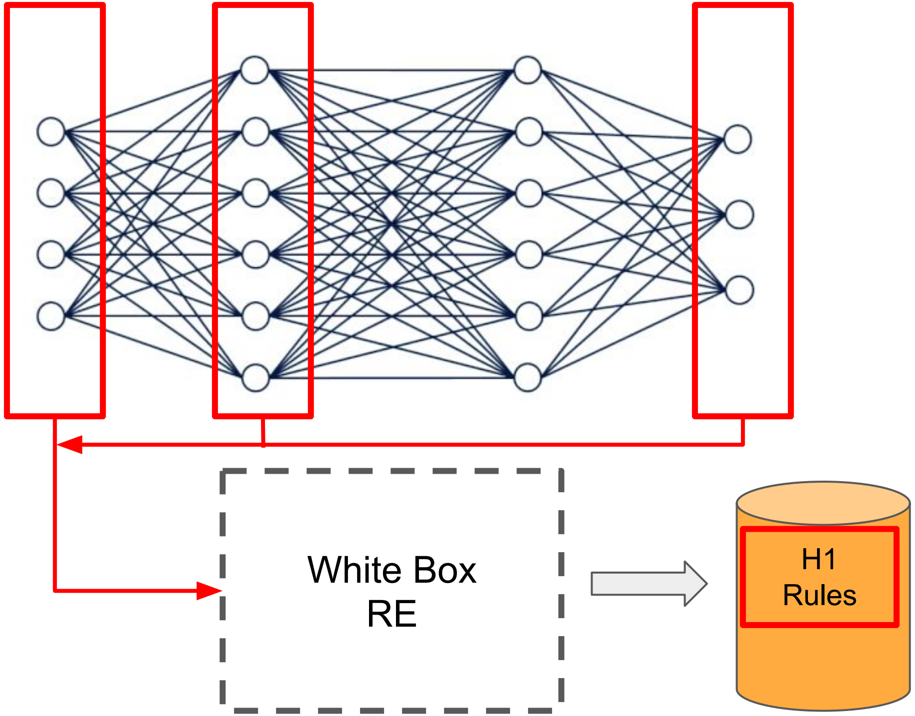




Rule Extraction

- **Eclectic**
  - Uses Inputs, weights, outputs
  - Extracts rules per layer
  - **Opens the black box**
  - Not as Expensive, but trustworthy



Rule Extraction

- **Eclectic**
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  - Extracts rules per layer
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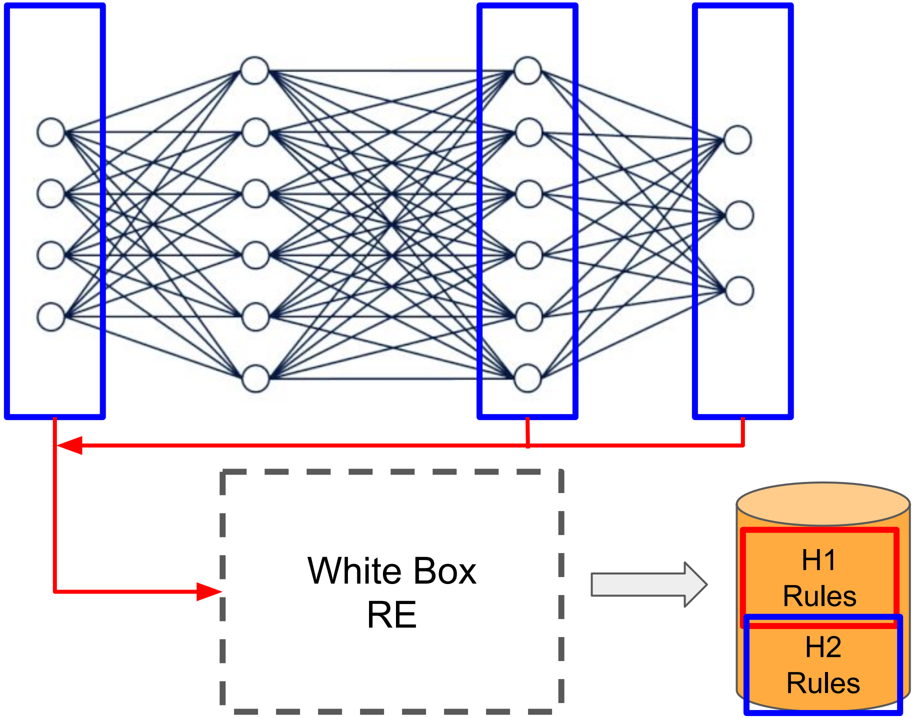
  - Not as Expensive, but trustworthy



Rule Extraction

Term

Feature Threshold

Petal Width (cm) > .6 && Petal Length (cm) <= 4.75 && Petal Width (cm) <= 1.6 && Sepal Width (cm) <= 3.15 == versicolor

Label

Rule

Ruleset

```
petal width (cm) <= 0.80 == setosa
petal width (cm) > 0.60 && petal length (cm) <= 4.75 && petal width (cm) <= 1.60 && sepal width (cm) <= 3.15 == versicolor
petal length (cm) <= 2.45 == setosa
petal width (cm) > 0.60 && petal length (cm) <= 4.75 && petal width (cm) <= 1.60 && sepal width (cm) <= 3.15 == versicolor
petal length (cm) > 4.75 && sepal width (cm) <= 2.90 && petal width (cm) <= 1.75 == virginica
petal length (cm) > 4.75 && petal width (cm) > 1.75 == virginica
petal length (cm) > 4.75 && sepal width (cm) <= 2.60 && petal length (cm) <= 5.05 && petal width (cm) <= 1.75 == virginica
petal length (cm) > 4.75 && sepal width (cm) > 2.90 && sepal length (cm) > 7.05 && petal width (cm) <= 1.75 == virginica
petal width (cm) > 1.60 && petal length (cm) <= 4.75 == virginica
petal length (cm) > 4.75 && petal width (cm) > 1.75 == virginica
petal width (cm) > 1.60 && petal length (cm) <= 4.75 == virginica
petal length (cm) > 4.75 && petal length (cm) > 5.05 && petal width (cm) <= 1.75 == virginica
sepal width (cm) <= 3.15 && sepal width (cm) > 2.90 && petal length (cm) > 4.75 && petal length (cm) <= 5.40 && petal width (cm) <= 1.75 == versicolor
sepal width (cm) <= 3.15 && sepal length (cm) > 6.50 && petal length (cm) > 4.75 && petal length (cm) <= 5.40 && petal width (cm) <= 1.75 == versicolor
sepal length (cm) > 6.35 && sepal width (cm) > 3.15 && petal width (cm) <= 1.65 == versicolor
petal width (cm) > 0.80 && sepal width (cm) > 3.15 && petal length (cm) <= 4.75 && sepal width (cm) <= 3.25 == versicolor
```

Eclectic Rule Extraction Algorithm

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

BEGIN

$R = set()$

$Y' =$ M.predict(X)

for hidden layer h_i in M **do**

  $X' = h_i(X)$

  $hidden_{dt} = DT_{alg}(X', Y')$

  $Rules_{hidden} =$ ExtractRules($hidden_{dt}$)

  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $R.add$(ExtractRules($input_{dt}$))

end for

return R

END

Eclectic Rule Extraction Algorithm

- Input a dataset, model, and decision tree algorithm

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

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  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $R.add(\text{ExtractRules}(input_{dt}))$

end for

return R

END

Eclectic Rule Extraction Algorithm

- Input a dataset, model, and decision tree algorithm
- Initialize a set to save rulesets

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

BEGIN

$R = set()$

$Y' =$ M.predict(X)

for hidden layer h_i in M **do**

  $X' = h_i(X)$

  $hidden_{dt} = DT_{alg}(X', Y')$

  $Rules_{hidden} = \text{ExtractRules}(hidden_{dt})$

  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $R.add(\text{ExtractRules}(input_{dt}))$

end for

return R

END

Eclectic Rule Extraction Algorithm

- Input a dataset, model, and decision tree algorithm
- Initialize a set to save rulesets
- Get dataset predictions from model

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

BEGIN

$R = set()$

$\boxed{Y' = \text{M.predict(X)}}$

for hidden layer h_i in M **do**

  $X' = h_i(X)$

  $hidden_{dt} = DT_{alg}(X', Y')$

  $Rules_{hidden} = \text{ExtractRules}(hidden_{dt})$

  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $R.add(\text{ExtractRules}(input_{dt}))$

end for

return R

END

Eclectic Rule Extraction Algorithm

- For each hidden layer:

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

BEGIN

$R = set()$

$Y' =$ M.predict(X)

for hidden layer h_i in M **do**

  $X' = h_i(X)$

  $hidden_{dt} = DT_{alg}(X', Y')$

  $Rules_{hidden} = \text{ExtractRules}(hidden_{dt})$

  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $R.add(\text{ExtractRules}(input_{dt}))$

end for

return R

END

Eclectic Rule Extraction Algorithm

- For each hidden layer:
  - Transform samples in X using hidden neuron values

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

BEGIN

$R = set()$

$Y' =$ M.predict(X)

for hidden layer h_i in M **do**

  $\boxed{X' = h_i(X)}$

  $hidden_{dt} = DT_{alg}(X', Y')$

  $Rules_{hidden} = \text{ExtractRules}(hidden_{dt})$

  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $R.add(\text{ExtractRules}(input_{dt}))$

end for

return R

END

Eclectic Rule Extraction Algorithm

- For each hidden layer:
  - Transform samples in X using hidden neuron values
  - Train a hidden layer decision tree

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

BEGIN

$R = set()$

$Y' =$ M.predict(X)

for hidden layer h_i in M **do**

    $X' = h_i(X)$

    $hidden_{dt} = DT_{alg}(X', Y')$

    $Rules_{hidden} = \text{ExtractRules}(hidden_{dt})$

    $\hat{Y} = Rules_{hidden}(X')$

    $input_{dt} = DT_{alg}(X, \hat{Y})$

    $R.add(\text{ExtractRules}(input_{dt}))$

end for

return R

END

Eclectic Rule Extraction Algorithm

- For each hidden layer:
  - Transform samples in X using hidden neuron values
  - Train a hidden layer decision tree
  - Extract rules from the trained hidden layer decision tree

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

BEGIN

$R = set()$

$Y' =$ M.predict(X)

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end for

return R

END

Eclectic Rule Extraction Algorithm

- For each hidden layer:
  - Transform samples in X using hidden neuron values
  - Train a hidden layer decision tree
  - Extract rules from the trained hidden layer decision tree
  - Predict using the hidden layer ruleset

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$\quad input_{dt} = DT_{alg}(X, \hat{Y})$

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end for

return R

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Eclectic Rule Extraction Algorithm

- For each hidden layer:
  - Transform samples in X using hidden neuron values
  - Train a hidden layer decision tree
  - Extract rules from the trained hidden layer decision tree
  - Predict using the hidden layer ruleset
  - Train input DT using hidden layer predictions and original dataset

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Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

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$R = set()$

$Y' =$ M.predict(X)

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  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $R.add(\text{ExtractRules}(input_{dt}))$

end for

return R

END

Eclectic Rule Extraction Algorithm

- For each hidden layer:
  - Transform samples in X using hidden neuron values
  - Train a hidden layer decision tree
  - Extract rules from the trained hidden layer decision tree
  - Predict using the hidden layer ruleset
  - Train input DT using hidden layer predictions and original dataset
  - Extract rules from the input DT and add them to the ruleset

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

Output: Final Ruleset (R)

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$R = set()$

$Y' =$ M.predict(X)

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  $hidden_{dt} = DT_{alg}(X', Y')$

  $Rules_{hidden} = \text{ExtractRules}(hidden_{dt})$

  $\hat{Y} = Rules_{hidden}(X')$

  $input_{dt} = DT_{alg}(X, \hat{Y})$

  $\boxed{R.add(\text{ExtractRules}(input_{dt}))}$

end for

return R

END

Eclectic Rule Extraction Algorithm

- For each hidden layer:
  - Transform samples in X using hidden neuron values
  - Train a hidden layer decision tree
  - Extract rules from the trained hidden layer decision tree
  - Predict using the hidden layer ruleset
  - Train input DT using hidden layer predictions and original dataset
  - Extract rules from the input DT and add them to the ruleset
- Return the final ruleset

Algorithm 1 DNN Rule Extraction

Input: Dataset (X), Model (M), Decision Tree Algorithm (DT_{alg})

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