

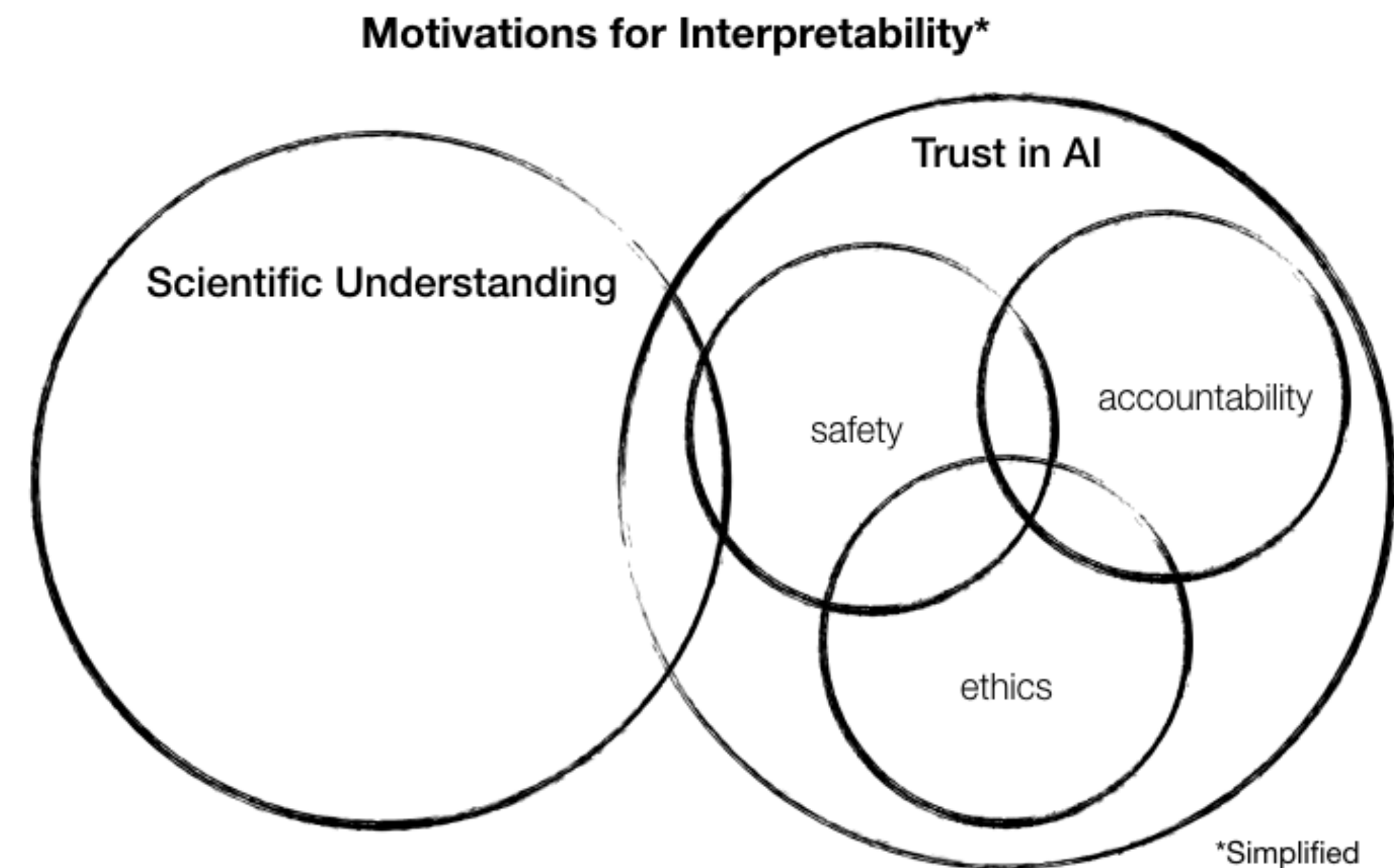
Interpreting LLMs

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The Trust Problem

- If we want to put an ML model into production, how do we gain confidence that it won't kill someone, cause financial damage, make biased decisions against minorities, etc.
- We need to trust it. But how can we trust an AI model?
- Just like how we trust people, we need to understand how it works.



Interpretability is the degree to which a human can understand the cause of a decision.

The higher the interpretability of an ML model, the easier it is to comprehend the model's predictions. Interpretability facilitates:

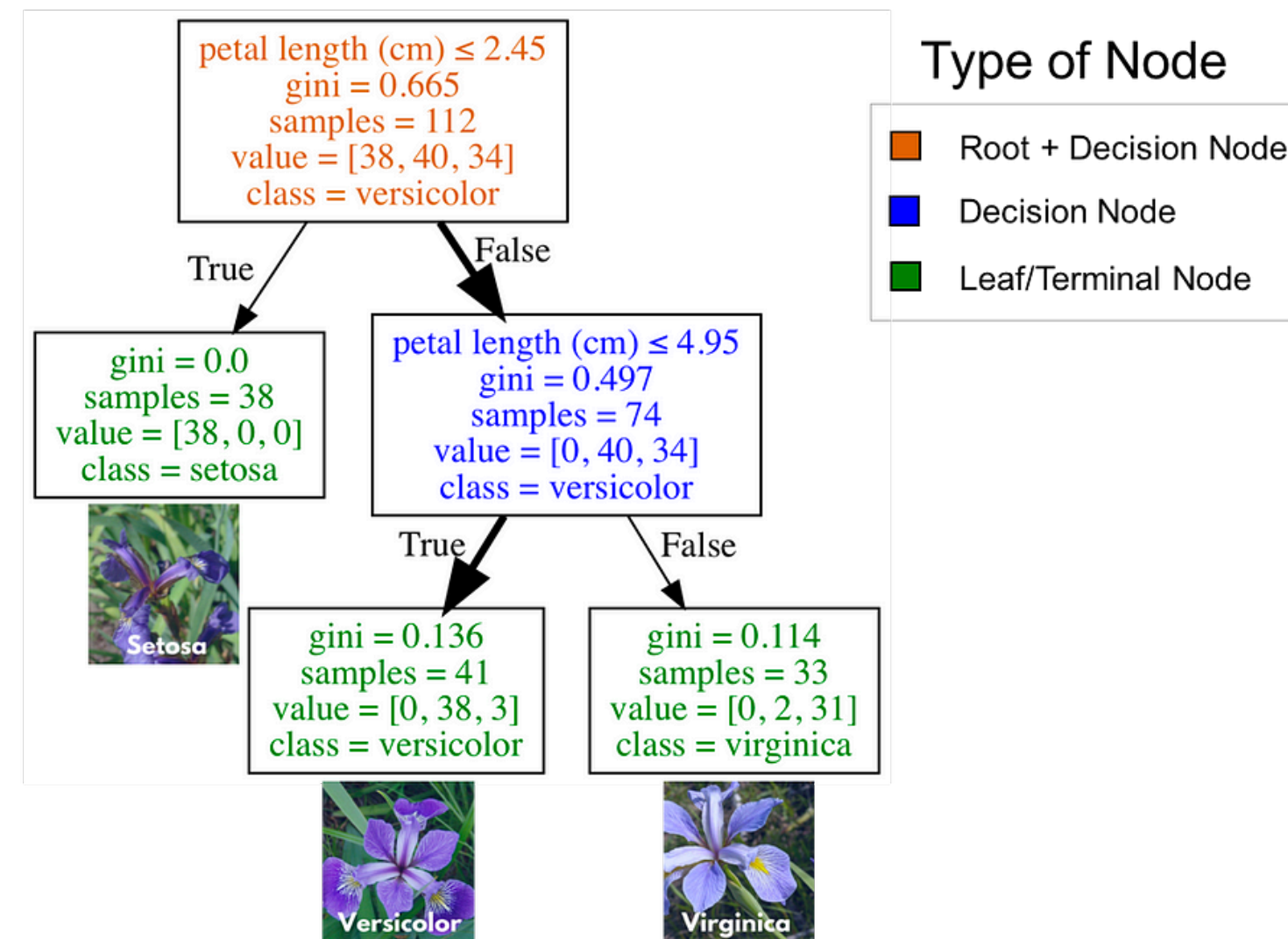
- Understanding
- Debugging and auditing ML model predictions
- Bias detection to ensure fair decision making
- Robustness checks to ensure that small changes in the input do not lead to large changes in the output
- Methods that provide recourse for those who have been adversely affected by model predictions

Trade-off between model complexity and interpretability

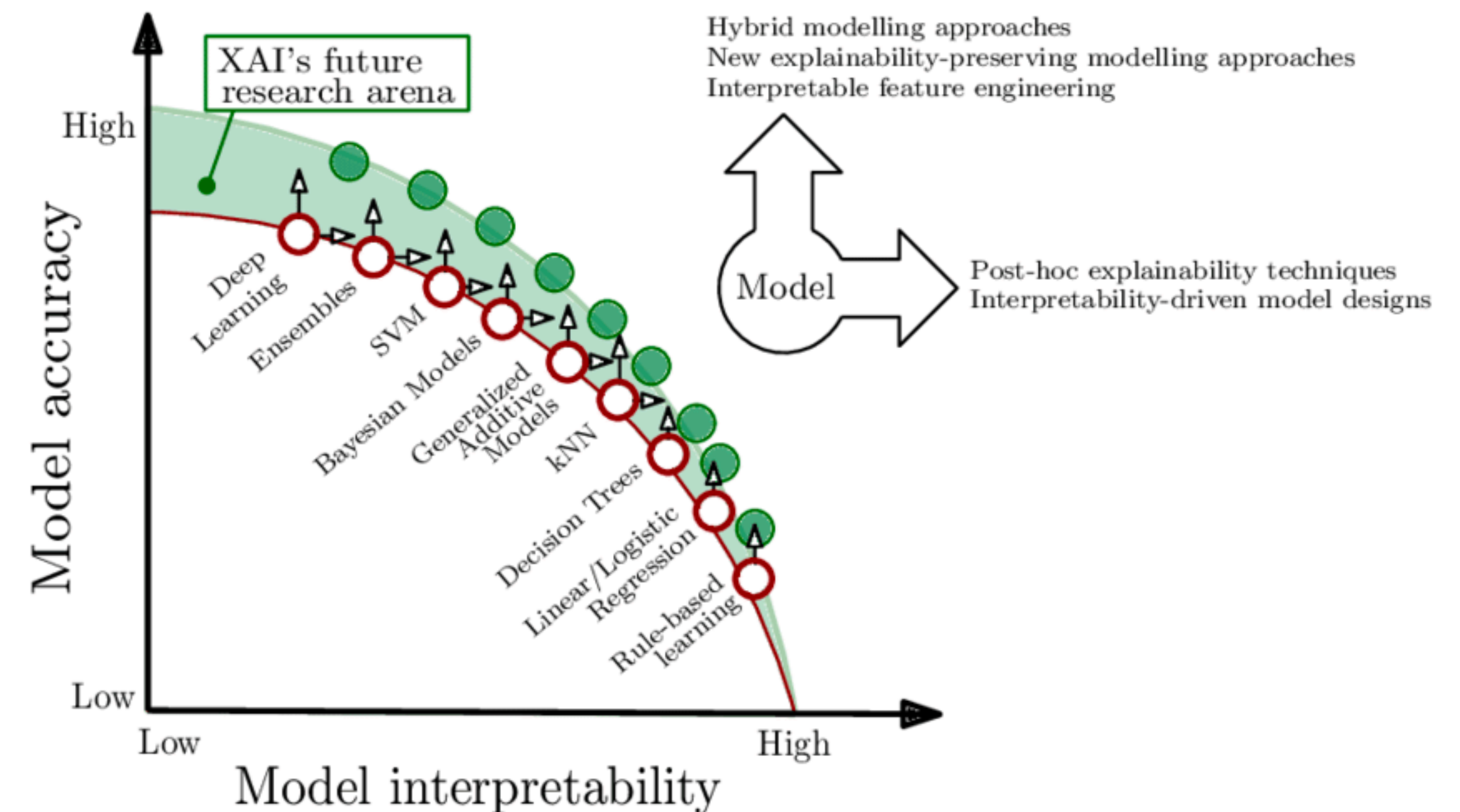
- Increase model complexity to improve performance, decrease to improve interpretability.
- By this definition, LLMs are EXTREMELY uninterpretable.

What class (species) is a flower with the following feature?

petal length (cm): 4.5



Species counts are: setosa=0, versicolor=38, virginica=3
Prediction is **versicolor** as it is the majority class

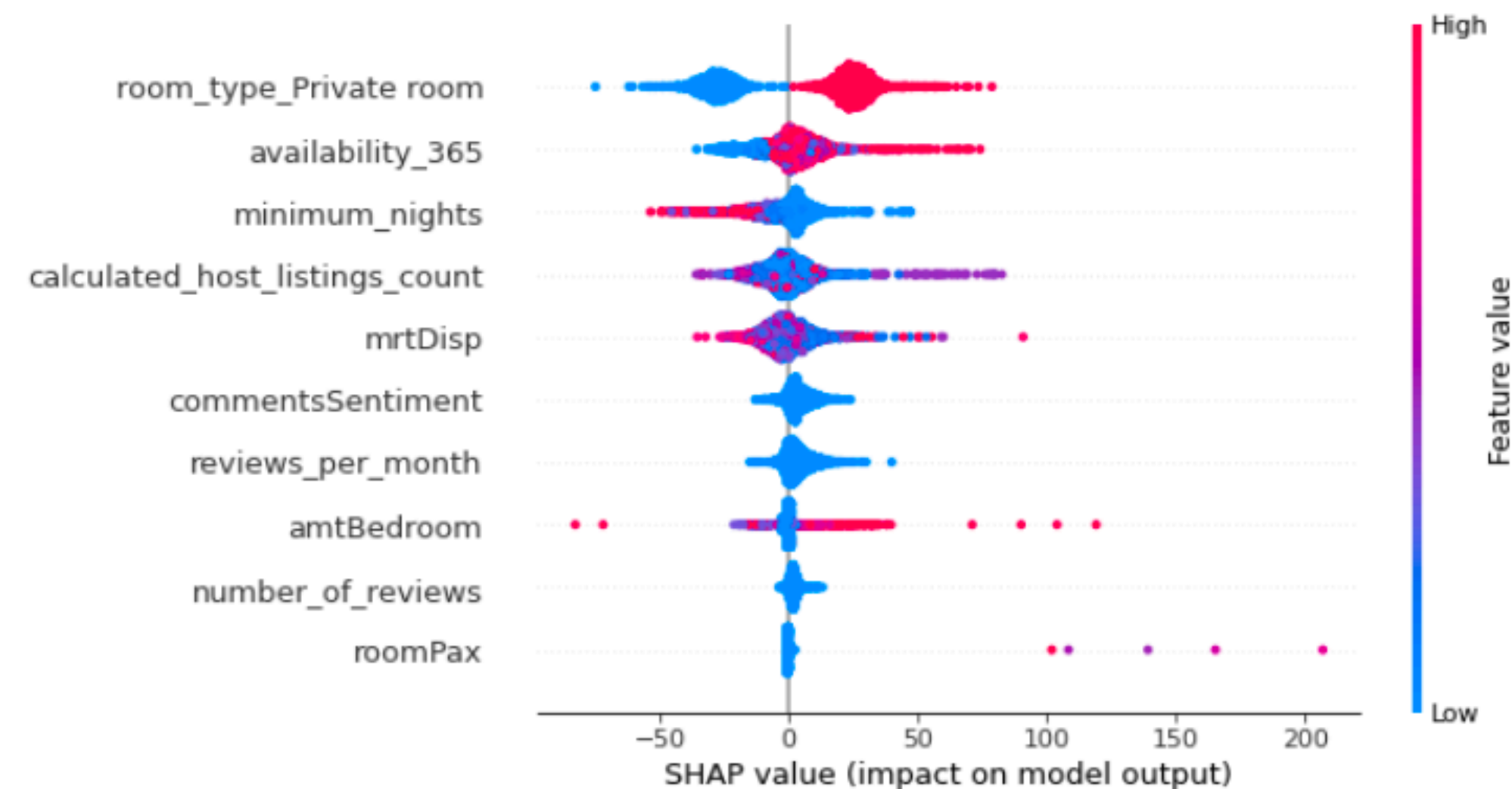


Decision tree to classify one of the three flower species using the famous IRIS Dataset

**We can approach interpretability through Explainable AI.
This means, to generate explanations for AI's behaviors.**

Problems with Explainable Models...

- The best performing solutions do not match with people's mental model
 - In other words, SHAP and similar methods explain which inputs caused the output. But that's simply not how non-technical people think.
- You have to learn how to interpret the outputs that serve to interpret the models...



SHAP output based on airbnb data

NOV 1, 2021 • 12 MIN READ • EXPLAINABLE AI

Explaining Machine Learning Models: A Non-Technical Guide to Interpreting SHAP Analyses

With interpretability becoming an increasingly important requirement for machine learning projects, there's a growing need for the complex outputs of techniques such as SHAP to be communicated to non-technical stakeholders.

With LLMs

- You can probe, question, and interpret LLMs just like how to do with a person.
- “I don’t think this is correct. What’s your evidence?”
- “Can you provide citations for these ideas that you just gave me?”
- “Is this true?”
- “Can you check your arguments to see what might be possible factual issues?”

Example with Color

- The experiment investigates the structural alignment between color term representations derived from text and a perceptual color space known as CIELAB. So that we can see whether language models, trained solely on text, can encode the perceptual structure of color without direct sensory grounding.
- The 3D CIELAB color space is constructed using three dimensions: L (lightness), A (position between red and green), and B (position between blue and yellow).
- Distances in this space correspond to perceptual differences in color.
- Compare the linguistic color term representations extracted from language models with human perceptual color differences.

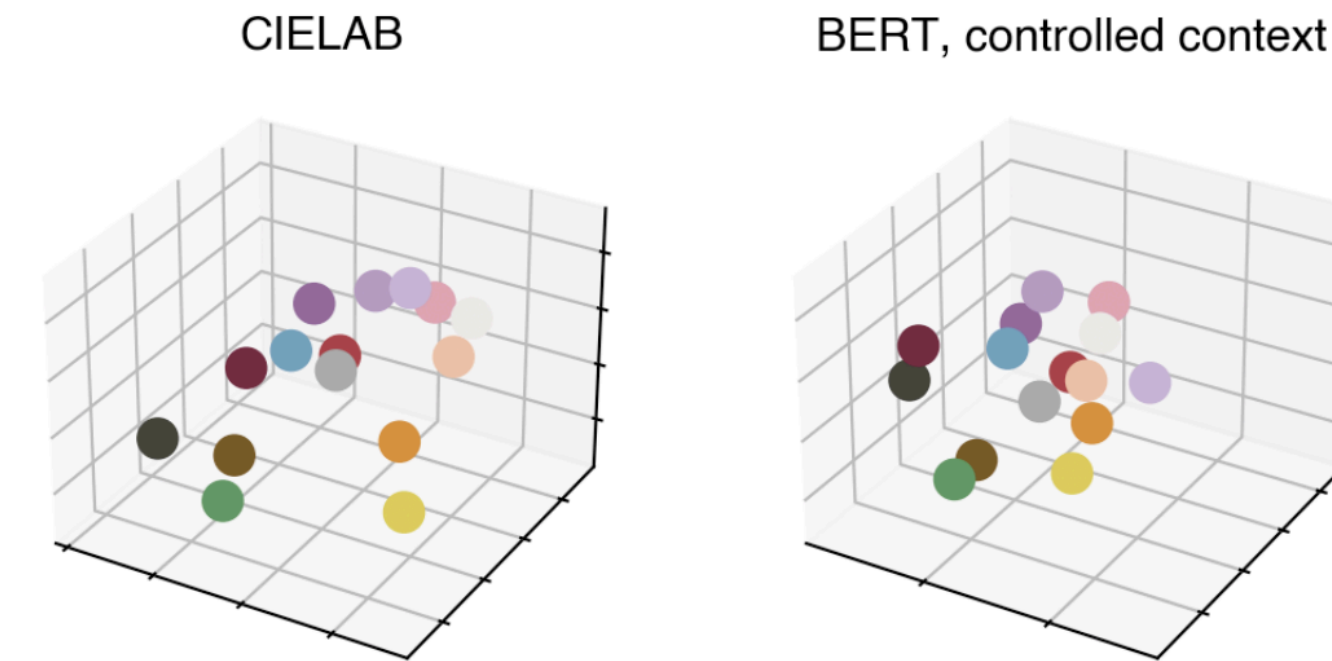


Figure 1: Right: Color orientation in 3d CIELAB space. Left: linear mapping from BERT (CC, see §2) color term embeddings to the CIELAB space.



Self-awareness - do LLMs know its wrong output?

- Hypothesis: truth or falsehood of a statement should be represented by, and therefore extractable from, the LLM's internal state.
- Interestingly, retrospectively “understanding” that a statement that an LLM has just generated is false does not entail that the LLM will not generate it in the first place.

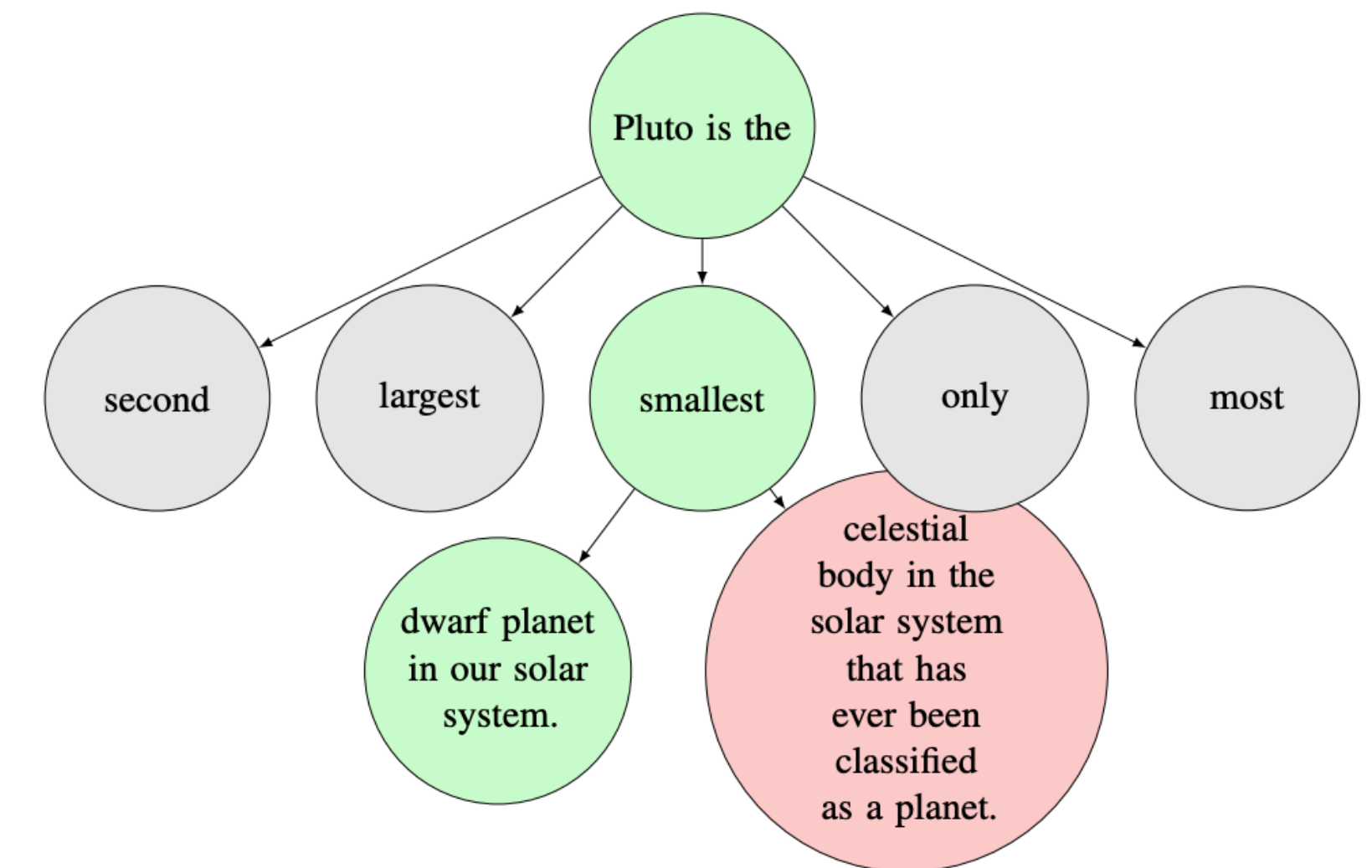
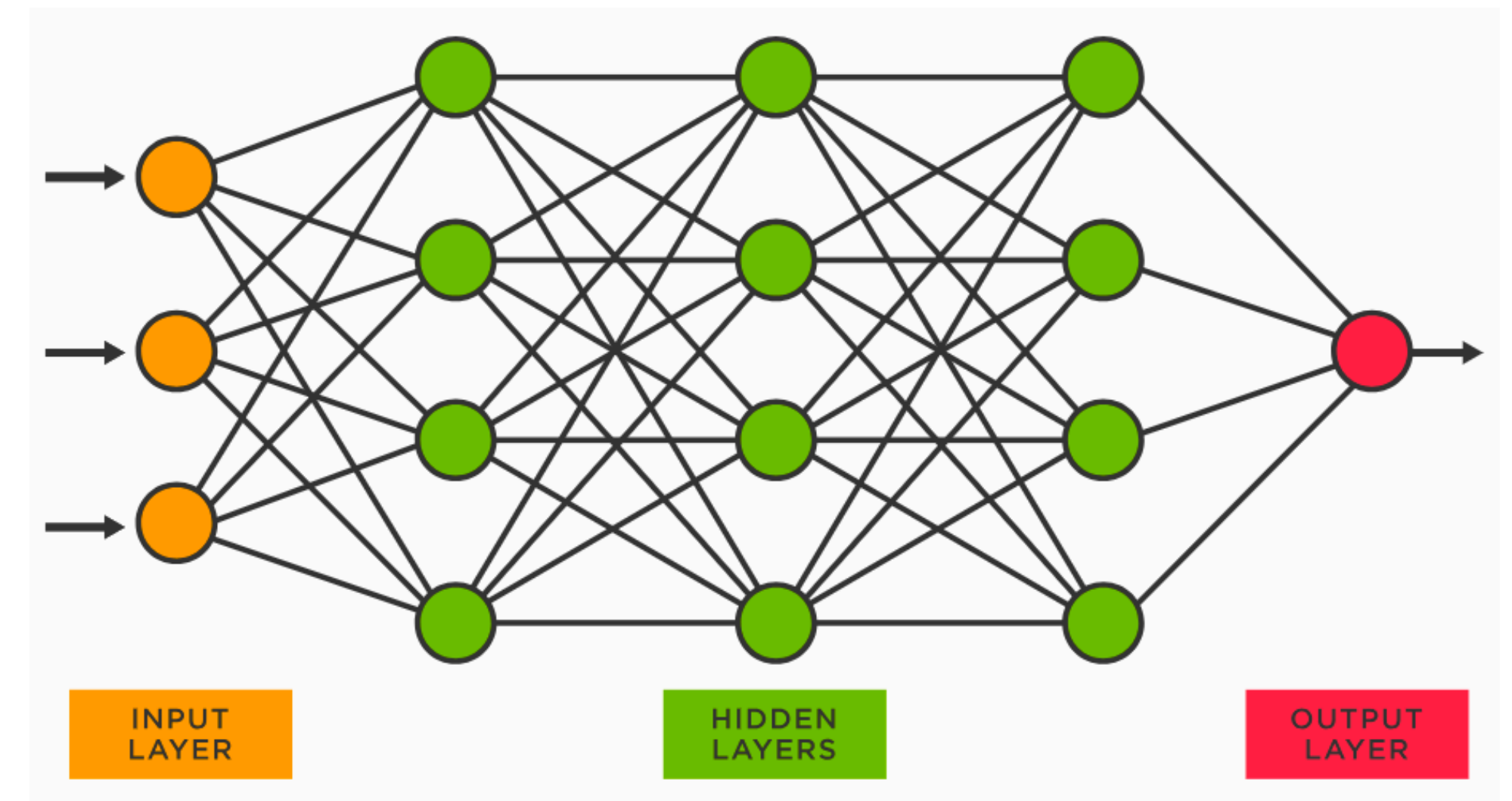


Figure 1: A tree diagram that demonstrates how generating words one at a time and committing to them may result in generating inaccurate information.