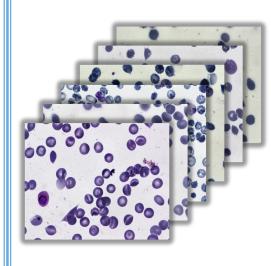
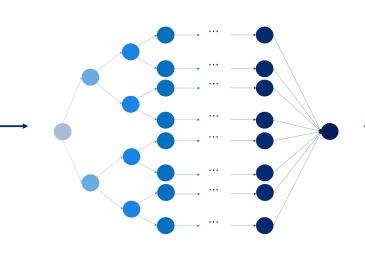


Background

The black box problem

In clinical computer vision settings, deep neural networks (DNNs) can diagnose diseases by creating complex mathematical relationships between image data, sometimes estimating millions of parameters. But how can clinicians trust and verify the conclusions of these DNNs, especially when these mathematical relationships are so complicated?





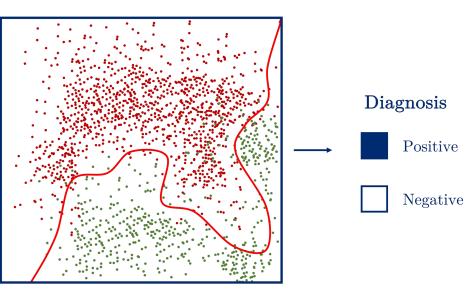


Image dataset

Black box neural network

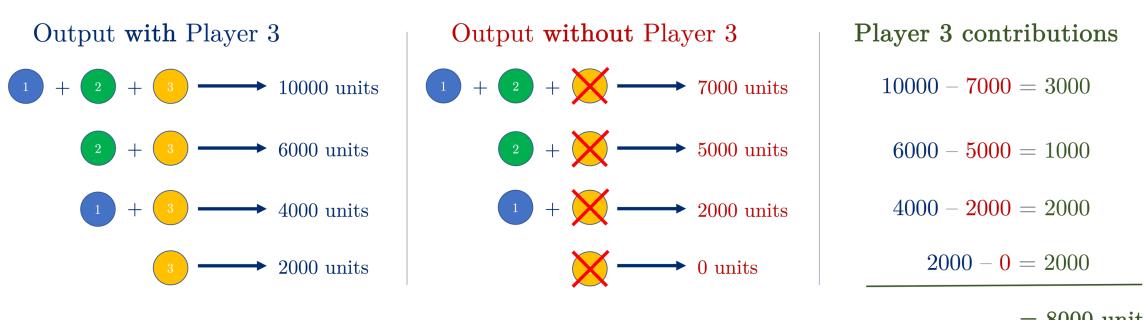
Decision boundary



A posteriori methods: Shapley values

Because DNNs are valuable for their raw predictive power, we can implement methods that can interpret the results of a DNN for us!

Shapley values, a tool inherited from cooperative game theory, offer a simple but elegant solution. A Shapley game computes the value added for each member of a team – or, likewise, each feature of an image.



= 8000 units

If we treat each feature of an image as players in a Shapley game as shown above, we can summarize the predictive values for a feature using a weighted sum to determine its overall importance:

$$\phi_j(v) = \phi_j = \sum_{S \subseteq M \setminus \{j\}} \frac{|S|!(M - |S| - 1)!}{M!} (v(S \cup \{j\}) - v(S)), \quad j = 1, ..., M,$$

Problems

But what constitutes a player in a Shapley game?

Computational feasibility

• How many players can we have before the problem becomes intractable?

Semantic Relevance

• How do we pinpoint features that have conceptual importance? Which "things," rather than pixels, does a DNN latch onto?

And how should we treat the players we remove?

Statistical Accuracy

• If we remove part of the image and replace it with a black space, we are creating an image that does not truly exist in our distribution. How do we fix this?

Generative approaches to Shapley-based explanations Ishan Kalburge, Siyu Wang, Kuai Yu Department of Biomedical Engineering, Johns Hopkins University

clustering

