Abstract

The natural way of obtaining different perspectives on any given topic is by conducting a debate, where participants argue for and against the topic. Here, we propose a novel debate framework for understanding the classifier's reasoning for making a particular prediction by modelling it as a multiplayer sequential zero-sum game. The players aim to maximise their utilities by adjusting their arguments with respect to other players' counterarguments. The contrastive nature of our framework encourages players to put forward diverse arguments, picking up the reasoning trails missed by their opponents. Thus, our framework answers the question: why did the classifier make a certain prediction?, by allowing players to argue for and against the classifier's decision. In the proposed setup, given the question and the classifier's latent knowledge, both agents take turns in proposing arguments to support or contradict the classifier's decision; arguments here correspond to the selection of specific features from the discretised latent space of the continuous classifier. By the end of the debate, we collect sets of supportive and manipulative features, serving as an explanation depicting the internal reasoning of the classifier. We demonstrate our Visual Debates on the geometric SHAPE and MNIST datasets for subjective validation, followed by the high-resolution AFHQ dataset. For further investigation, our framework is available at https://github.com/koriavinash1/VisualDebates.

1 Introduction

A black-box deep learning model can be explained in various ways, including feature-attribution (Ribeiro, Singh, and Guestrin 2016; Lundberg and Lee 2017; Shrikumar, Greenside, and Kundaje 2017), attention maps (Selvaraju et al. 2017; Chattopadhay et al. 2018; Sattarzadeh et al. 2021), counterfactual explanations (Goyal et al. 2019), or concept-based methods (Ghorbani et al. 2019; Ghahdarioun et al. 2021; Kori et al. 2021). Each method possesses advantages and disadvantages. In general, explanations for any predictive model have multiple implications, including improving the transparency and understanding of the model's reasoning process (Doshi-Velez, Budish, and Kortz 2017; Kroll 2015), uncovering model biases (Kim et al. 2018), identifying biases in the data-generating process (Narayanaswamy et al. 2020), and ultimately fulfilling legal obligations for model deployment (Bibal et al. 2021).

Explanation methods for understanding neural networks range from neuron level inspection (Olah, Mordvintsev, and Schubert 2017; Olah et al. 2020) to concept level explanations (Ghorbani et al. 2019). However, in the case of computer vision, most of the methods providing visual explanations are either in the form of heatmaps or localised image segments that are deemed responsible for making a decision (Selvaraju et al. 2017; Ribeiro, Singh, and Guestrin 2016; Lundberg and Lee 2017; Shrikumar, Greenside, and Kundaje 2017). These explanations capture straightforward input-output relations and do not provide any insights about the model from a debugging or bias mitigation standpoint; thus, they fall under the category of shallow explanations. Another major drawback of these explanation methods is that they are a function of the data and the model's prediction, rather than the model's internal state. Thus, the faithfulness of these explanations towards the model's reasoning can not be effectively quantified.

Most of the current explanation methods do not follow concept-based reasoning as expressed by humans (Armstrong, Gleitman, and Gleitman 1983; Burnston and Haueis 2021), with a few exceptions (Ghandharioun et al. 2021; Kori et al. 2021) focusing on generating disentangled concepts and traces between them to explain the model's reasoning. Recent approaches like (Kori, Glocker, and Toni 2022) and (Santhirasekaram et al. 2022) are developed considering the faithfulness of explanations in mind. They generate explanations using the model's latent knowledge rather than the original data.

All the methods described so far fall under the category of post-hoc explanations, where the trained model is diagnosed to extract reasons for making a particular decision. Instead, methods such as (Stammer, Schramowski, and Kersting 2021; Lampinen et al. 2021; Irving, Christiano, and Amodei 2018) aim to develop an intrinsically transparent and aligned model. We borrow some ideas from (Irving, Christiano, and Amodei 2018) in this work to develop our post-hoc explainability framework. However, (Irving, Christiano, and Amodei 2018) focuses on advocating debate as an ideal candidate for aligning AI objectives with human values and demonstrate a toy debate game on the MNIST dataset, which proved challenging to scale to other natural imaging datasets. Our explanation framework models players as recurrent attention models (Mnih et al. 2014) to ensure generalisability and scalability of the framework. (Irving, Christiano, and Amodei 2018) argue how short
Figure 1: Above figure provides an overview of the proposed framework, in which \( f \) is the trained feature extractor, \( E \) is the codebook, and \( C_q \) quantised classifier is used in distilling continuous latent knowledge of the trained classifier in a discrete form. \( \Gamma \) corresponds the debate game with players \( P^1 \) and \( P^2 \), \( A^i \) and \( C^i \) corresponds to the argument made by a player \( P^i \) at iteration \( t \) and the claim made by the player. (We restrict attention to two players for simplicity)

debates are influential in bringing out various view points for any given question. For example, if we consider a question “Why did the classifier classify this image as a cat?”, debating players may point out features in the image that are both for and against the classifier’s decision. In this case, the player supporting the classifier’s decision may pick concepts like whiskers, pointy-ears, or eyes, while another player may argue about pointy-ears being characteristic of a fox. In the case of a complex environment, the arguments may not have semantic meaning, but they may nonetheless provide useful information about the model biases and can be used for debugging. Compared to other existing explanation mechanisms, debating not only focuses on supporting features but also points to features that oppose the classifier’s decision.

Methodologically, our approach distills the knowledge of a trained classifier into a discrete surrogate model and uses the discrete features in a debate environment. The players involved in the debate provide arguments by picking the relevant features from the obtained discrete set of features for a particular image. Finally, all the arguments and players’ claims are used to estimate utilities that are progressively used to update debate parameters. The obtained arguments in the debate process are used to extract visual semantics by means of a deterministic process formulated in (Bau et al. 2017), which serves as an explanation. Since we use the latent knowledge from the classifier rather than data directly, the generated explanations can be deemed to be faithful to the classifier. Overall, our main contributions in this work include:

- **Debate Framework (Section 3.3)**: Novel explainability framework that extracts features responsible for both supporting and opposing the classifier’s decision.
- **Equilibrium Analysis (Section 3.6)**: Analysis of player behaviour and argument properties at “Equilibrium”.
- **Explanations (Section 3.7) and their evaluation (Section 4)**: Generation of faithful explanations in the form of visual debates from generated arguments, for three datasets (SHAPE (Dataset 2016), MNIST (Deng 2012) and AFHQ (Choi et al. 2020)).

2 Related Work

Our proposed debate framework can be seen as generating explanations as “contests” between fictional agents (arguing for and against a class). There is an emerging interest in developing contestable algorithms; recent policies for deploying AI systems require the possibility to consider arguments against AI decisions (Lyons, Velloso, and Miller 2021; Society 2022). (Almada 2019; Bayamlioglu 2018; Hirsch et al. 2017) apply this notion of contestability to sociotechnical systems. The idea of contestability encourages AI systems to collaborate with humans rather than blind delegation of responsibility. This is achieved by providing different avenues of human interactions in the decision-making process (Klutz, Kohli, and Mulligan 2022). In our framework, instead, contestability is the very essence of explanation.

A parallel line of research in XAI involves computational argumentation (ˇCyras et al. 2021). A common aim for computational argumentation is to evaluate a particular claim by considering arguments that support and attack the claim with respect to a specific argumentative framework (e.g. of the kinds advocated in (Dung 1995) or in (Baroni, Rago, and Toni 2018)). At a high-level of comparison, bipolar argumentation frameworks (Carroly and Lagasque-Schiex 2005) align closely with our debates, as they accommodate attack and support, as we do. Differently from existing approaches using bipolar argumentation for explanation (as overviewed in (ˇCyras et al. 2021)), we focus on image classifiers and generate debates as interactive game-playing among reinforcement learning players for extracting reasons for models’ predictions. Our proposed debate game uses models’ latent knowledge to extract arguments and counterarguments, preserving the arguments’ faithfulness to the given model. (Lakkaraju et al. 2022) advocates the importance of thinking of explainability as a dialog rather than a fixed attention
map or feature attribution. We provide a practical framework in this direction.

3 Methods

In this section, we describe the steps involved in the proposed framework, which mainly includes the feature discretisation step, followed by the game, player, and utility design. The proposed framework is illustrated in Figure 1 where \( f \circ g \) is the trained model that requires explanations, \( E \) corresponds to the codebook with the set of discrete features mapping to a continuous output of \( f \). \( C_q \) is a quantised classifier which classifies the discrete features into a particular category, \( \Gamma \) and \( P^p \) correspond to the debate game and the players in it. Our framework is applicable to any number of players, but we focus for simplicity on two players only.

3.1 Preliminaries

Let \( D \subseteq X \times Y \) be a dataset, such that \( X \in \mathbb{R}^{s \times s} \) and \( Y = \{1, 2, 3, \ldots, N\} \), where \( s \times s \) and \( N \) corresponds to the dimension of an input image and total number of classes, respectively. Our debate game aims to explain individual predictions made by a classifier \( C : X \rightarrow Y \) trained on \( D \).

**Assumption 1.** We assume that any given classifier \( C \) can be decomposed in the form of \( C = g \circ f \), where \( g \) and \( f \) correspond to a feature classifier and a feature extractor, respectively.

3.2 Discretisation

The output of \( f \) in the given classifier is continuous, posing multiple challenges for extracting meaningful explanations about its latent reasoning. To address this, we first distill the classifier’s latent knowledge into a codebook \( E \) with \( \hat{n} \) discrete features each of dimension \( d \) using the process of vector quantisation, similar to the method described in [Van Den Oord, Vinyals et al. 2017]. However, instead of sampling across pixels, we sample along channels, and these channels are disentangled using hessian penalty [Peebles et al. 2020] for obtaining various features in the codebook. We initialise the codebook with a uniform discrete prior, with all \( \hat{n} \) features being uniformly distributed in the range \((-1/\hat{n}, 1/\hat{n})\). This is done for two main reasons: (i) to bound the vectors with respect to a total number of discrete features, and (ii) to spread all the features within the given range. The quantisation is achieved by deterministically mapping \( \hat{z} = f(x) \) for \( x \in X \) to the nearest codebook vector \( z \in E \), formally \( z = \arg\min_{j} \| \hat{z} - E_j \|_2^2 \), for all \( E_j \in E \).

The above defined sampling process is non-differentiable: to resolve this issue for weight updates, we apply straight through gradient approximation using quantisation loss as proposed in [Van Den Oord, Vinyals et al. 2017]: \( \| sg(z) - E_j \|_2^2 + \beta \| \hat{z} - sg(E_j) \|_2^2 \), where \( sg \) is a stop gradient operand.

To distill the knowledge from the continuous to the discrete space, we introduce a quantised classifier \( C_q \), which maps the average pooled sampled vector \( z \) to the classifier’s decision \( C(x) \) for any given \( x \in X \). The parameters in the quantised classifier are trained using knowledge distillation loss \( L_{dist} \), which is the cross-entropy loss between the classifier’s decision \( C(x) \) and the quantised classifier’s prediction.

3.3 Debate Game

The proposed debate game consists of two players \( \{P^1, P^2\} \) who sequentially argue about a common question \( Q \) for \( n \) iterations to make a final claim of \( \{C^1, C^2\} \). The common question \( Q \) in the context of explanation may be something like “Why did the classifier predict this image as a cat?”.

The player \( P^1 \)’s objective is to provide relevant arguments \( \{A^1 = \{A_{11}^1, A_{12}^1, \ldots, A_{1n}^1\}\} \) supporting the decision made by the classifier, while player \( P^2 \)’s objective is to provide relevant counterarguments \( \{A^2 = \{A_{21}^2, A_{22}^2, \ldots, A_{2n}^2\}\} \) against \( A^1 \) that oppose the classifier’s decision on a given image \( X \sim X \). Let \( U^1, U^2 \) denote the utility function followed by the players, respectively. Formally the debate game is defined as:

\[
\Gamma = \langle \{Q, z\}, \{P^1, P^2\}, \{A^1, A^2\}, \{C^1, C^2\}, \{U^1, U^2\} \rangle .
\]

This debate game considers discrete features obtained as a result of distilling the continuous latent space of the trained classifier as an environment. Players argue about selecting these features for supporting the classifier’s reasoning.

In our setup, player \( P^1 \) makes the first argument, followed by player \( P^2 \)’s counterargument. Due to the debate’s sequential and fully observable nature, an argument made by player \( P^1 \) at iteration \( t \) can be used by both players in all the subsequent iterations. The proposed game falls under the category of finite player, finite strategy, fully observable, zero-sum sequential games, which guarantees the existence of at least one mixed strategy Nash equilibrium (NE). In any NE, both players try to find arguments that align closely with the classifier’s reasoning about the given image, trying to uncover the information that the other player failed to capture, similar to the behaviour observed in [Irving, Christiano, and Amodei 2018]. Next, we discuss how individual players are designed and the learning rules associated with them.

3.4 Players

![Player architecture followed in the proposed debate game.](image)

**Figure 2:** Player architecture followed in the proposed debate game. \( M \) corresponds to a modulator network, \( \zeta \) is an unrolled gated recurrent unit, \( B \) and \( \Pi \) correspond to the baseline and policy network, respectively.

**Assumption 2.** Players \( P^1 \) and \( P^2 \) follow a Partially Observable Markov Decision Process (POMDP) structure. In this setup, players never observe the entire environment at once; this is done to encourage players to reason about the environment only via arguments and the classifier’s feedback.
We model each player with gated recurrent units (GRU) as a backbone network \( \zeta \), allowing the player to perceive the argument history uniquely. In addition to \( \zeta \), each player also includes a policy network \( P \), which maps discrete features \( z \sim \mathcal{E} \) to arguments, a modulator network \( M \) converting arguments to the hidden state dimension in \( \zeta \), and a claim network \( C \) estimating the final class label argument using the combined knowledge of all the arguments. Figure 2 overviews the player structure.

Here, an argument corresponds to a particular discrete feature \( z_k \sim \mathcal{E} \) for a given image \( x \). At every iteration, both players pick a single feature from \( z \), which they believe is important in response to their opponent’s argument.

**Definition 1. Argument:** We define an argument as a tuple \((z_k, s)\), where \( s \in \{-1, 0, 1\} \) corresponds to the argument strength, measuring the argument’s quality.

Each obtained argument is later used to update the memory of a player’s core network \( \zeta \). The policy network \( P \) considers \( b(z) \) conditioned on the masked environment \( \hat{z} \) and the classifier’s decision \( \hat{y} \) as an input to estimate argument \( \mathcal{A}_{t+1}^i \), where \( \hat{z} \) is generated by masking the environment with respect to \( A^i_1 \) and \( A^i_2 \). Later, the modulator network \( M \) transforms \( A^i_{t+1} \) to the required dimension, which is later used in \( \zeta \) to accumulate the sequential knowledge of arguments made by the players. Player \( P^2 \) estimates the first argument \( A^1_1 \) using a sampled feature and randomly initialised hidden state vector. Once estimated, arguments are considered common knowledge, and both players can use this information to estimate their subsequent arguments.

The argument strength \( s \) measures the relevance of a particular argument with respect to the “judge” network \( C_\eta \). Here, \( C_\eta \) serves as a proxy for the trained classifier \( g \); we use the proxy network to operate on discrete features rather than continuous features. To measure \( s \) we compute the classifier’s confidence scores on the masked and the original features and use the difference between the two scores to assign the strength to an argument.

**Definition 2. Argument Strength:** Let \( \Delta = \mathcal{C}_\eta(z) - \mathcal{C}_\eta(z; \text{do}(A^i_1, A^i_2)) \). Then, the argument strength \( s^1 \) and \( s^2 \) for players \( P^1 \) and \( P^2 \) respectively is defined as follows (for \( \tau \) a threshold hyper parameter):

\[
s^1 = \begin{cases} 
1, & \Delta > \tau \\
-1, & \text{otherwise}
\end{cases} \quad s^2 = \begin{cases} 
1, & \Delta < \tau \\
-1, & \text{otherwise}
\end{cases}
\]

Thus, the notion of argument strength differs between players: player \( P^1 \), supporting the classifier’s decision, considers a higher value of \( \Delta \) to give a weak argument, while player \( P^2 \) considers that to indicate a strong argument, in the spirit of zero-sum reward.

We constrain the policy network using arguments properties in Definitions 1 and 2 below to obtain more meaningful and diverse arguments. The first notion amounts to entropy minimisation, which ensures that the probability distribution over features is focused on a selected few features, generating more meaningful arguments. This is formally described as:

**Definition 3. Argument Entropy:** \( AH(\Pi^i_t) = - \sum p \log p \), where \( p \) corresponds to the probability for considering a particular feature as an argument.

To preserve the diversity in arguments we maximise the variance between the arguments made by both the players, formally described as:

**Definition 4. Argument Diversity:** \( AD(A^1, A^2) = (\mathbb{E}((sg(A^1) - A^2)^2) + \mathbb{E}((A^1 - sg(A^1))^2)) + \lambda_2 \mathbb{E}(\mathcal{A} - A^2)^2 \), where \( \mathcal{A} = \frac{1}{n} \sum \mathcal{A}^i \).

The first term in the above expression measures diversity in arguments and counterarguments made by the players, while the last term captures the diversity within a player’s arguments. Later, we will apply sigmoid transformation to bound this metric.

Finally, at the end of the debate, both players make their final claim about the environment using the collective information from all the arguments. This is done by mapping the internal representation of an environment to a softmax distribution over class logit using a claim network \( C_\theta \) in each player, which is later used to define their utilities.

Here, we define strategies as the sets of all the features that arguments can be picked from in every iteration along with the final claim (i.e., \( S^i \in z \times z \times \cdots \times z \times \mathcal{Y} \), where \( z \in \mathcal{E} \) and the Cartesian product is considered for \( 2t \) times, as in each iteration of the debate each player has to choose features from \( z \), conditioned on other’s and own arguments). Let \( \delta^i = \{p^i_k : z_k \in \mathcal{E} \} \) be a probability over arguments which define a mixed strategy for player \( P^i \). After each argument \( A^i_t \), an argument stage reward \( r^i_t \) is computed, while the claim reward \( r^i_T \) is computed at the end of the debate. The argument stage reward encourages players to make quality arguments at every step of the debate, while the claim stage reward depicts players’ complete understanding of the environment. The objective of each player is to maximise the cumulative reward, which in our case is sparse and delayed, formally described as \( U^i(S^1, S^2) = \sum r^i_t + r^i_T \). We design utility functions preserving the zero-sum nature of the debate game; we use argument strength \( s^i \) as an argument stage reward. For claim reward \( r^i_T \), we mask all the features not present in \( A^1 \cup A^2 \) and compute the prediction using \( C_\eta \). If \( C_\eta \)’s prediction matches any of the players’ claims, they are rewarded \( r^i_T = 1 \), while the other player is awarded \( r^i_T = -1 \). In the case when the judge’s prediction does not match the claims made by the players, they get zero reward, \( r^i_T = 0 \). The zero-sum nature of the game encourages players to focus on different concepts in a given environment, where players \( P^1 \) and \( P^2 \) provide supportive and opposing arguments about the environment.

The debates can be categorised into committed and non-committed debates (Irving, Christiano, and Amodei 2018). In the case of committed debates, players are expected to make a claim about the environment at the beginning or at the end of the debate. In contrast, in the case of non-committed debates, players argue about the environment without making any claims. (Irving, Christiano, and Amodei 2018) compare the debate with pre-committed and non-committed behaviour and observe that debates with pre-committed claims perform much better in comparison with non-committed debates. Pre-committed debates have similar properties as non-committed
debates, assuming the judge is honest in all the cases. In [Iványi et al. 2018], players reason out all the possibilities without revealing them and make a claim first and provide reasons based on opponents’ arguments. However, in our setup, as the players are modelled as POMDPs, they reason about an environment only via exchanging arguments and finally use those arguments to make a claim. We conduct ablations demonstrating the performance of both committed and non-committed behaviour in debate. In the case of non-committed debates, the claim made by a player is only used in regularisation and not in policy updates, and player \( P^1 \) gets a positive reward if the debate outcome is the same as the classifier’s decision.

### 3.5 Training

The parameters for a player \( P^i \) can be represented as \( \theta^i = \{ \theta^i, \theta^i_{11}, \theta^i_{34} \} \), where \( \theta^i, \theta^i_{11}, \) and \( \theta^i_{34} \) corresponds to the parameters in GRU network \( \zeta \), policy network \( IL \), and modulator network \( M \) respectively. We consider REINFORCE learning rule with the baseline value to reduce variance in estimates as proposed in (Mnih et al. 2014) to update the parameters \( \theta^i \).

\[
\frac{1}{M} \sum_m \sum_t \nabla_{\theta^i} \log \Pi(h_t^i | z_t, y^i; \theta^i)(U_t^i - b_t^i)
\]

**Figure 3:** Players diverging from supportive to contrastive training, in the case of supportive training, both the players follow similar gradients (represented by a solid curve), and in the case of contrastive training, the gradients differ (represented by dashed lines)

Where \( U_t^i = \sum_k s^i_k + r^i_k \) corresponds to cumulative argument rewards along with the reward for a final claim, and \( b_t^i \) corresponds to the baseline value learned by reducing the squared error between \( U_t^i \)’s and \( b_t \). The gradient in the above learning rule \( \nabla_{\theta^i} \log \Pi(\cdot; \theta^i) \) can be mapped to gradients of the GRU network that defines the player \( P^i \) obtained at iteration \( t \), which can be computed by considering standard backpropagation method (Wierstra et al. 2007). The REINFORCE learning algorithm described above allows the agent to make an optimal argument sequence based on feedback obtained via delayed cumulative reward at the end of every episode. In our case, we can gauge the debate outcome by considering the quantised classifier as a judge \( C_q \), and we compare the final claims by both the players with the \( C_q \)’s prediction based on the arguments and update the parameters.

The policy network is always trained with REINFORCE learning rule, the corresponding loss term is described as \( L_{REINFORCE} = -\sum_t \log \Pi(h_t^i | z_t, y^i; \theta^i)(U_t^i - b_t^i) \) along with argument entropy and argument mutual information regularisation terms described in definitions 3 and 4, represented by \( L_{AH} \) and \( L_{AD} \) respectively. Where \( L_{AH} = AH(A^i_1) \) and \( L_{AD} = -AD(A^1, A^2) \). These regularisation terms ensure players make a meaningful argument in any given iteration of a debate. The negative sign in \( L_{AD} \) and \( L_{AH} \) is to accommodate the properties in minimisation in a final objective.

Our training setup consists of two steps, (i) **Supportive training:** where both the players are trained to support the classifier’s decisions, followed by (ii) **Contrastive training:** where the players are trained in debate setup generating arguments and counterarguments. In the case of supportive training, we consider the objection function with utility \( U^i \) for both the players along with minimisation of negative log-likelihood term \( L_{NLL} \) between \( C \)’s decision and \( P^1 \)’s final claim. Supportive training is considered a pre-debate step to provide an initial knowledge base for both the players to generate arguments and counterarguments in the debate. The \( L_{NLL} \) helps to learn better representations in GRU network \( \zeta \), by distilling the classifier’s knowledge. The collective loss during supportive training is described as \( L_{supportive} = L_{REINFORCE} + \lambda_1 L_{NLL} + \lambda_2 L_{AH} - \lambda_3 L_{AD} \). The actual debate takes place in the contrastive training step, players are trained with their respective utilities. The combined loss in contrastive setting is described as \( L_{contrastive} = L_{REINFORCE} + \lambda_2 L_{AH} + \lambda_3 L_{AD} \). We do not enforce \( L_{NLL} \) during the contrastive training step to preserve the min-max aspect of the debate objective. Figure 3 describes the change in the gradient direction when players are switched from supportive to contrastive training. During the supportive training phase, the parameters of both the players are updated similarly. However, in the case of contrastive training, player \( P^1 \)’s parameters still follow a similar gradient direction. In contrast, player \( P^2 \)’s parameters follow orthogonal gradient direction with respect to the direction followed in its supportive training phase.

### 3.6 Equilibrium Analysis

In the case of contrastive training described above, the joint objective of both the players without regularisation terms can be described as (we consider \( U^1(\cdot) = -U^2(\cdot) \) due to the zero-sum behavior of the game):

\[
\begin{align*}
V(P^1, P^2) &= \min_{\theta^1} \max_{\theta^2} \mathbb{E} \left[ \sum_t \log \Pi_{\theta^1}(h_t^1 | z_t, y^1) U_t^1(S^1, S^2) \right] \\
&\quad - \mathbb{E} \left[ \sum_t \log \Pi_{\theta^2}(h_t^2 | z_t, y^2) U_t^2(S^1, S^2) \right]
\end{align*}
\]

**Definition 5. Nash Equilibrium (NE):** The players \( P^1 \) and \( P^2 \) with parameters \( \theta^1 \) and \( \theta^2 \) are said to be in NE iff every strategy \( S^i \) made by a player \( P^i \) is the best response to the opponent’s strategy \( S^{-i} \).

**Remark:** Argument \( A^i_k \) made by \( P^i \) is considered as a best response to \( P^2 \)’s argument \( A^j_{k-1} \), if \( U^i(S^1, S^2; \theta^1) \geq U^i(S^1, S^2; \theta^1) \) for all other arguments \( \theta^i \).

In most cases, pure strategy NE may not exist, but for finite strategy and finite player games, there exists at least
one mixed strategy NE (Nash 1951). Given the structure of the debate game, it falls under the above category ensuring the existence of at least one mixed strategy Nash Equilibrium, for some parameters $\theta^1, \theta^2$. At NE the debate objective follows: $V(P^1_{\theta^1}, P^2_{\theta^2}) \leq V(P^1_{\theta^1}, P^2_{\theta^2}) \leq V(P^1_{\theta^1}, P^2_{\theta^2}) \forall \theta^1, \theta^2$

**Hypothesis 1.** In the proposed debate game, both the players converge at NE, making true and honest arguments about the given environment (Irving, Christiano, and Amodei 2018). (Irving, Christiano, and Amodei 2018) argues certain properties of debates that include:

- **Honesty:** At NE, it is hard for a player to lie; both players try to raise an honest and truthful argument about the environment in the most convincing way possible.
- **Convergence at NE:** In a zero-sum setup, players will converge at any of the pure or mixed strategy NE

**Remark:** We provide qualitative validation for honest behaviour in the later sections of this work.

Here, for convenience, we ignore the baseline term in the game objective (ref. Equation[1]) note that baseline was included to reduce the variance in arguments (Mnih et al. 2014) and does not affect equilibrium properties between both the players.

**Hypothesis 2.** At any NE, sampled features $z$ for any given image can be divided into $z_1$ and $z_2$, such that $z_1, z_2 \subseteq z$ such that $z_1 \cup z_2 = z$ and $z_1 \cap z_2 = \emptyset$, where $z_1$ is a set of features uniquely observed for a given class of images while $z_2$ is a set of features that can be observed for multiple classes (Figure[2]).

**Remark:** This is plausible due to the design of argument level rewards (as $r^1$ is 1 if the $A_i^1 \in z_1$, and the other way around for player $P^2$). The notion of $z_1$ and $z_2$ corresponds to semi- and counterfactual features as described in (Kenny and Keane 2021).

Based on above hypothesis, at convergence the arguments made by $P^1$ and $P^2$ are sampled from a probability distribution over features $z_1$ and $z_2$ respectively (i.e., $\Pi_{\theta^1}(.) = P(z_1)$, $\Pi_{\theta^2}(.) = P(z_2)$). In the proposed debate game, the player $P^1$ supporting the classifier’s claim performs semifactual perturbation, while player $P^2$ performs counterfactual perturbation. Here, semi-factual corresponds to the perturbation that affects the internal state of the player while preserving the class properties, but in the case of counterfactual perturbation, the internal state is affected such that it changes the class properties (Kenny and Keane 2021). Due to this behaviour, players end up splitting the latent features into two components, $z_1$ and $z_2$. We experimentally verify the existence of two unique splits $z_1$ and $z_2$ in all three SHAPE, MNIST, and AFHQ datasets.

**Hypothesis 3.** In the case of any NE, given an optimal horizon length $n$, if arguments and counterarguments made by both players in each and every step are optimal, the debate results in a similar outcome with or without post committing to any claim.

**Remark:** we demonstrate this by comparing argument properties and debate convergence via multiple ablations.

### 3.7 Visual semantics and Explanations

We exploit the hypothesis[1] to obtain explanations from the debate game. Given the hypothesis[1] the arguments and counterarguments made by both the players will serve as an explanation for a given image. To obtain a visual semantics $VS(.)$, we follow a deterministic approach based on (Bau et al. 2017). We consider an attention map $F \sim z$ based on a specific argument $A_i^1$. Then compare the low-resolution attention map $F$ with original image by resizing it to input-dimension using bilinear interpolation, anchoring the interpolation with respect to the features’ receptive field. To obtain the semantic concept for a given argument, we first normalise the resized attention map between 0 to 1 using minmax normalisation and overlay it on an original image.

### 4 Results

To demonstrate the explanations from our framework we consider three different classifiers trained on SHAPE (Dataset 2016), MNIST (Deng 2012) and AFHQ (Choi et al. 2020) datasets respectively. In the case of SHAPE, MNIST and A HFQ, we used images to dimension $32 \times 32, 32 \times 32$, and $128 \times 128$ respectively. The details about the trained classifiers and training strategies are described in the appendix. To establish argument behaviour and hypothesis[2] we conducted ablation on debate length $n$. All the obtained findings are
Figure 5: Arguments behaviour at convergence for the model trained on SHAPE dataset, the plots from left to right corresponds to 4, 6, and 10 argument debates.

Table 1 and Table 2 tabulate the existence of splits; $z_1$ and $z_2$, we consider an average split ratio $Z_R$, defined as a ratio of the total number of uniquely sampled features by $P_1$ with respect to $P_2$, to the total number of unique features over the entire training set. Higher the value of $Z_R$ indicates higher diversity in arguments made by both the players. The $Z_R$ curves in Figure 5 demonstrate the above described behaviour. In the initial training phase, $Z_R$ is almost near zero since both players agree on the set of features, while in contrastive training, their opinion differs about 40-60% of the time. From Figure 5 it can also be observed that the debate length is proportional to debate accuracy, which plateaus after a fixed length. Figure 5 also hints toward the existence of equilibrium in the game due to the non-oscillatory behaviour of debate accuracy and argument properties. We conducted ablations on various combinations of argument rewards and claimed the reward, but a slight variation in argument properties was observed. The findings obtained are documented in the appendix.

Figure 6: Illustration of existing explanation techniques: top-left, top-right, bottom-left, and bottom-right correspond to LIME, DeepLIFT, DeepSHAP, and GradCAM respectively.

To provide qualitative differences in the feature attribution based explanations and the debate explanations, we consider LIME (Ribeiro, Singh, and Guestrin 2016), DeepSHAP (Lundberg and Lee 2017), deepLIFT (Shrikumar, Greenside, and Kundaje 2017), and gradCAM (Selvaraju et al. 2017) methods. Figure 6 provides a visual explanations for the above mentioned methods. Most of these feature attribution methods provide simple input-output explanations. They do not motivate the idea of concepts’ existence, which limits many real applications to debug or reason about the underpinning model. Figure 7 describes the explanations obtained via debate; the first, second, and third row correspond to SHAPE, MNIST and AFHQ examples, demonstrating arguments in terms of unique features. More examples of MNIST, AFHQ, and SHAPE datasets are described in the appendix. Here, we do not claim about human understandability of these arguments; in this work, the interpretability of these arguments is completely subjective. When compared to existing post-hoc explanations, debate arguments provide additional insights to deduce the model’s reasoning. In the case of the SHAPE model, example described in the first row of Figure 7 Player $P_1$ claims the shape to be a star, while player $P_2$ claims it to be a circle. Here, we subjectively argue that the arguments made by player $P_1$ corresponds to the pointy regions and corners in the star, while player $P_2$ focuses more on center and corner regions. Similar interpretations can be deduced from an MNIST example (second row, Figure 7), where player $P_1$ focuses on different curvatures of digit and make the right claim as class 3, while player $P_2$ only focus on lower curvature of the digit making a wrong claim of class 5.

Figure 7: Debate explanations on CNN models trained on SHAPE, MNIST, and AFHQ datasets.

5 Conclusion

We defined a novel debate framework for generating post-hoc explanations. We experimentally demonstrated the convergence of player behaviour at Nash Equilibrium and the existence of different sets of features from which players can sample their arguments during debates, confirming our hypotheses. Our results on the SHAPE, MNIST, and AFHQ datasets show that our explanations provide added value when compared to feature attribution explanations.

We did not explore the possibility of assigning semantic meaning to arguments but analysed them subjectively. We believe our method can be further used for ontology alignment in terms of aligning the model’s latent knowledge to human knowledge. This formulation of debates can also be further explored to develop stand-alone transparent and aligned large scale visual models. We plan to extend this method with domain experts to assign semantic meaning to arguments and extract a high-level reasoning chain possibly used by classifiers in making decisions.
6 Acknowledgments

This study was supported by UKRI centre for Doctoral Training in Safe and Trusted AI (EPS023356/1).

References

Almada, M. 2019. Human intervention in automated decision-making: Toward the construction of contestable systems. In Proceedings of the Seventeenth International Conference on Artificial Intelligence and Law, 2–11.

Armstrong, S. L.; Gleitman, L. R.; and Gleitman, H. 1983. What some concepts might not be. Cognition, 13(3): 263–308.

Baroni, P.; Rago, A.; and Toni, F. 2018. How many properties do we need for gradual argumentation? In Proceedings of the AAAI Conference on Artificial Intelligence, volume 32.

Bau, D.; Zhou, B.; Khosla, A.; Oliva, A.; and Torralba, A. 2017. Network dissection: Quantifying interpretability of deep visual representations. In Proceedings of the IEEE conference on computer vision and pattern recognition, 6541–6549.

Bayamlioglu, E. 2018. Contesting automated decisions. Eur. Data Prot. L. Rev., 4: 433.

Bibal, A.; Lognoul, M.; De Stroef, A.; and Frénay, B. 2021. Legal requirements on explainability in machine learning. Artificial Intelligence and Law, 29(2): 149–169.

Burnston, D. C.; and Haueis, P. 2021. Evolving concepts of “hierarchy” in systems neuroscience. In Neural Mechanisms, 113–141. Springer.

Cayrol, C.; and Lagasquie-Schiex, M.-C. 2005. On the acceptability of arguments in bipolar argumentation frameworks. In European Conference on Symbolic and Quantitative Approaches to Reasoning and Uncertainty, 378–389. Springer.

Chattopadhay, A.; Sarkar, A.; Howlader, P.; and Balasubramanian, V. N. 2018. Grad-cam++: Generalized gradient-based visual explanations for deep convolutional networks. In 2018 IEEE winter conference on applications of computer vision (WACV), 839–847. IEEE.

Choi, Y.; Uh, Y.; Yoo, J.; and Ha, J.-W. 2020. Stargan v2: Diverse image synthesis for multiple domains. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, 8188–8197.

Čyras, K.; Rago, A.; Albini, E.; Baroni, P.; and Toni, F. 2021. Argumentative XAI: a survey. arXiv preprint arXiv:2105.11266.

Dataset, K. S. 2016. SHAPES Dataset. https://www.kaggle.com/datasets/smgeschke/fourseashapes?resource=download.

Deng, L. 2012. The mnist database of handwritten digit images for machine learning research [best of the web]. IEEE signal processing magazine, 29(6): 141–142.

Doshi-Velez, F.; Budish, R.; and Kortz, M. 2017. The Role of Explanation in Algorithmic Trust. Technical report, Technical report, Artificial Intelligence and Interpretable Working Group . . . .

Dung, P. M. 1995. On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. Artificial intelligence, 77(2): 321–357.

Ghandeharioun, A.; Kim, B.; Li, C.-L.; Jou, B.; Eooff, B.; and Picard, R. W. 2021. DISSECT: Disentangled Simultaneous Explanations via Concept Traversals. arXiv preprint arXiv:2105.15164.

Ghorbani, A.; Wexler, J.; Zou, J.; and Kim, B. 2019. Towards automatic concept-based explanations. arXiv preprint arXiv:1902.03129.

Goyal, Y.; Wu, Z.; Ernst, J.; Batra, D.; Parikh, D.; and Lee, S. 2019. Counterfactual visual explanations. In International Conference on Machine Learning, 2376–2384. PMLR.

Hirsch, T.; Merced, K.; Narayanan, S.; Imel, Z. E.; and Atkins, D. C. 2017. Designing contestability: Interaction design, machine learning, and mental health. In Proceedings of the 2017 Conference on Designing Interactive Systems, 95–99.

Irving, G.; Christiano, P.; and Amodei, D. 2018. AI safety via debate. arXiv preprint arXiv:1805.00899.

Kenny, E. M.; and Keane, M. T. 2021. On generating plausible counterfactual and semi-factual explanations for deep learning. In Proceedings of the AAAI Conference on Artificial Intelligence, volume 35, 11575–11585.

Kim, B.; Wattenberg, M.; Gilmer, J.; Cai, C.; Wexler, J.; Viegas, F.; et al. 2018. Interpretability beyond feature attribution: Quantitative testing with concept activation vectors (tcav). In International conference on machine learning, 2668–2677. PMLR.

Klutz, D. N.; Kohli, N.; and Mulligan, D. K. 2022. Shaping our tools: Contestability as a means to promote responsible algorithmic decision making in the professions. In Ethics of Data and Analytics, 420–428. Auerbach Publications.

Kori, A.; Glocker, B.; and Toni, F. 2022. GLANCE: Global to Local Architecture-Neutral Concept-based Explanations. arXiv preprint arXiv:2207.01917.

Kori, A.; Natekar, P.; Srivinasan, B.; and Krishnamurthi, G. 2021. Interpreting deep neural networks for medical imaging using concept graphs. In International Workshop on Health Intelligence, 201–216. Springer.

Kroll, J. A. 2015. Accountable algorithms. Ph.D. thesis, Princeton University.

Lakkaraju, H.; Slack, D.; Chen, Y.; Tan, C.; and Singh, S. 2022. Rethinking Explainability as a Dialogue: A Practitioner’s Perspective. arXiv preprint arXiv:2202.01875.

Lampinen, A. K.; Roy, N. A.; Dasgupta, I.; Chan, S. C.; Tam, A. C.; McClelland, J. L.; Yan, C.; Santoro, A.; Rabinowitz, N. C.; Wang, J. X.; et al. 2021. Tell me why!–Explanations support learning of relational and causal structure. arXiv preprint arXiv:2112.03753.

Lundberg, S. M.; and Lee, S.-I. 2017. A Unified Approach to Interpreting Model Predictions. In Guyon, I.; Luxburg, U. V.; Bengio, S.; Wallach, H.; Fergus, R.; Vishwanathan, S.; and Garnett, R., eds., Advances in Neural Information Processing Systems, volume 30. Curran Associates, Inc.
Lyons, H.; Velloso, E.; and Miller, T. 2021. Conceptualising contestability: Perspectives on contesting algorithmic decisions. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1): 1–25.

Mnih, V.; Heess, N.; Graves, A.; et al. 2014. Recurrent models of visual attention. *Advances in neural information processing systems*, 27.

Narayanaswamy, A.; Venugopalan, S.; Webster, D. R.; Peng, L.; Corrado, G. S.; Ruamviboonsuk, P.; Bavishi, P.; Brenner, M.; Nelson, P. C.; and Varadarajan, A. V. 2020. Scientific discovery by generating counterfactuals using image translation. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 273–283. Springer.

Nash, J. 1951. Non-cooperative games. *Annals of mathematics*, 286–295.

Olah, C.; Cammarata, N.; Schubert, L.; Goh, G.; Petrov, M.; and Carter, S. 2020. *Zoom In: An Introduction to Circuits*. *Distill*. Https://distill.pub/2020/circuits/zoom-in.

Olah, C.; Mordvintsev, A.; and Schubert, L. 2017. Feature Visualization. *Distill*. Https://distill.pub/2017/feature-visualization.

Peebles, W.; Peebles, J.; Zhu, J.-Y.; Efros, A.; and Torralba, A. 2020. The hessian penalty: A weak prior for unsupervised disentanglement. In *European Conference on Computer Vision*, 581–597. Springer.

Ribeiro, M. T.; Singh, S.; and Guestrin, C. 2016. “Why should i trust you?” Explaining the predictions of any classifier. In *Proceedings of the 22nd ACM SIGKDD international conference on knowledge discovery and data mining*, 1135–1144.

Santhirasekaram, A.; Kori, A.; Rockall, A.; Winkler, M.; Toni, F.; and Glocker, B. 2022. Hierarchical Symbolic Reasoning in Hyperbolic Space for Deep Discriminative Models. arXiv preprint arXiv:2207.01916.

Sattarzadeh, S.; Sudhakar, M.; Plataniotis, K. N.; Jang, J.; Jeong, Y.; and Kim, H. 2021. Integrated Grad-CAM: Sensitivity-Aware Visual Explanation of Deep Convolutional Networks via Integrated Gradient-Based Scoring. In *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, 1775–1779. IEEE.

Selvaraju, R. R.; Cogswell, M.; Das, A.; Vedantam, R.; Parikh, D.; and Batra, D. 2017. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE international conference on computer vision*, 618–626.

Shrikumar, A.; Greenside, P.; and Kundaje, A. 2017. Learning important features through propagating activation differences. In *International conference on machine learning*, 3145–3153. PMLR.

Society, R. 2022.

Stammer, W.; Schramowski, P.; and Kersting, K. 2021. Right for the right concept: Revising neuro-symbolic concepts by interacting with their explanations. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 3619–3629.
7 Debate Objective

As previously described, the joint objective in a minmax format can be described as:

\[
V(\mathcal{P}_{\theta^1}, \mathcal{P}_{\theta^2}) = \min_{\theta^1} \max_{\theta^2} \mathbb{E} \left[ \sum_t \log \Pi_{\theta^1}(h_t^1 | \hat{z}_t, \hat{y}) \mathcal{U}_t^1(S^1, S^2) \right] - \mathbb{E} \left[ \sum_t \log \Pi_{\theta^2}(h_t^2 | \hat{z}_t, \hat{y}) \mathcal{U}_t^2(S^1, S^2) \right]
\]

(3)

Based on our argument strength and utility definition, we can claim that the utility \( \mathcal{U}^1 > 0 \) iff the majority of the arguments have positive argument strength. This ensures that the sampled arguments belong to the semifactual feature set (features, when masked affect class probability but not class outcome). While for player \( \mathcal{P}^2 \) we can claim that utility \( \mathcal{U}^2 > 0 \) the majority of features that are sampled as arguments belong to the counterfactual feature set (features when masked affect the class probability and class outcome).

With this knowledge, if we binarize the utility values, we can restructure the debate objective defined in Equation 3 as follows:

\[
\hat{V}(\mathcal{P}_{\theta^1}, \mathcal{P}_{\theta^2}) = \min_{\theta^1} \max_{\theta^2} \mathbb{E} \left[ \sum_t \log \Pi_{\theta^1}(\cdot) \right] - \mathbb{E} \left[ \sum_t \log \Pi_{\theta^2}(\cdot) \right]
\]

(4)

such that: \( \mathcal{A}_{\theta^1}^1 \subseteq z_1, \mathcal{A}_{\theta^2}^2 \subseteq z_2 \)

Where \( z_1 \) and \( z_2 \) correspond to semifactual and counterfactual feature set. This brings us to our second Hypothesis, which argues about the existence of \( z_1 \) and \( z_2 \), such that \( z_1, z_2 \subseteq z \) such that \( z_1 \cup z_2 = z \) and \( z_1 \cap z_2 = \phi \) and at convergence forces arguments to follow \( \Pi_{\theta^1}^1(\cdot) = \mathbb{P}(z_1), \Pi_{\theta^2}^2(\cdot) = \mathbb{P}(z_2) \).

8 Pre-trained models

Models on MNIST and SHAPE datasets: For both MNIST and SHAPE datasets, we use the same custom architecture consisting 7 convolutional layers with \( 3 \times 3 \) kernel with batch-norm and ReLU activation layer. Finally, we project the global average pooled vector onto a class probability space using a linear layer followed by softmax activation. To reduce the dimensionality of features, we apply the max pooling layer after the first, third, and fifth layers. We train this classifier for 50 epochs with a batch size of 64. We use Adam optimiser with an initial learning rate of 0.001 and weight decay of 0.001. We achieve 99.3% accuracy with this pre-trained classifier.

Model for AFHQ dataset: For evaluating our framework on high resolution images, we consider the standard DenseNet-121 architecture and train the model on the AFHQ dataset. We use Adam optimiser with an initial learning rate of 0.001 and weight decay of 0.005. The model is trained for 64 epochs achieving 98% accuracy.

9 Codebook Ablation and Argument Properties

Here, in this ablation study, we restrict our analysis to committed debates. To understand the effect of codebook size on debate accuracy and argument properties, we also tabulate the resulting debate outcome accuracy and split ratio as a result of codebook size and debate length variation.

Table 3 demonstrates the debate accuracy by varying codebook size and debate length on all three datasets, while Table 4 demonstrates the variation in split ratio with respect to debate length and codebook size.

Based on this ablation we claim that:

- The debate length helps in achieving better debate accuracy irrespective of codebook size. However, the improvement in performance plateaus after certain length, depending upon dataset.
- Increase in codebook size has an effect on debate performance; we believe this might be because after a certain threshold over codebook size, it makes it easier for players to differentiate between \( z_1 \) and \( z_2 \).

10 Additional Results

Figure 8, 9, 10, and 11 demonstrates the visual debates on several other examples from SHAPE, MNIST, and AFHQ datasets on multiple debate lengths. Note that we don’t claim anything about human understandability of arguments generated, which we plan to extend in future work.
Figure 8: Debate explanations on CNN models trained on SHAPE, MNIST, and AFHQ datasets for debate length 4.
Table 3: Debate accuracy by varying codebook size (total number of discrete features) on SHAPE, MNIST, and AFHQ datasets.

| Codebook Size in $E$ | SHAPE | MNIST | AFHQ |
|----------------------|-------|-------|------|
| 1024                 | 0.61  | 0.74  | 0.83 | 0.79 |
| 512                  | 0.63  | 0.79  | 0.83 | 0.83 |
| 256                  | 0.61  | 0.78  | 0.78 | 0.82 |
| 128                  | 0.59  | 0.82  | 0.93 | 0.94 |
| 64                   | 0.58  | 0.80  | 0.93 | 0.94 |

Table 4: Split ratio by varying codebook size (total number of discrete features) on SHAPE, MNIST, and AFHQ datasets.

| Codebook Size in $E$ | SHAPE | MNIST | AFHQ |
|----------------------|-------|-------|------|
| 1024                 | 0.53  | 0.52  | 0.60 | 0.60 |
| 512                  | 0.53  | 0.58  | 0.56 | 0.56 |
| 256                  | 0.50  | 0.58  | 0.58 | 0.58 |
| 128                  | 0.59  | 0.60  | 0.82 | 0.88 |
| 64                   | 0.58  | 0.60  | 0.88 | 0.94 |

Figure 9: Debate explanations on CNN models trained on SHAPE, MNIST, and AFHQ datasets for debate length 6.
Figure 10: Debate explanations on CNN models trained on SHAPE, MNIST, and AFHQ datasets for debate length 10.

Figure 11: Debate explanations on CNN models trained on SHAPE, MNIST, and AFHQ datasets for debate length 20.