Bluff-Bot

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Abstract

Deep reinforcement learning (DRL) has achieved remarkable success in perfect-information games, yet applying these techniques to environments with hidden information and strategic deception remains an open challenge. In this work, we introduce Bluff-Bot, an intelligent agent designed to operate in Bluff Game, a simplified, variant of Texas hold'em, an incomplete information game. Unlike traditional poker AI, Bluff-Bot does not rely on predefined heuristics but instead learns to model opponent behavior and come up with near-optimal decision-making strategies under uncertainty. We first implement a baseline Deep Q-Network (DQN) agent, demonstrating that reinforcement learning can adapt to imperfect-information environments. However, due to the deterministic limitations of Q-learning, we propose a novel alternative: a Variational Autoencoder (VAE)-inspired approach with an LSTM-based continuous encoder that estimates hidden opponent states as a probabilistic latent representation. This probabilistic modeling would allow Bluff-Bot to reason about uncertainty and deploy mixed strategies, approximating Nash equilibrium solutions. This paper demonstrates the potential of probabilistic deep learning frameworks in imperfect-information settings and provides a foundation for future advancements in strategic AI decision-making.

1 Introduction

Deep reinforcement learning has demonstrated remarkable success across a wide range of domains, from mastering Atari games to conquering board games like Go. However, applying these techniques to games where agents only receive **partial information** from the environment remains a challenge. In this work, we introduce *Bluff-Bot*, an intelligent agent designed to adapt robustly to various adversarial opponents in a modified version of Texas hold'em, which we call *Bluff Game*.

With a focus on training agents to operate effectively under **incomplete information**, *Bluff Game* eliminates the need to learn intricate game-specific rules and heuristics, such as assessing the relative strengths of card combinations. This allows our agent *Bluff-Bot* to instead focus on modeling opponent behavior and making **informed decisions despite uncertainty**. By leveraging reinforcement learning and neural networks, our agent dynamically adapts to opponents, refines its strategy through experience, and optimizes decision-making in complex, hidden-information environments.

2 Problem

We have simulated a simplified version of Texas hold'em called *Bluff Game* by using *RLCard* [1], described in Section 3.1.

In *Bluff Game*, each round, every player is assigned a random integer value between 1 and 10 in the form of a card, representing the strength of their hand—where 1 is the weakest and 10 is the strongest. On their turn, which occurs multiple times within a round, players can choose from four standard actions: **check, call, raise, or fold**. The game follows traditional *Texas Hold'em* rules for small and big blinds (required initial bets), round termination, and determining the winner. Additionally, two adjustable parameters can influence the game's dynamics: the **number of rounds per game** and the **maximum number of raises per round**. Unlike *Texas Hold'em*, there are no public cards or shared values; each player only knows their own hand strength and the number of chips each player is

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betting. To simplify the game, we assume that each player has an unlimited supply of chips. However, to prevent unrestricted betting, a fixed betting structure is imposed. Raises occur in increments of 5 chips, with a maximum bet cap of 100 per round, ensuring that the game remains focused on decision-making under uncertainty rather than resource hacking.

In this modified version, each agent's available information can be classified as follows in Table 1:

Information Type	Details
Complete Information	Player Card/Value
	Each Player's Chip Bet for the Round
Incomplete Information	Adversarial Card/Value
	Adversarial Betting Patterns
	Adversarial Bluffing Patterns

Table 1: Complete vs. Incomplete Information in the Game

To develop an agent that can navigate this game, we must first understand the problem better. Unlike **perfect-information games**, where all relevant details are available, *Bluff Game* introduces uncertainty through hidden information and strategic deception. Players can bluff by misrepresenting their hand strength—either by over-representing weak hands to induce folds or under-representing strong hands to extract larger bets. Since no physical tells exist in this setting, bluffing manifests purely through betting behavior [2].

This uncertainty makes poker particularly challenging for AI. Unlike deterministic games, where optimal strategies can be computed precisely, poker requires **decision-making under partial observability**. Game-theoretic approaches, such as **Nash equilibrium**, provide a theoretically optimal solution by modeling bluffing as a Bayesian inference problem. However, computing the exact Nash equilibrium is intractable in complex settings, making it impractical for real-time decision-making [3]. Instead, we aim to approximate it using a Bayesian approach, allowing the agent to infer hidden information by estimating an opponent's hand strength and playing style based on their past actions—cross-referenced with the outcomes revealed at the end of each round [4].

Given these challenges, our agent must not only estimate hidden information but also **adapt to opponent behavior**. Since betting decisions are based on uncertain information, a purely deterministic approach would fail to capture the complexity of the game. Instead, treating actions probabilistically [5] allows the model to balance exploration and exploitation, refining its decision-making over time while responding effectively to different playing styles.

3 Framework

3.1 Virtual Game Environment

To train our reinforcement learning agent, we first developed a virtual environment that simulates *Bluff Game*. This environment provides a controlled setting for agent training and evaluation, integrating a reinforcement learning framework to facilitate learning through self-play.

Our implementation is based on *RLCard*, a card game simulation toolkit developed by Zha et al. [1]. RLCard provides pre-configured environments for multiple card games and supports reinforcement learning algorithms for training agents. Each game environment in RLCard consists of five key files:

1. **judger.py**: Defines round termination conditions and reward distribution.
2. **dealer.py**: Manages deck composition, card values, and card distribution to players.
3. **player.py**: Represents player states, including hand strength, chip count, and available actions.
4. **round.py**: Oversees the betting rounds, tracking actions and updating the game state.
5. **game.py**: Initializes the game environment, including players, the dealer, and the judger, with betting rounds managed by a `Round` object.

Rather than building an environment from scratch, we modified *Leduc Hold'em*, an existing RLCard game, to align with our simplified bluffing mechanics (see Appendix A). The following summarizes the key modifications made to RLCard's five game files from Leduc Hold'em to simulate *Bluff Game*:

1. **judger.py**: Removed the public card comparison logic, as our game determines the winner solely based on private hand values.
2. **dealer.py**: Replaced face cards with integer values (1–10) and eliminated suits. The modified `Dealer.py` assigns values independently, ensuring a uniform hand strength distribution.
3. **player.py**: Removed public state from get_state method.
4. **round.py**: No modifications were made; the existing round management structure was sufficient.
5. **game.py**: Removed all mechanics related to public cards. Players receive one private card each, and small/big blinds are randomly assigned. Modified all methods related to observation space, as it has changed since there are more possible cards a player can obtain. The implemented game currently follows a two-round betting system, where the currently fixed raise amount doubles in the second round. Available actions remain standard (call, raise, fold, check), and payoffs are determined by the judger, normalized by the big blind. This will be modified later on to make the game more complex to provide a better environment for our agent.

The full implementation details, including code for the environment, dealer, player, and game logic, can be found in Appendix B.

3.2 Baseline Reinforcement Learning (RL) Algorithm

The RLCard framework provides multiple deep-learning algorithms for agent training. Since we have developed a new game, we will use an existing reinforcement learning (RL) framework to establish baseline performance and gameplay metrics. We implemented a **Deep Q-Network (DQN)** agent using a **multi-layer perceptron (MLP)** for Q-learning. While this approach allows us to evaluate the learnability of *Bluff Game*, it may not be optimal for handling **incomplete information** games; this will be further explored in Section 4.

Q-learning trains agents by estimating **Q-values**, representing the expected reward of taking an action in a given state. The Q-value update rule is given by:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_{t+1} + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right]$$

where $Q(s_t, a_t)$ is the Q-value for state-action pair (s_t, a_t), α is the learning rate, r_{t+1} is the reward, and γ is the discount factor.

Our current baseline model uses a **DQN agent** with a **replay memory** to store past transitions and train on batches of sampled experiences. The network architecture consists of **four MLP layers** with outputs of 64, 128, 64, and 32 neurons, followed by a final linear layer to estimate Q-values. Each MLP block applies a **Tanh activation function** to introduce non-linearity. To balance **exploration and exploitation**, the **epsilon-greedy strategy** [6] is used: the agent chooses a random action with probability ε and the greedy (best-estimated) action with probability $1 - \varepsilon$. The value of ε decays over time, initially favoring exploration and later shifting toward exploitation.

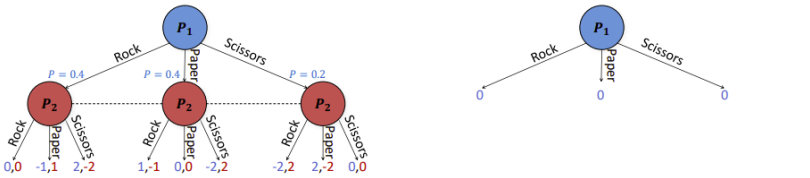
This approach helps prevent the agent from converging to suboptimal strategies while allowing it to refine its decision-making over time. However, Q-learning is known to struggle in **imperfect-information games** [5], as it assumes deterministic state-action evaluations, which may be insufficient for modeling hidden opponent behavior. We discuss an alternative novel approach to address this challenge in Section 4.

4 Comments on Baseline Approach

The baseline approach adopts a **Q-learning** approach with a fully connected neural network. However, prior research suggests that this method struggles in **imperfect-information** settings due to its reliance on fixed-value state-action evaluations [7].

4.1 Probabilistic State Values

A key example is the modified Rock-Paper-Scissors game introduced by Brown et al., where one player moves first, but their action remains hidden from the second player.



(1a) Variant of Rock-Paper-Scissors in which the optimal player 1 policy is (R=0.4, P=0.4, S=0.2). Terminal values are color-coded. The dotted lines mean player 2 does not know which node they are in.

(1b) The player 1 subgame when using perfect-information one-ply search. Leaf values are determined by the full-game equilibrium. There is insufficient information for finding (R=0.4, P=0.4, S=0.2).

Figure 1: Modified Rock-Paper-Scissors with Imperfect Information

In this scenario, the optimal strategy requires probabilistic action selection, but deterministic Q-learning fails to find this solution due to the lack of comprehensive state values. More broadly, imperfect-information games present a fundamental challenge: the value of an action is contingent on the probability that our observation is mapped to the correct perfect-information state. This makes deterministic, fixed-value learning approaches inadequate. While Q-learning provides useful heuristics for evaluating game learnability, it is insufficient for our setting. Instead, an approach that models the **distributional nature of state values** from action and observation sequences is essential for effective decision-making in imperfect-information scenarios.

4.2 Adapatbility vs. Multiple Agents

Q-learning is an RL algorithm designed for **single-agent** environments [8]. However, for poker-related games, any comprehensive agent must be able to play and succeed against multiple agents at a time. In its standard form, Q-learning assumes a stationary environment with fixed transition dynamics and reward structures. However, in the presence of multiple agents, the environment becomes non-stationary from each agent's perspective, as other agents are also learning and continuously updating their policies.

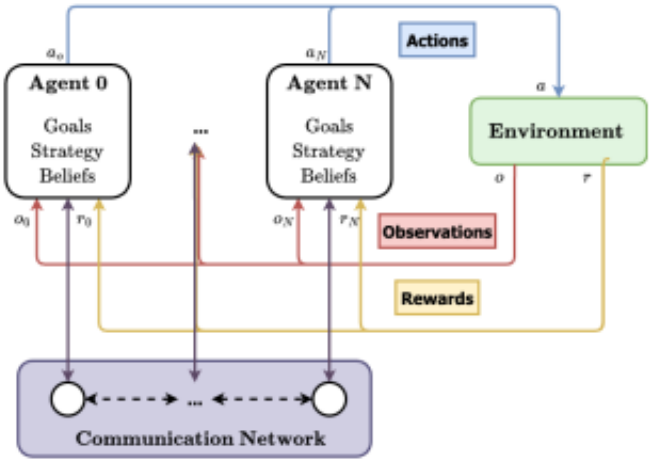


Figure 2: Generalized multi-agent system for multi-agent reinforcement learning

The diagram illustrates a multi-agent reinforcement learning (MARL) framework where multiple agents, each with their own goals, strategies, and beliefs, interact with a shared environment. Each agent receives individual observations and rewards based on the joint actions taken by all agents. A communication network allows agents to share information, enabling coordination or cooperation.

However, this setup presents significant challenges for standard Q-learning. Q-learning assumes a stationary environment, meaning the reward and transition dynamics do not change over time. In a multi-agent setting, this assumption breaks down because the behavior of other agents is constantly evolving as they learn, making the environment non-stationary from each agent's perspective [9]. This non-stationarity causes instability in Q-value updates, as past experiences become outdated and predictions less reliable. Consequently, Q-learning does not inherently account for communication between agents, making it ill-equipped to exploit the collaborative potential of the communication network. As a result, Q-learning often fails to converge or produces suboptimal policies in complex multi-agent environments like the one depicted.

5 Novel Approach: LSTM - Variational Autoencoder

5.1 General Architecture

To model the distribution of possible game states given our observations, we propose an approach similar to a **Variational Autoencoder (VAE)**. Our model utilizes an LSTM-based neural network as a continuous encoder, which takes as input the previously estimated state concatenated with the current observation and outputs a predicted next state. This predicted state functions analogously to the latent space in VAE architectures, where each dimension represents hidden information—with one crucial dimension encoding the opponent's hand strength and our agent's confidence in that estimate, modeled as a Gaussian distribution. Other latent dimensions can encode broader opponent characteristics, including aggressiveness, unpredictability, and patience, along with a measure of uncertainty regarding these traits. The Gaussian structure, defined by distinct mean and variance vectors, enables our model to represent latent states as probabilistic estimates that capture both expected values and their inherent uncertainty.

When it is the agent's turn to act, it transforms the Gaussian-distributed latent state representation into a probability distribution over Q-values for each available action using an **MLP decoder**, addressing the problem in Section 4.1. By sampling from these Q-value distributions, the model selects an action that balances strategic exploitation with unpredictability. This formulation enables the agent to reason probabilistically about the uncertainty inherent in imperfect-information games by approximating a model of the current situation that includes the unknown information. It also allows the integration of mixed strategies akin to Nash equilibrium solutions. Indeed, by introducing controlled randomness into its decision-making, the agent remains difficult for adversaries to exploit, particularly those attempting to model and counter its behavior. This approach allows the agent to refine its opponent modeling efficiently while simultaneously maximizing its expected long-term rewards.

This is illustrated in Figure 3.

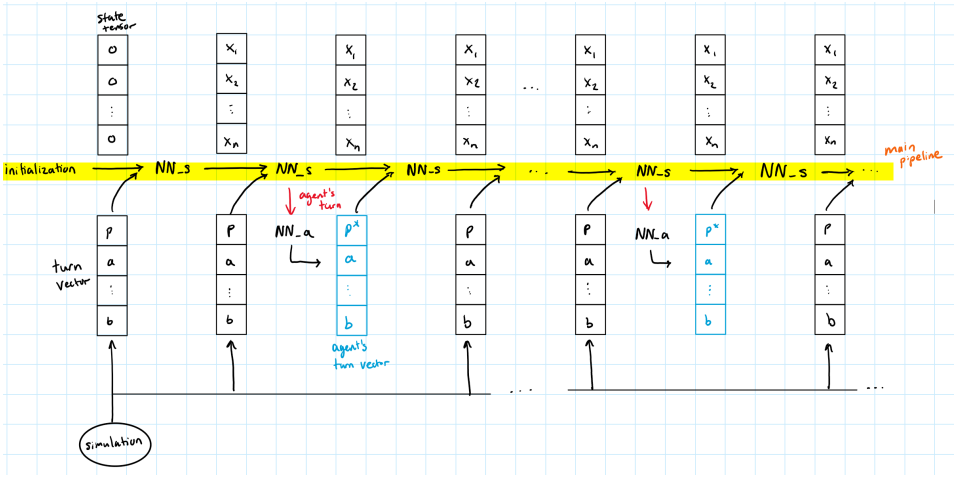


Figure 3: LSTM continuous encoder (NN_s) and MLP decoder (NN_a)

5.2 Training: Multi-Agent Environments

To develop a robust agent in a multi-agent setting, we extended RLCard by implementing a custom multi-agent training environment. Rather than limiting our agent's training to a single fixed oppo-

nent—such as a random agent, a rules-based agent, or even a static pretrained DQN—we created a dynamic training framework where learning alternates between multiple distinct agents (specifically, a standard DQN and our novel LSTM-VAE DQN) over fixed blocks of episodes.

Before describing the training process, we introduce two non-learning agents: the Random Agent and the Aggressive Agent. The Random Agent selects uniformly at random from the set of legal actions on its turn. Due to the extended game length—where the number of allowed raises was increased from 2 to 5—this randomness becomes highly exploitable. With a 1/3 chance of folding on each move, the probability that it eventually folds becomes quite high, making it vulnerable to strategies that simply keep raising to stay in the game.

Initially, our training environment included only the two learning agents and the Random Agent. However, we quickly observed that the learning agents were not truly learning to generalize or adapt—they were instead reward hacking by over-exploiting the Random Agent and largely ignoring each other.

To address this, we introduced the Aggressive Agent, a rules-based opponent that only raises or calls, never folding. This ensures that strategies which try to exploit the Random Agent by always raising will inevitably be punished, as the Aggressive Agent will "call the bluff" every time. Including this agent improves the robustness of the training setup and encourages the learning agents to develop strategies that are effective across a wider range of opponents, rather than overfitting to a single exploitable one.

During each training block, the active learning agent is paired with an opponent randomly chosen from a diverse pool: the fixed baseline agents (Random and Aggressive) and the other learning agent. By competing against both static and evolving opponents, each agent is forced to adapt to a broad variety of behaviors, fostering more generalizable and effective decision-making.

For details on the implementation and training setup, see Appendix C, which also includes the architectural specifics of all four agents used in this multi-agent training environment.

6 General Results

6.1 Reward Graphs for DQN and LSTM-VAE DQN against Random Agent

According to RLCard, rewards are measured in big blinds per hand, where a reward of 0.5 (-0.5) indicates that the player wins (loses) 0.5 times the big blind amount. For this experiment, we set the big blind to 2 units.

We first conducted a training run of the DQN and LSTM-VAE DQN agent in Bluff Game against Random Agents, with each game consisting of a single round and allowing up to two raises per player. This resulted in a better learned exploitation strategy from the LSTM-VAE DQN agent which converged to approximately a reward of 2 as opposed to the vanilla DQN which only converged to approximately a reward of 1.5. For complete graphs of reward progression, refer to Appendix D

6.1.1 DQN and LSTM-VAE DQN in Multi-Agent Environment

We then transitioned to the aforementioned Multi-Agent Environment with up to 5 raises allowed.

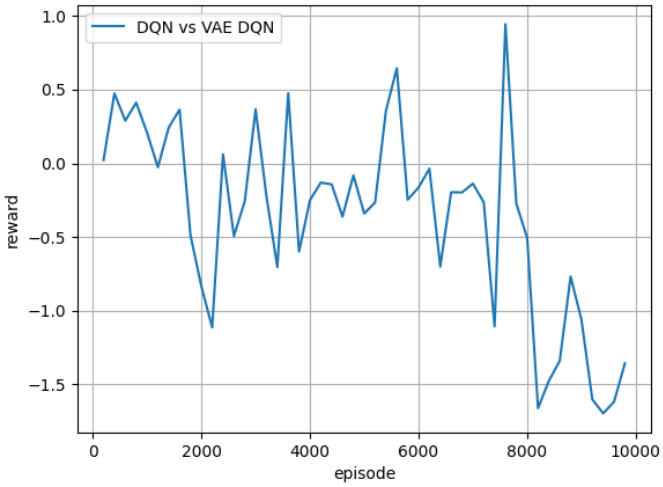


Figure 4: DQN vs LSTM-VAE DQN over 10000 episodes with both training

In the figure above, the vanilla DQN agent initially performs reasonably well, achieving rewards comparable to those of the LSTM-VAE DQN against each of the other agents (see Appendix D). In fact, it even occasionally outperforms the LSTM-VAE DQN in head-to-head evaluations conducted every 100 games during training. However, this early promise quickly fades as the vanilla DQN fails to adapt to both the evolving behavior of the LSTM-VAE DQN and the vastly different playstyles of the Aggressive and Random agents.

The core issue lies in the architecture of the vanilla DQN: it is both deterministic and lacks any explicit mechanism for state approximation. This severely limits its ability to infer which opponent it is currently facing, making it incapable of strategic adaptation. As a result, it converges to a local minimum—opting to consistently exploit the Random Agent, which offers the easiest and most immediate reward signal. While this does lead to slightly higher performance against the Random Agent compared to the LSTM-VAE DQN, it ultimately fails in broader terms, losing both to the Aggressive Agent and in direct competition with the LSTM-VAE DQN.

In contrast, the LSTM-VAE DQN demonstrates a much higher degree of adaptability. The LSTM component allows it to utilize past observations, while the VAE contributes a more expressive and compact representation of state information. This includes not only an inferred belief about the opponent's card strength, but also a probabilistic estimate of which agent it is currently facing—information that directly influences the Q-value predictions through a shared linear layer.

One additional hypothesis—still under investigation but supported by qualitative observations from specific games—is that the non-deterministic nature of the LSTM-VAE DQN allows it to occasionally "trick" its opponent. That is, even when observing the same sequence of states or history, it may play differently, leading the opponent to falsely assume it's facing a particular agent, and then capitalizing on that mistaken belief.

Ultimately, these capabilities enable the LSTM-VAE DQN to significantly outperform all other agents, achieving reward scores greater than 1.0 against each opponent (see Appendix D). By contrast, the vanilla DQN records losses of at least -0.5 against both the LSTM-VAE DQN and the Aggressive Agent, further underscoring its failure to generalize.

6.2 Empirical Analysis of move distributions between LSTM-VAE DQN Agent and DQN Agent

It is insightful to analyze the action distributions of the two trained agents to better understand their learned policies and how they evaluate the effectiveness of different moves within the game.

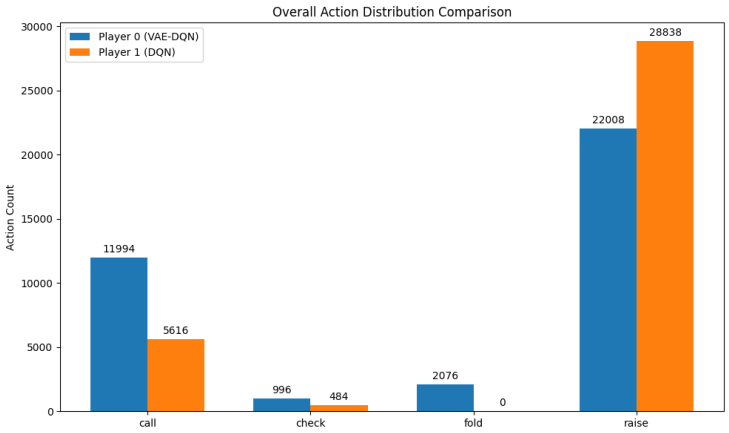


Figure 5: Action Distibutions of DQN and LSTM-VAE DQN in Head to Head

As shown in the figure above, the vanilla DQN agent exhibits a markedly more aggressive playstyle. This behavior likely stems from its strategy of maximizing rewards by consistently exploiting the Random Agent. Since raising repeatedly is an effective and straightforward approach against the Random Agent, the DQN converges on this pattern—even if it means underperforming against both the LSTM-VAE DQN and the Aggressive Agent. This is reflected in its move distribution, which heavily favors raising and calling, while almost never folding.

In contrast, our LSTM-VAE DQN agent displays a much more balanced and adaptive distribution of actions. Notably, it makes use of folding with meaningful frequency, which is a crucial behavior when facing highly aggressive opponents such as the DQN and Aggressive Agents. This suggests that the LSTM-VAE DQN has learned to recognize when folding is strategically advantageous, allowing it to better respond to a variety of playstyles and thereby achieve more consistent performance across opponents.

6.3 LSTM-VAE DQN Agent Hyperparameter Tuning

Due to the heavy computational cost of training, requiring tens of thousands of episodes for stabilization, extensive hyperparameter tuning was not feasible. Instead, we adversarially selected hyperparameters for the vanilla DQN in an effort to outperform our DQN agent. For example, one configuration involved reducing the number of parameters in the DQN and lowering its learning rate, making generalization more challenging. Although this adjustment diminished our LSTM-VAE DQN's win margin, it still maintained a respectable advantage. Two additional adversarial hyperparameter combinations are discussed in Appendix E.

7 Conclusion

In conclusion, our results indicate that integrating an LSTM-based VAE into the DQN framework enhances strategic decision-making in imperfect-information games by effectively capturing hidden states and adapting to diverse opponents through probabilistic reasoning and mixed strategies. Moreover, the split architecture's ability to incorporate intermediate reward signals improves training efficiency, guiding a dynamic balance between exploration and exploitation that drives convergence toward Nash equilibrium strategies.

7.1 Future Work

For future work, we aim to explore more complex multi-agent scenarios, refine intermediate reward signals, and further optimize the balance between exploration and exploitation to better approximate Nash equilibria in adversarial settings.

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Scope Change Statement.

We are not changing the scope of our proposal. The context and goals of our project remain as originally outlined in the initial proposal.

A Leduc Hold'em Overview

Leduc Hold'em is a simplified version of *Limit Texas Hold'em*, introduced in *Bayes' Bluff: Opponent Modeling in Poker* [4]. It uses a **six-card deck**, consisting of two copies of each rank (King, Queen, Jack), and features two betting rounds. Each game follows these steps:

1. Each player posts an initial blind bet and is dealt one private card.
2. Players place bets in the first round.
3. A single public card is revealed.
4. Players place bets in the second round.
5. The player whose private card matches the public card wins; otherwise, the higher-ranked private card wins.

We used Leduc Hold'em as the basis for our game environment due to its **structured betting mechanics** and **reduced game complexity**, making it an ideal starting point for modifying into *Bluff Game*.

B Bluff Game Implementation Details

This section provides the implementation details of *Bluff Game*, including the game environment, dealer, player, and round management. The following code snippets outline our modifications to the RLCard framework:

B.1 Game Environment

```
# game.py - Contains classes necessary to initialize game
    environment

class BluffGame(Game):

    def __init__(self, allow_step_back=False, num_players=2):
        ''' Initialize the class bluffgame Game
        '''
        self.allow_step_back = allow_step_back
        self.np_random = np.random.RandomState()
        ''' No big/small blind
        # Some configarations of the game
        # These arguments are fixed in Bluff-Game

        # Raise amount and allowed times
        self.raise_amount = 2
        self.allowed_raise_num = 2

        self.num_players = 2
        '''
        # Some configarations of the game
        # These arguments can be specified for creating new games

        # Small blind and big blind
        self.small_blind = 1
        self.big_blind = 2 * self.small_blind

        # Raise amount and allowed times
        self.raise_amount = self.big_blind
        self.allowed_raise_num = 2

        self.num_players = num_players

    def configure(self, game_config):
```

```
        ''' Specifiy some game specific parameters, such as number
            of players
        '''
        self.num_players = game_config['game_num_players']

    def init_game(self):
        ''' Initialilze the game of Limit Texas Hold'em

        This version supports two-player limit texas hold'em

        Returns:
            (tuple): Tuple containing:

                (dict): The first state of the game
                (int): Current player's id
        '''
        # Initilize a dealer that can deal cards
        self.dealer = Dealer(self.np_random)

        # Initilize two players to play the game
        self.players = [Player(i, self.np_random) for i in range(
            self.num_players)]

        # Initialize a judger class which will decide who wins in
            the end
        self.judger = Judger(self.np_random)

        # Prepare for the first round
        for i in range(self.num_players):
            self.players[i].hand = self.dealer.deal_card()
        # Randomly choose a small blind and a big blind
        s = self.np_random.randint(0, self.num_players)
        b = (s + 1) % self.num_players
        self.players[b].in_chips = self.big_blind
        self.players[s].in_chips = self.small_blind

        # The player with small blind plays the first
        self.game_pointer = s

        # Initilize a bidding round, in the first round, the big
            blind and the small blind needs to
        # be passed to the round for processing.
        self.round = Round(raise_amount=self.raise_amount,
                           allowed_raise_num=self.
                               allowed_raise_num,
                           num_players=self.num_players,
                           np_random=self.np_random)

        self.round.start_new_round(game_pointer=self.game_pointer,
            raised=[p.in_chips for p in self.players])

        # Count the round. There are 2 rounds in each game.
        self.round_counter = 0

        # Save the hisory for stepping back to the last state.
        self.history = []

        state = self.get_state(self.game_pointer)
```

```
        return state, self.game_pointer

    def step(self, action):
        ''' Get the next state

        Args:
            action (str): a specific action. (call, raise, fold,
                or check)

        Returns:
            (tuple): Tuple containing:

                (dict): next player's state
                (int): next plater's id
        '''
        if self.allow_step_back:
            # First snapshot the current state
            r = copy(self.round)
            r_raised = copy(self.round.raised)
            gp = self.game_pointer
            r_c = self.round_counter
            d_deck = copy(self.dealer.deck)
            ps = [copy(self.players[i]) for i in range(self.
                num_players)]
            ps_hand = [copy(self.players[i].hand) for i in range(
                self.num_players)]
            self.history.append((r, r_raised, gp, r_c, d_deck, ps,
                ps_hand))

        # Then we proceed to the next round
        self.game_pointer = self.round.proceed_round(self.players,
            action)

        # If a round is over, ...
        if self.round.is_over():
            #Double the raise amount for the second round
            if self.round_counter == 0:
                self.round.raise_amount = 2 * self.raise_amount

            self.round_counter += 1
            self.round.start_new_round(self.game_pointer)

        state = self.get_state(self.game_pointer)

        return state, self.game_pointer

    def get_state(self, player):
        ''' Return player's state

        Args:
            player_id (int): player id

        Returns:
            (dict): The state of the player
        '''
        chips = [self.players[i].in_chips for i in range(self.
            num_players)]
        legal_actions = self.get_legal_actions()
```

```
        state = self.players[player].get_state(chips,
            legal_actions)
        state['current_player'] = self.game_pointer

        return state

    def is_over(self):
        ''' Check if the game is over

        Returns:
            (boolean): True if the game is over
        '''
        alive_players = [1 if p.status=='alive' else 0 for p in
            self.players]
        # If only one player is alive, the game is over.
        if sum(alive_players) == 1:
            return True

        # If all rounds are finshed
        if self.round_counter >= 2:
            return True
        return False

    def get_payoffs(self):
        ''' Return the payoffs of the game

        Returns:
            (list): Each entry corresponds to the payoff of one
                player
        '''
        chips_payoffs = self.judger.judge_game(self.players)
        payoffs = np.array(chips_payoffs) / (self.big_blind)
        return payoffs

    def step_back(self):
        ''' Return to the previous state of the game

        Returns:
            (bool): True if the game steps back successfully
        '''
        if len(self.history) > 0:
            self.round, r_raised, self.game_pointer, self.
                round_counter, d_deck, self.players, ps_hand =
                self.history.pop()
            self.round.raised = r_raised
            self.dealer.deck = d_deck
            for i, hand in enumerate(ps_hand):
                self.players[i].hand = hand
            return True
        return False

# bluffgame.py - Initializes the game environment

DEFAULT_GAME_CONFIG = {
        'game_num_players': 2,
        }

class BluffGameEnv(Env):
    ''' bluff-game Environment
```

```
'''

def __init__(self, config):
    ''' Initialize the Limitholdem environment
    '''
    self.name = 'bluffgame'
    self.default_game_config = DEFAULT_GAME_CONFIG
    self.game = Game()
    super().__init__(config)
    self.actions = ['call', 'raise', 'fold', 'check']
    self.state_shape = [[40] for _ in range(self.num_players)]
        #? what is 40 --> observation size
    self.action_shape = [None for _ in range(self.num_players)
       ]

    with open(os.path.join(rlcard.__path__[0], 'games/
       bluffgame/card2index.json'), 'r') as file:
        self.card2index = json.load(file)

def _get_legal_actions(self):
    ''' Get all leagal actions

    Returns:
        encoded_action_list (list): return encoded legal
            action list (from str to int)
    '''
    return self.game.get_legal_actions()

def _extract_state(self, state):
    ''' Extract the state representation from state dictionary
        for agent

    Args:
        state (dict): Original state from the game

    Returns:
        observation (list): combine the player's score and
            dealer's observable score for observation
    '''
    extracted_state = {}

    legal_actions = OrderedDict({self.actions.index(a): None
       for a in state['legal_actions']})
    extracted_state['legal_actions'] = legal_actions

    hand = state['hand']
    obs = np.zeros(40) # Changed all obs
    obs[self.card2index[hand]] = 1
    obs[state['my_chips']+10] = 1
    obs[sum(state['all_chips'])-state['my_chips']+25] = 1 #???
    extracted_state['obs'] = obs

    extracted_state['raw_obs'] = state
    extracted_state['raw_legal_actions'] = [a for a in state['
       legal_actions']]
    extracted_state['action_record'] = self.action_recorder

    return extracted_state
```

```
    def get_payoffs(self):
        ''' Get the payoff of a game

        Returns:
            payoffs (list): list of payoffs
        '''
        return self.game.get_payoffs()

    def _decode_action(self, action_id):
        ''' Decode the action for applying to the game

        Args:
            action id (int): action id

        Returns:
            action (str): action for the game
        '''
        legal_actions = self.game.get_legal_actions()
        if self.actions[action_id] not in legal_actions:
            if 'check' in legal_actions:
                return 'check'
            else:
                return 'fold'
        return self.actions[action_id]

    def get_perfect_information(self):
        ''' Get the perfect information of the current state

        Returns:
            (dict): A dictionary of all the perfect information of
                the current state
        '''
        state = {}
        state['chips'] = [self.game.players[i].in_chips for i in
           range(self.num_players)]
        state['hand_cards'] = [self.game.players[i].hand.get_index
           () for i in range(self.num_players)]
        state['current_round'] = self.game.round_counter
        state['current_player'] = self.game.game_pointer
        state['legal_actions'] = self.game.get_legal_actions()
        return state
```

B.2 Dealer Implementation

```
# dealer.py - Handles card distribution
class BluffDealer(Dealer):

    def __init__(self, np_random):
        ''' Initialize a bluff-game dealer class
        '''
        self.np_random = np_random
        self.deck = [Card('S', 'A'), Card('S', '2'), Card('S',
            '3'), Card('S', '4'), Card('S', '5'), Card('S', '6'),
           Card('S', '7'), Card('S', '8'), Card('S', '9'), Card('
           S', 'T'),
                     Card('H', 'A'), Card('H', '2'), Card('H',
                         '3'), Card('H', '4'), Card('H', '5'),
                        Card('H', '6'), Card('H', '7'), Card('H',
                          '8'), Card('H', '9'), Card('H', 'T')]
        self.shuffle()
```

```
        self.pot = 0
```

B.3 Player Implementation

```
# player.py - Defines player state
class BluffPlayer:

    def __init__(self, player_id, np_random):
        ''' Initilize a player.

        Args:
            player_id (int): The id of the player
        '''
        self.np_random = np_random
        self.player_id = player_id
        self.status = 'alive'
        self.hand = None

        # The chips that this player has put in until now
        self.in_chips = 0

    def get_state(self, all_chips, legal_actions):
        ''' Encode the state for the player

        Args:
            all_chips (int): The chips that all players have put
                in

        Returns:
            (dict): The state of the player
        '''
        # removed public state from get_state method
        state = {}
        state['hand'] = self.hand.get_index()
        state['all_chips'] = all_chips
        state['my_chips'] = self.in_chips
        state['legal_actions'] = legal_actions
        return state

    def get_player_id(self):
        ''' Return the id of the player
        '''
        return self.player_id
```

B.4 Round Management

```
# round.py - Manages betting rounds
class BluffRound(Round):
    ''' Round can call other Classes' functions to keep the game
        running
    '''

    def __init__(self, raise_amount, allowed_raise_num,
        num_players, np_random):
        ''' Initilize the round class

        Args:
            raise_amount (int): the raise amount for each raise
            allowed_raise_num (int): The number of allowed raise
                num
```

```
            num_players (int): The number of players
        '''
        super(BluffRound, self).__init__(raise_amount,
            allowed_raise_num, num_players, np_random=np_random)
```

These modifications create a simplified environment that retains the fundamental aspects of bluffing, allowing us to focus on solving the problem of decision making under uncertainty instead of being sidetracked by game-specific mechanics.

C Training Implementation

This section provides the code used for training both the DQN and LSTM-VAE DQN agent against an ensemble of agents with alternate learning.

This script trains the two learning agents (DQN and LSTM-VAE DQN) for a total of 10000 episodes, with the two agents alternating every 100 episodes and getting a random agent chosen from the remaining learning agent, Random Agent and Aggressive agent chosen for it to train against.

The model architecture chosen as hyperparameters for the DQN agent consists of four MLP layers with Tanh activations, followed by a final linear layer predicting Q-values for each action.

The model architecture chosen as hyperparameters for the LSTM-VAE DQN agent consists of 1 recurring LSTM block with only a single layer (128 hidden params) that feeds into 2 parallel linear layers that finally feed into a final linear layer predicting probabilities of Q-values for each action, from which we sample Q-values.

C.1 Training Script

```
''' Training DQN and VAEDQN agent on custom bluff-game environment
'''

import os
import argparse
import random # Needed for opponent selection
import numpy as np # Needed for opponent selection

import torch

import rlcard
# Import necessary agents
from rlcard.agents import RandomAgent
from rlcard.agents import AggressiveAgent\
# Import your custom VAE agent - REPLACE 'vaedqn_agent_lstm' with
    your actual file name
# Make sure this file (e.g., vaedqn_agent_lstm.py) is in the
    correct path to be imported
from rlcard.agents import VAEDQNAgent as VAEDQNAgent
# Import other standard agents
from rlcard.agents import DQNAgent as StandardDQNAgent
from rlcard.agents import NFSPAgent

from rlcard.utils import (
    get_device,
    set_seed,
    tournament,
    reorganize,
    Logger,
    MultiLogger,
    plot_curve,
)

# Original train function (kept for reference/potential use)
```

```
def train(args):
    # ... (original train function remains exactly as provided
        before) ...
    # Check whether gpu is available
    device = get_device()

    # Seed numpy, torch, random
    set_seed(args.seed)

    # Make the environment with seed
    env = rlcard.make(
        args.env,
        config={
            'seed': args.seed,
        }
    )

    # Initialize the agent and use ensemble of agents as opponents
    if args.algorithm == 'vaedqn':
        # NOTE: Ensure necessary parameters for VAEDQNAgent are
            passed or set default
        agent = VAEDQNAgent(
            num_actions=env.num_actions,
            state_shape=env.state_shape[0],
            device=device,
            # Add other necessary VAEDQN params here, e.g.:
            lstm_hidden_size=64, latent_dim=20, kld_weight=0.005,
                learning_rate=0.0005
        )
    elif args.algorithm == 'nfsp':
        agent = NFSPAgent(
            num_actions=env.num_actions,
            state_shape=env.state_shape[0],
            hidden_layers_sizes=[64,64],
            q_mlp_layers=[64,64],
            device=device,
        )
    elif args.algorithm == 'dqn': # Standard DQN
         agent = StandardDQNAgent(
             num_actions=env.num_actions,
             state_shape=env.state_shape[0],
             mlp_layers=[64, 64], # Example MLP layers
             device=device,
         )
    else:
         raise ValueError("Unsupported algorithm specified")

    # Setup default opponents (e.g., RandomAgent) for single train
    opponents = [RandomAgent(num_actions=env.num_actions) for _ in
        range(1, env.num_players)]
    agents = [agent] + opponents
    env.set_agents(agents)

    # Start training
    with Logger(args.log_dir) as logger:
        for episode in range(args.num_episodes):

            if args.algorithm == 'nfsp':
                agents[0].sample_episode_policy()
```

```
            # Generate data from the environment
            trajectories, payoffs = env.run(is_training=True)

            # Reorganaize the data to be state, action, reward,
                next_state, done
            trajectories = reorganize(trajectories, payoffs)

            # Feed transitions into agent memory, and train the
                agent
            for ts in trajectories[0]:
                agent.feed(ts)

            # Evaluate the performance. Play with random agents.
            if episode % args.evaluate_every == 0:
                logger.log_performance(
                    episode,
                    tournament(
                        env, # evaluates against opponents
                            currently in env
                        args.num_eval_games,
                    )[0]
                )

        # Get the paths
        csv_path, fig_path = logger.csv_path, logger.fig_path

    # Plot the learning curve
    plot_curve(csv_path, fig_path, args.algorithm)

    # Save model - Use original saving logic
    save_path = os.path.join(args.log_dir, 'model.pth') # Use os.
        path.join if os is imported
    # save_path = args.log_dir + '/model.pth' # Original style if
        os not imported
    try:
        torch.save(agent, save_path)
        print('Model saved in', save_path)
    except Exception as e:
        print(f"Error saving model object directly: {e}")
        print("If using a custom agent with checkpointing,
            consider using its save method.")

#
    ++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

# +++ Modified Multi-Train Function (Alternating, MultiLogger,
    Mutual Log/Plot - Original plot_curve) +++
#
    ++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++

def multi_train(args):
    ''' Train DQN and VAEDQN agents, alternating training.
        Evaluates BOTH agents against RandomAgent AND against each
            other.
        Uses MultiLogger to log performance vs RandomAgent AND
            Mutual performance separately.
        Plots all results using the ORIGINAL plot_curve function.
    '''
```

```
device = get_device()
set_seed(args.seed)
switch_frequency = 100

# Get env parameters
dummy_env = rlcard.make(args.env, config={'seed': args.seed})
num_actions = dummy_env.num_actions
state_shape = dummy_env.state_shape[0]
num_players = dummy_env.num_players
del dummy_env

# --- Initialize ALL potential agents ---
print("Initializing agents...")
agent_dqn = StandardDQNAgent(
    num_actions=num_actions, state_shape=state_shape,
    mlp_layers=[64, 128, 128, 64], device=device,
        learning_rate=0.0005,
)
agent_vaedqn = VAEDQNAgent(
    num_actions=num_actions, state_shape=state_shape,
    lstm_hidden_size=128, latent_dim=20, kld_weight=0.005,
    learning_rate=0.0005, device=device,
)
agent_random = RandomAgent(num_actions=num_actions)
agent_aggressive = AggressiveAgent(num_actions=num_actions)
print("Agents initialized.")

learning_agents = [agent_dqn, agent_vaedqn]
agent_keys = [
    "DQN vs Random", "VAE_DQN vs Random", # Performance vs
        fixed baseline
    "DQN vs Aggressive", "VAE_DQN vs Aggressive", #
        Performance vs aggressive baseline
    "DQN vs VAE_DQN" # Mutual performance (logging DQN's score
        )
]

# Training Loop Setup
total_episodes_trained = 0
current_learner_idx = 0

# Use the MultiLogger with all keys
with MultiLogger(args.log_dir, agent_keys) as multi_logger:
    while total_episodes_trained < args.num_episodes:

        # Determine current learner and opponent pool
        current_agent = learning_agents[current_learner_idx]
        current_agent_name = "DQN" if current_learner_idx == 0
            else "VAE_DQN" # Cleaner name for printing
        other_learner_agent = learning_agents[1 -
            current_learner_idx]
        other_learner_name = "VAE_DQN" if current_learner_idx
            == 0 else "DQN"

        # Define opponent pool for training this chunk
        opponent_pool_options = [other_learner_agent,
            agent_random, agent_aggressive]
        opponent_agent = random.choice(opponent_pool_options)
```

```
opponent_name_print = opponent_agent.__class__.
    __name__
if opponent_agent == other_learner_agent:
    opponent_name_print = other_learner_name

print(f"\n--- Episodes {total_episodes_trained+1} -> {
    min(total_episodes_trained + switch_frequency,
    args.num_episodes)} ---")
print(f"--- Training: {current_agent_name} ---
    Opponent: {opponent_name_print} ---")

# Configure Environment for Training
env = rlcard.make(args.env, config={'seed': args.seed
    + total_episodes_trained})
agents = [current_agent] + [opponent_agent] * (
    num_players - 1)
env.set_agents(agents)

# Run Episodes for this Chunk
episodes_in_chunk = 0
while episodes_in_chunk < switch_frequency and
    total_episodes_trained < args.num_episodes:
     current_episode_num = total_episodes_trained

     # Run environment episode
     trajectories, payoffs = env.run(is_training=True)
     trajectories = reorganize(trajectories, payoffs)

     # Feed transitions only to the current learner
     for ts in trajectories[0]:
         current_agent.feed(ts)

     # --- Evaluation Step ---
     if total_episodes_trained > 0 and
        total_episodes_trained % args.evaluate_every
        == 0:
         print(f"\n--- Evaluating ALL agents at episode
             {total_episodes_trained} ---")
         eval_env = rlcard.make(args.env, config={'seed
             ': args.seed + total_episodes_trained +
             10000})

         # === Evaluation vs Random ===
         print("  --- vs RandomAgent ---")
         eval_opponents_random = [RandomAgent(
             num_actions=eval_env.num_actions) for _ in
              range(1, eval_env.num_players)]
         # DQN vs Random
         eval_agents_dqn = [agent_dqn] +
             eval_opponents_random; eval_env.set_agents
             (eval_agents_dqn)
         perf_dqn_vs_random = tournament(eval_env, args
             .num_eval_games)[0]
         multi_logger.log_performance("DQN vs Random",
             total_episodes_trained, perf_dqn_vs_random
             )
         print(f"    DQN vs Random: {perf_dqn_vs_random
             }")
         # VAEDQN vs Random
```

```
eval_agents_vaedqn = [agent_vaedqn] +
    eval_opponents_random; eval_env.set_agents
    (eval_agents_vaedqn)
perf_vaedqn_vs_random = tournament(eval_env,
    args.num_eval_games)[0]
multi_logger.log_performance("VAE_DQN vs
    Random", total_episodes_trained,
    perf_vaedqn_vs_random)
print(f"    VAE_DQN vs Random: {
    perf_vaedqn_vs_random}")

# === Evaluation vs Aggressive ===
print("  --- vs AggressiveAgent ---")
eval_opponents_aggressive = [AggressiveAgent(
    num_actions=eval_env.num_actions) for _ in
     range(1, eval_env.num_players)]
# DQN vs Aggressive
eval_agents_dqn_agg = [agent_dqn] +
    eval_opponents_aggressive; eval_env.
    set_agents(eval_agents_dqn_agg)
perf_dqn_vs_agg = tournament(eval_env, args.
    num_eval_games)[0]
multi_logger.log_performance("DQN vs
    Aggressive", total_episodes_trained,
    perf_dqn_vs_agg) # Log
print(f"    DQN vs Aggressive: {
    perf_dqn_vs_agg}")
# VAEDQN vs Aggressive
eval_agents_vaedqn_agg = [agent_vaedqn] +
    eval_opponents_aggressive; eval_env.
    set_agents(eval_agents_vaedqn_agg)
perf_vaedqn_vs_agg = tournament(eval_env, args
    .num_eval_games)[0]
multi_logger.log_performance("VAE_DQN vs
    Aggressive", total_episodes_trained,
    perf_vaedqn_vs_agg) # Log
print(f"    VAE_DQN vs Aggressive: {
    perf_vaedqn_vs_agg}")

# === Mutual Evaluation (DQN vs VAEDQN) ===
print("  --- Mutual Evaluation ---")
dqn_mutual_score = 0
if num_players >= 2:
    mutual_eval_opponents = [RandomAgent(
        num_actions=eval_env.num_actions) for
        _ in range(num_players - 2)]
    eval_env.set_agents([agent_dqn,
        agent_vaedqn] + mutual_eval_opponents)
    payoffs_mutual = tournament(eval_env, args
        .num_eval_games)
    dqn_mutual_score = payoffs_mutual[0]
    vaedqn_mutual_score = payoffs_mutual[1]
    print(f"    DQN score (vs VAE_DQN w/
        Randoms): {dqn_mutual_score}")
    print(f"    VAE_DQN score (vs DQN w/
        Randoms): {vaedqn_mutual_score}")
    multi_logger.log_performance("DQN vs
        VAE_DQN", total_episodes_trained,
        dqn_mutual_score)
```

```
                    else:
                        print("    Mutual evaluation requires at
                            least 2 players.")
                    print("----------------------------------")

                episodes_in_chunk += 1
                total_episodes_trained += 1

            # Switch the learning agent for the next chunk
            current_learner_idx = 1 - current_learner_idx

        # --- Retrieve paths AFTER the 'with' block ---
        log_paths = {}
        for key in agent_keys:
            log_paths[key] = multi_logger.get_paths(key)


    # --- Plotting and Saving (outside 'with MultiLogger') ---
    print(f"\nTraining finished. Plotting learning curves using
        ORIGINAL plot_curve...")

    # Plot all logged curves
    for key in agent_keys:
        csv_path, fig_path = log_paths.get(key, (None, None))
        if csv_path and os.path.exists(csv_path):
            print(f"  Plotting {key}: {csv_path} -> {fig_path}")
            plot_curve(csv_path, fig_path, key.replace("_", " "))
                # Use key as label, replace underscore
        else:
            print(f"  Warning: CSV file not found for {key} at {
                csv_path}, cannot plot.")

    # Save both trained learning agents
    print("Saving final trained models...")
    save_path_dqn = os.path.join(args.log_dir, 'model_dqn_final.
        pth')
    save_path_vaedqn = os.path.join(args.log_dir, '
        model_vaedqn_final.pth')
    try: torch.save(agent_dqn, save_path_dqn); print(f'Standard
        DQN model object saved in {save_path_dqn}')
    except Exception as e: print(f"Error saving Standard DQN model
         object: {e}")
    try: torch.save(agent_vaedqn, save_path_vaedqn); print(f'
        VAEDQN model object saved in {save_path_vaedqn}')
    except Exception as e: print(f"Error saving VAEDQN model
        object: {e}")



# ... (Keep if __name__ == '__main__': block as before) ...
if __name__ == '__main__':
    parser = argparse.ArgumentParser("Alternating DQN/VAEDQN
        Training in RLCard")
    parser.add_argument('--env', type=str, default='bluffgame')
    parser.add_argument('--cuda', type=str, default='')
    parser.add_argument('--seed', type=int, default=42)
    parser.add_argument('--num_episodes', type=int, default=10000)
    parser.add_argument('--num_eval_games', type=int, default
        =2000)
```

```
    parser.add_argument('--evaluate_every', type=int, default=200)
    parser.add_argument('--log_dir', type=str, default='
        experiments/bluffgame_dqn_vs_vaedqn_mutual_eval_v5/') #
        Changed default dir

    args = parser.parse_args()

    os.environ["CUDA_VISIBLE_DEVICES"] = args.cuda

    # Call the revised multi_train function
    multi_train(args)
```

C.2 Agent Architectures

C.2.1 Random Agent

```
class RandomAgent(object):
    ''' A random agent. Random agents is for running toy examples
        on the card games
    '''

    def __init__(self, num_actions):
        ''' Initilize the random agent

        Args:
            num_actions (int): The size of the ouput action space
        '''
        self.use_raw = False
        self.num_actions = num_actions

    @staticmethod
    def step(state):
        ''' Predict the action given the curent state in
            gerenerating training data.

        Args:
            state (dict): An dictionary that represents the
                current state

        Returns:
            action (int): The action predicted (randomly chosen)
                by the random agent
        '''
        return np.random.choice(list(state['legal_actions'].keys()
            ))

    def eval_step(self, state):
        ''' Predict the action given the current state for
            evaluation.
            Since the random agents are not trained. This function
                is equivalent to step function

        Args:
            state (dict): An dictionary that represents the
                current state

        Returns:
            action (int): The action predicted (randomly chosen)
                by the random agent
            probs (list): The list of action probabilities
        '''
```

```
        probs = [0 for _ in range(self.num_actions)]
        for i in state['legal_actions']:
            probs[i] = 1/len(state['legal_actions'])

        info = {}
        info['probs'] = {state['raw_legal_actions'][i]: probs[list
            (state['legal_actions'].keys())[i]] for i in range(len
            (state['legal_actions']))}
```

C.2.2 Agressive Agent

```
class AggressiveAgent(object):
    ''' An aggressive agent. aggresive agents is for running toy
        examples on the card games
    '''

    def __init__(self, num_actions):
        ''' Initilize the aggresive agent

        Args:
            num_actions (int): The size of the ouput action space
        '''
        self.use_raw = False
        self.num_actions = num_actions

    @staticmethod
    def step(state):
        ''' Predict the action given the curent state in
            gerenerating training data.

        Args:
            state (dict): An dictionary that represents the
                current state

        Returns:
            action (int): The action predicted (randomly chosen)
                by the random agent
        '''
        actions = list(state['raw_legal_actions'])
        if 'raise' in actions:
            return list(state['raw_legal_actions']).index('raise')
        elif 'call' in actions:
            return list(state['raw_legal_actions']).index('call')
        elif 'check' in actions:
            return list(state['raw_legal_actions']).index('check')

    def eval_step(self, state):
        ''' Predict the action given the current state for
            evaluation.
            Since the aggressive agents are not trained. This
                function is equivalent to step function

        Args:
            state (dict): An dictionary that represents the
                current state

        Returns:
            action (int): The action predicted (randomly chosen)
                by the random agent
            probs (list): The list of action probabilities
```

```
        '''
        # probs = [0 for _ in range(self.num_actions)]
        # for i in state['legal_actions']:
        #     probs[i] = 1/len(state['legal_actions'])

        info = {}
        # info['probs'] = {state['raw_legal_actions'][i]: probs[
            list(state['legal_actions'].keys())[i]] for i in range
            (len(state['legal_actions']))}

        info['?'] = 'aggro'

        return self.step(state), info
```

C.2.3 LSTM-VAE DQN Agent

```
class VAEDQNAgent(object):
    '''
    DQN Agent using an LSTM-VAE Estimator network.
    Modified to handle LSTM-VAE parameters and checkpointing.
    '''
    def __init__(self,
                 replay_memory_size=20000,
                 replay_memory_init_size=100,
                 update_target_estimator_every=1000,
                 discount_factor=0.99,
                 epsilon_start=1.0,
                 epsilon_end=0.1,
                 epsilon_decay_steps=20000,
                 batch_size=32,
                 num_actions=2,
                 state_shape=None,
                 train_every=1,
                 # ADD LSTM-VAE parameters
                 lstm_input_size=None,
                 lstm_hidden_size=128,
                 lstm_num_layers=1,
                 latent_dim=32,
                 kld_weight=0.001, # Added KLD weight param here
                 learning_rate=0.00005,
                 device=None,
                 save_path=None,
                 save_every=float('inf'),):

        self.use_raw = False
        self.replay_memory_init_size = replay_memory_init_size
        self.update_target_estimator_every =
            update_target_estimator_every
        self.discount_factor = discount_factor
        self.epsilon_decay_steps = epsilon_decay_steps
        self.batch_size = batch_size
        self.num_actions = num_actions
        self.train_every = train_every

        if device is None:
            self.device = torch.device('cuda:0' if torch.cuda.
                is_available() else 'cpu')
        else:
            self.device = device
```

```
        self.total_t = 0
        self.train_t = 0
        self.epsilons = np.linspace(epsilon_start, epsilon_end,
            epsilon_decay_steps)

        # Create estimators using LSTM-VAE parameters
        estimator_args = {
            'num_actions': num_actions,
            'learning_rate': learning_rate,
            'state_shape': state_shape,
            'device': self.device,
            'lstm_input_size': lstm_input_size,
            'lstm_hidden_size': lstm_hidden_size,
            'lstm_num_layers': lstm_num_layers,
            'latent_dim': latent_dim,
            'kld_weight': kld_weight
        }
        self.q_estimator = Estimator(**estimator_args)
        self.target_estimator = Estimator(**estimator_args)

        # Synchronize target network weights initially
        self.target_estimator.qnet.load_state_dict(self.
            q_estimator.qnet.state_dict())
        self.target_estimator.qnet.eval()

        self.memory = Memory(replay_memory_size, batch_size)

        self.save_path = save_path
        self.save_every = save_every

    def feed(self, ts):
        ''' Store data in to replay buffer and train the agent.
            '''
        (state, action, reward, next_state, done) = tuple(ts)
        current_obs = state['obs']
        next_obs = next_state['obs']
        legal_actions_keys = list(next_state['legal_actions'].keys
            ())

        self.feed_memory(current_obs, action, reward, next_obs,
            legal_actions_keys, done)
        self.total_t += 1
        tmp = self.total_t - self.replay_memory_init_size
        if tmp>=0 and tmp%self.train_every == 0:
            self.train()

    def step(self, state):
        ''' Predict the action using epsilon-greedy policy. '''
        q_values = self.predict(state)
        epsilon = self.epsilons[min(self.total_t, self.
            epsilon_decay_steps-1)]
        legal_actions = list(state['legal_actions'].keys())

        if not legal_actions:
            return 0

        if random.random() < epsilon:
            action = random.choice(legal_actions)
        else:
```

```
            q_subset = q_values[legal_actions]
            if np.all(np.isinf(q_subset)):
                action = random.choice(legal_actions)
            else:
                action = legal_actions[np.argmax(q_subset)]

        return action

    def eval_step(self, state):
        ''' Predict the action for evaluation purpose. '''
        q_values = self.predict(state)
        legal_actions = list(state['legal_actions'].keys())

        if not legal_actions:
            best_action = 0
            info = {'values': {}}
            return best_action, info

        q_subset = q_values[legal_actions]
        if np.all(np.isinf(q_subset)):
            best_action = random.choice(legal_actions)
        else:
            best_action = legal_actions[np.argmax(q_subset)]

        info = {}
        raw_legal_actions = state.get('raw_legal_actions',
            legal_actions)
        values_dict = {}
        for i, action_key in enumerate(legal_actions):
            # This assumes raw_legal_actions[i] corresponds to
                legal_actions[i]
            # Ensure this correspondence holds in your
                environment data
            raw_key = raw_legal_actions[i]
            q_val = q_values[action_key]
            values_dict[raw_key] = float(q_val) if np.isfinite(
                q_val) else -float('inf')
        info['values'] = values_dict

        return best_action, info

    def predict(self, state):
        ''' Predict the masked Q-values '''
        obs = np.array(state['obs'])
        q_values = self.q_estimator.predict_nograd(np.expand_dims(
            obs, 0))[0]

        masked_q_values = -np.inf * np.ones(self.num_actions,
            dtype=float)
        legal_actions = list(state['legal_actions'].keys())
        valid_legal_actions = [a for a in legal_actions if 0 <= a
            < self.num_actions]

        if valid_legal_actions:
            masked_q_values[valid_legal_actions] = q_values[
                valid_legal_actions]

        return masked_q_values
```

```
def train(self):
    ''' Train the network. '''
    state_batch, action_batch, reward_batch, next_state_batch,
        done_batch, legal_actions_batch = self.memory.sample
       ()

    # Calculate best next actions using Q-network (Double DQN
       - Step 1: Action Selection)
    q_values_next = self.q_estimator.predict_nograd(
       next_state_batch)
    best_actions = np.zeros(self.batch_size, dtype=int)
    for i in range(self.batch_size):
        legal_acts = legal_actions_batch[i]
        if not legal_acts:
            best_actions[i] = 0
            continue
        valid_legal_acts = [a for a in legal_acts if 0 <= a <
            self.num_actions]
        if not valid_legal_acts:
            best_actions[i] = 0
            continue
        q_subset = q_values_next[i, valid_legal_acts]
        if np.all(np.isinf(q_subset)):
            best_actions[i] = random.choice(valid_legal_acts
               )
        else:
            argmax_local = np.argmax(q_subset)
            best_actions[i] = valid_legal_acts[argmax_local]


    # Evaluate best next actions using Target-network (Double
       DQN - Step 2: Action Evaluation)
    q_values_next_target = self.target_estimator.
       predict_nograd(next_state_batch)
    target_q_for_best_action = q_values_next_target[np.arange(
       self.batch_size), best_actions]

    # Calculate TD Target (y)
    target_batch = reward_batch + np.invert(done_batch).astype
       (np.float32) * \
        self.discount_factor * target_q_for_best_action

    # Perform gradient descent update
    state_batch = np.array(state_batch)
    loss = self.q_estimator.update(state_batch, action_batch,
       target_batch)

    print('\rINFO - Step {}, rl-loss: {:.4f}'.format(self.
       total_t, loss), end='')

    # Update the target estimator using load_state_dict
    if self.train_t > 0 and self.train_t % self.
       update_target_estimator_every == 0:
        self.target_estimator.qnet.load_state_dict(self.
           q_estimator.qnet.state_dict())
        print("\nINFO - Copied model parameters to target
           network.")

    self.train_t += 1
```

```
        # Save checkpoint logic remains the same externally
        if self.save_path and self.train_t % self.save_every == 0:
            self.save_checkpoint(self.save_path)
            print("\nINFO - Saved model checkpoint.")

        return loss

    def feed_memory(self, state, action, reward, next_state,
        legal_actions, done):
        ''' Feed transition to memory '''
        self.memory.save(state, action, reward, next_state,
            legal_actions, done)

    def set_device(self, device):
        ''' Set the device for the agent and its estimators. '''
        self.device = device
        self.q_estimator.device = device
        self.q_estimator.qnet.to(device)
        self.target_estimator.device = device
        self.target_estimator.qnet.to(device)

    def checkpoint_attributes(self):
        ''' Return the current checkpoint attributes (dict). '''
        q_estimator_attrs = self.q_estimator.checkpoint_attributes
            ()

        current_epsilon = self.epsilons[min(self.total_t, self.
            epsilon_decay_steps - 1)]
        epsilon_start_val = self.epsilons[0]
        epsilon_end_val = self.epsilons[-1]

        return {
            'agent_type': 'VAEDQNAgent',
            'q_estimator': q_estimator_attrs,
            'memory': self.memory.checkpoint_attributes(),
            'total_t': self.total_t,
            'train_t': self.train_t,
            'epsilon_start_val': epsilon_start_val,
            'epsilon_end_val': epsilon_end_val,
            'epsilon_decay_steps': self.epsilon_decay_steps,
            'current_epsilon': current_epsilon,
            'discount_factor': self.discount_factor,
            'update_target_estimator_every': self.
                update_target_estimator_every,
            'batch_size': self.batch_size,
            'num_actions': self.num_actions,
            'train_every': self.train_every,
            'device': self.device
        }

    @classmethod
    def from_checkpoint(cls, checkpoint):
        ''' Restore the model from a checkpoint. '''
        print("\nINFO - Restoring LSTM-VAE DQN model from
            checkpoint...")
        q_estimator_attrs = checkpoint['q_estimator']

        agent_instance = cls(
```

```
            replay_memory_size=checkpoint['memory']['memory_size
                '],
            update_target_estimator_every=checkpoint['
                update_target_estimator_every'],
            discount_factor=checkpoint['discount_factor'],
            epsilon_start=checkpoint['epsilon_start_val'],
            epsilon_end=checkpoint['epsilon_end_val'],
            epsilon_decay_steps=checkpoint['epsilon_decay_steps'],
            batch_size=checkpoint['batch_size'],
            num_actions=checkpoint['num_actions'],
            state_shape=q_estimator_attrs['state_shape'],
            train_every=checkpoint['train_every'],
            lstm_input_size=q_estimator_attrs['lstm_input_size'],
            lstm_hidden_size=q_estimator_attrs['lstm_hidden_size
                '],
            lstm_num_layers=q_estimator_attrs['lstm_num_layers'],
            latent_dim=q_estimator_attrs['latent_dim'],
            kld_weight=q_estimator_attrs['kld_weight'],
            learning_rate=q_estimator_attrs['learning_rate'],
            device=checkpoint['device']
        )

        agent_instance.total_t = checkpoint['total_t']
        agent_instance.train_t = checkpoint['train_t']

        agent_instance.q_estimator = Estimator.from_checkpoint(
            q_estimator_attrs)

        estimator_args = {
            'num_actions': agent_instance.num_actions,
            'learning_rate': agent_instance.q_estimator.
                learning_rate,
            'state_shape': agent_instance.q_estimator.state_shape,
            'device': agent_instance.device,
            'lstm_input_size': agent_instance.q_estimator.
                lstm_input_size,
            'lstm_hidden_size': agent_instance.q_estimator.
                lstm_hidden_size,
            'lstm_num_layers': agent_instance.q_estimator.
                lstm_num_layers,
            'latent_dim': agent_instance.q_estimator.latent_dim,
            'kld_weight': agent_instance.q_estimator.kld_weight
        }
        agent_instance.target_estimator = Estimator(**
            estimator_args)
        agent_instance.target_estimator.qnet.load_state_dict(
            agent_instance.q_estimator.qnet.state_dict())
        agent_instance.target_estimator.qnet.eval()

        agent_instance.memory = Memory.from_checkpoint(checkpoint
            ['memory'])

        print(f"INFO - Model restored. total_t={agent_instance.
            total_t}, train_t={agent_instance.train_t}")
        return agent_instance

    def save_checkpoint(self, path, filename='checkpoint_dqn.pt'):
        ''' Save the model checkpoint '''
        # User must ensure the path directory exists.
```

```
        filepath = path + '/' + filename # Using simple
            concatenation
        try:
            torch.save(self.checkpoint_attributes(), filepath)
        except Exception as e:
             print(f"Error saving checkpoint to {filepath}: {e}")


class Estimator(object):
    '''
    Q-Value Estimator using the LSTMEstimatorNetwork.
    Manages network training including Q-loss and KLD loss.
    '''
    def __init__(self, num_actions=2, learning_rate=0.001,
        state_shape=None,
                 device=None,
                 lstm_input_size=None, lstm_hidden_size=128,
                     lstm_num_layers=1,
                 latent_dim=32, kld_weight=0.001):

        self.num_actions = num_actions
        self.learning_rate=learning_rate
        self.state_shape = state_shape
        self.device = device
        self.lstm_input_size = lstm_input_size
        self.lstm_hidden_size = lstm_hidden_size
        self.lstm_num_layers = lstm_num_layers
        self.latent_dim = latent_dim
        self.kld_weight = kld_weight

        # Setup Q model using LSTMEstimatorNetwork
        qnet = LSTMEstimatorNetwork(num_actions, state_shape,
                                    lstm_input_size,
                                        lstm_hidden_size,
                                        lstm_num_layers,
                                    latent_dim, device)
        qnet = qnet.to(self.device)
        self.qnet = qnet
        self.qnet.eval()

        # Initialize weights
        for name, p in self.qnet.named_parameters():
            if 'weight' in name and 'lstm' not in name and len(p.
                data.shape) > 1:
                nn.init.xavier_uniform_(p.data)
            elif 'bias' in name:
                nn.init.constant_(p.data, 0)

        self.mse_loss = nn.MSELoss(reduction='mean')
        self.optimizer = torch.optim.Adam(self.qnet.parameters(),
            lr=self.learning_rate)

    def predict_nograd(self, s):
        ''' Predicts action values deterministically (using mu),
            without gradients. '''
        with torch.no_grad():
            s_tensor = torch.from_numpy(s).float().to(self.device)
            q_as, _, _ = self.qnet(s_tensor, sample_latent=False)
            q_as_numpy = q_as.cpu().numpy()
```

```
        return q_as_numpy

    def update(self, s, a, y):
        ''' Updates the estimator: calculates combined loss (Q +
            KLD) and backpropagates. '''
        self.optimizer.zero_grad()
        self.qnet.train()

        s = torch.from_numpy(s).float().to(self.device)
        a = torch.from_numpy(a).long().to(self.device)
        y = torch.from_numpy(y).float().to(self.device)

        q_as_pred, mu, log_var = self.qnet(s, sample_latent=True)

        Q_pred = torch.gather(q_as_pred, dim=-1, index=a.unsqueeze
            (-1)).squeeze(-1)
        q_loss = self.mse_loss(Q_pred, y)

        kld_loss = -0.5 * torch.sum(1 + log_var - mu.pow(2) -
            log_var.exp(), dim=1).mean()

        total_loss = q_loss + self.kld_weight * kld_loss
        total_loss.backward()
        self.optimizer.step()

        q_loss_item = q_loss.item()
        self.qnet.eval()
        return q_loss_item

    def checkpoint_attributes(self):
        ''' Return the attributes needed to restore the model from
            a checkpoint. '''
        return {
            'qnet': self.qnet.state_dict(),
            'optimizer': self.optimizer.state_dict(),
            'num_actions': self.num_actions,
            'learning_rate': self.learning_rate,
            'state_shape': self.state_shape,
            'lstm_input_size': self.lstm_input_size,
            'lstm_hidden_size': self.lstm_hidden_size,
            'lstm_num_layers': self.lstm_num_layers,
            'latent_dim': self.latent_dim,
            'kld_weight': self.kld_weight,
            'device': self.device
        }

    @classmethod
    def from_checkpoint(cls, checkpoint):
        ''' Restore the model from a checkpoint. '''
        estimator = cls(
            num_actions=checkpoint['num_actions'],
            learning_rate=checkpoint['learning_rate'],
            state_shape=checkpoint['state_shape'],
            device=checkpoint['device'],
            lstm_input_size=checkpoint['lstm_input_size'],
            lstm_hidden_size=checkpoint['lstm_hidden_size'],
            lstm_num_layers=checkpoint['lstm_num_layers'],
            latent_dim=checkpoint['latent_dim'],
            kld_weight=checkpoint['kld_weight']
```

```
        )
        estimator.qnet.load_state_dict(checkpoint['qnet'])
        estimator.optimizer.load_state_dict(checkpoint['optimizer
            '])
        return estimator


class LSTMEstimatorNetwork(nn.Module):
    '''
    An LSTM-based VAE-like network structure for the Q-Value
        Estimator.
    '''
    def __init__(self, num_actions=2, state_shape=None,
                 lstm_input_size=None, lstm_hidden_size=128,
                     lstm_num_layers=1,
                 latent_dim=32, device=None):

        super(LSTMEstimatorNetwork, self).__init__()
        self.num_actions = num_actions
        self.state_shape = state_shape
        self.flat_state_dim = np.prod(self.state_shape)
        self.lstm_input_size = lstm_input_size if lstm_input_size
            is not None else self.flat_state_dim
        self.lstm_hidden_size = lstm_hidden_size
        self.lstm_num_layers = lstm_num_layers
        self.latent_dim = latent_dim
        self.device = device

        if self.lstm_input_size != self.flat_state_dim:
            self.input_proj = nn.Linear(self.flat_state_dim, self.
                lstm_input_size)
            self.input_activation = nn.Tanh()
        else:
            self.input_proj = None
            self.input_activation = None

        self.lstm = nn.LSTM(input_size=self.lstm_input_size,
                            hidden_size=self.lstm_hidden_size,
                            num_layers=self.lstm_num_layers,
                            batch_first=True)

        self.fc_mu = nn.Linear(self.lstm_hidden_size, self.
            latent_dim)
        self.fc_log_var = nn.Linear(self.lstm_hidden_size, self.
            latent_dim)
        self.fc_q = nn.Linear(self.latent_dim, self.num_actions)

    def reparameterize(self, mu, log_var):
        std = torch.exp(0.5 * log_var)
        eps = torch.randn_like(std)
        return mu + eps * std

    def forward(self, s, sample_latent=True):
        ''' Forward pass: state -> [projection] -> LSTM -> mu,
            log_var -> z -> Q-values '''
        batch_size = s.size(0)
        s_flat = s.view(batch_size, -1)

        if self.input_proj:
```

```
            s_processed = self.input_proj(s_flat)
            if self.input_activation:
                s_processed = self.input_activation(s_processed)
        else:
            s_processed = s_flat

        s_lstm_input = s_processed.unsqueeze(1)

        h0 = torch.zeros(self.lstm_num_layers, batch_size, self.
            lstm_hidden_size).to(s_lstm_input.device)
        c0 = torch.zeros(self.lstm_num_layers, batch_size, self.
            lstm_hidden_size).to(s_lstm_input.device)
        lstm_out, _ = self.lstm(s_lstm_input, (h0, c0))
        lstm_out_last = lstm_out[:, -1, :]

        mu = self.fc_mu(lstm_out_last)
        log_var = self.fc_log_var(lstm_out_last)

        if sample_latent:
            z = self.reparameterize(mu, log_var)
        else:
            z = mu

        q_values = self.fc_q(z)
        return q_values, mu, log_var


class Memory(object):
    ''' Memory for saving transitions '''
    def __init__(self, memory_size, batch_size):
        self.memory_size = memory_size
        self.batch_size = batch_size
        self.memory = []

    def save(self, state, action, reward, next_state,
        legal_actions, done):
        ''' Save transition into memory '''
        if len(self.memory) == self.memory_size:
            self.memory.pop(0)
        transition = Transition(state, action, reward, next_state,
            done, legal_actions)
        self.memory.append(transition)

    def sample(self):
        ''' Sample a minibatch from the replay memory '''
        samples = random.sample(self.memory, self.batch_size)
        try:
            samples_unzipped = tuple(zip(*samples))
            return tuple(map(np.array, samples_unzipped[:-1])) + (
                samples_unzipped[-1],)
        except ValueError as e:
            print(f"Error converting samples to numpy arrays: {e
                }")
            print("Check if all 'state' and 'next_state'
                observations in the memory have the same shape.")
            raise e
        except Exception as e:
            print(f"Error during memory sampling: {e}")
            raise e
```

```
    def checkpoint_attributes(self):
        ''' Returns the attributes that need to be checkpointed
            '''
        return {
            'memory_size': self.memory_size,
            'batch_size': self.batch_size,
            'memory': self.memory
        }

    @classmethod
    def from_checkpoint(cls, checkpoint):
        ''' Restores the attributes from the checkpoint '''
        instance = cls(checkpoint['memory_size'], checkpoint['
            batch_size'])
        instance.memory = checkpoint['memory']
        return instance
```

C.2.4 DQN Agent

```
class DQNAgent(object):
    '''
    Approximate clone of rlcard.agents.dqn_agent.DQNAgent
    that depends on PyTorch instead of Tensorflow
    '''
    def __init__(self,
                 replay_memory_size=20000,
                 replay_memory_init_size=100,
                 update_target_estimator_every=1000,
                 discount_factor=0.99,
                 epsilon_start=1.0,
                 epsilon_end=0.1,
                 epsilon_decay_steps=20000,
                 batch_size=32,
                 num_actions=2,
                 state_shape=None,
                 train_every=1,
                 mlp_layers=None,
                 learning_rate=0.00005,
                 device=None,
                 save_path=None,
                 save_every=float('inf'),):

        '''
        Q-Learning algorithm for off-policy TD control using
            Function Approximation.
        Finds the optimal greedy policy while following an epsilon
            -greedy policy.

        Args:
            replay_memory_size (int): Size of the replay memory
            replay_memory_init_size (int): Number of random
                experiences to sample when initializing
              the reply memory.
            update_target_estimator_every (int): Copy parameters
                from the Q estimator to the
              target estimator every N steps
            discount_factor (float): Gamma discount factor
            epsilon_start (float): Chance to sample a random
                action when taking an action.
```

```
        Epsilon is decayed over time and this is the start
            value
      epsilon_end (float): The final minimum value of
          epsilon after decaying is done
      epsilon_decay_steps (int): Number of steps to decay
          epsilon over
      batch_size (int): Size of batches to sample from the
          replay memory
      evaluate_every (int): Evaluate every N steps
      num_actions (int): The number of the actions
      state_space (list): The space of the state vector
      train_every (int): Train the network every X steps.
      mlp_layers (list): The layer number and the dimension
          of each layer in MLP
      learning_rate (float): The learning rate of the DQN
          agent.
      device (torch.device): whether to use the cpu or gpu
      save_path (str): The path to save the model
          checkpoints
      save_every (int): Save the model every X training
          steps
  '''
  self.use_raw = False
  self.replay_memory_init_size = replay_memory_init_size
  self.update_target_estimator_every =
      update_target_estimator_every
  self.discount_factor = discount_factor
  self.epsilon_decay_steps = epsilon_decay_steps
  self.batch_size = batch_size
  self.num_actions = num_actions
  self.train_every = train_every

  # Torch device
  if device is None:
      self.device = torch.device('cuda:0' if torch.cuda.
          is_available() else 'cpu')
  else:
      self.device = device

  # Total timesteps
  self.total_t = 0

  # Total training step
  self.train_t = 0

  # The epsilon decay scheduler
  self.epsilons = np.linspace(epsilon_start, epsilon_end,
      epsilon_decay_steps)

  # Create estimators
  self.q_estimator = Estimator(num_actions=num_actions,
      learning_rate=learning_rate, state_shape=state_shape,
      \
      mlp_layers=mlp_layers, device=self.device)
  self.target_estimator = Estimator(num_actions=num_actions,
      learning_rate=learning_rate, state_shape=state_shape,
      \
      mlp_layers=mlp_layers, device=self.device)
```

```
        # Create replay memory
        self.memory = Memory(replay_memory_size, batch_size)

        # Checkpoint saving parameters
        self.save_path = save_path
        self.save_every = save_every

    def feed(self, ts):
        ''' Store data in to replay buffer and train the agent.
            There are two stages.
            In stage 1, populate the memory without training
            In stage 2, train the agent every several timesteps

        Args:
            ts (list): a list of 5 elements that represent the
                transition
        '''
        (state, action, reward, next_state, done) = tuple(ts)
        self.feed_memory(state['obs'], action, reward, next_state
            ['obs'], list(next_state['legal_actions'].keys()),
            done)
        self.total_t += 1
        tmp = self.total_t - self.replay_memory_init_size
        if tmp>=0 and tmp%self.train_every == 0:
            self.train()

    def step(self, state):
        ''' Predict the action for genrating training data but
            have the predictions disconnected from the computation
                graph

        Args:
            state (numpy.array): current state

        Returns:
            action (int): an action id
        '''
        q_values = self.predict(state)
        epsilon = self.epsilons[min(self.total_t, self.
            epsilon_decay_steps-1)]
        legal_actions = list(state['legal_actions'].keys())
        probs = np.ones(len(legal_actions), dtype=float) * epsilon
            / len(legal_actions)
        best_action_idx = legal_actions.index(np.argmax(q_values))
        probs[best_action_idx] += (1.0 - epsilon)
        action_idx = np.random.choice(np.arange(len(probs)), p=
            probs)

        return legal_actions[action_idx]

    def eval_step(self, state):
        ''' Predict the action for evaluation purpose.

        Args:
            state (numpy.array): current state

        Returns:
            action (int): an action id
            info (dict): A dictionary containing information
```

```
        '''
        q_values = self.predict(state)
        best_action = np.argmax(q_values)

        info = {}
        info['values'] = {state['raw_legal_actions'][i]: float(
            q_values[list(state['legal_actions'].keys())[i]]) for
            i in range(len(state['legal_actions']))}

        return best_action, info

    def predict(self, state):
        ''' Predict the masked Q-values

        Args:
            state (numpy.array): current state

        Returns:
            q_values (numpy.array): a 1-d array where each entry
                represents a Q value
        '''

        q_values = self.q_estimator.predict_nograd(np.expand_dims(
            state['obs'], 0))[0]
        masked_q_values = -np.inf * np.ones(self.num_actions,
            dtype=float)
        legal_actions = list(state['legal_actions'].keys())
        masked_q_values[legal_actions] = q_values[legal_actions]

        return masked_q_values

    def train(self):
        ''' Train the network

        Returns:
            loss (float): The loss of the current batch.
        '''
        state_batch, action_batch, reward_batch, next_state_batch,
             done_batch, legal_actions_batch = self.memory.sample
            ()

        # Calculate best next actions using Q-network (Double DQN)
        q_values_next = self.q_estimator.predict_nograd(
            next_state_batch)
        legal_actions = []
        for b in range(self.batch_size):
            legal_actions.extend([i + b * self.num_actions for i
                in legal_actions_batch[b]])
        masked_q_values = -np.inf * np.ones(self.num_actions *
            self.batch_size, dtype=float)
        masked_q_values[legal_actions] = q_values_next.flatten()[
            legal_actions]
        masked_q_values = masked_q_values.reshape((self.batch_size
            , self.num_actions))
        best_actions = np.argmax(masked_q_values, axis=1)

        # Evaluate best next actions using Target-network (Double
            DQN)
```

```
        q_values_next_target = self.target_estimator.
            predict_nograd(next_state_batch)
        target_batch = reward_batch + np.invert(done_batch).astype
            (np.float32) * \
                self.discount_factor * q_values_next_target[np.arange(
                    self.batch_size), best_actions]

        # Perform gradient descent update
        state_batch = np.array(state_batch)

        loss = self.q_estimator.update(state_batch, action_batch,
            target_batch)
        print('\rINFO - Step {}, rl-loss: {}'.format(self.total_t,
            loss), end='')

        # Update the target estimator
        if self.train_t % self.update_target_estimator_every == 0:
            self.target_estimator = deepcopy(self.q_estimator)
            print("\nINFO - Copied model parameters to target
                network.")

        self.train_t += 1

        if self.save_path and self.train_t % self.save_every == 0:
            # To preserve every checkpoint separately,
            # add another argument to the function call
                parameterized by self.train_t
            self.save_checkpoint(self.save_path)
            print("\nINFO - Saved model checkpoint.")


    def feed_memory(self, state, action, reward, next_state,
        legal_actions, done):
        ''' Feed transition to memory

        Args:
            state (numpy.array): the current state
            action (int): the performed action ID
            reward (float): the reward received
            next_state (numpy.array): the next state after
                performing the action
            legal_actions (list): the legal actions of the next
                state
            done (boolean): whether the episode is finished
        '''
        self.memory.save(state, action, reward, next_state,
            legal_actions, done)

    def set_device(self, device):
        self.device = device
        self.q_estimator.device = device
        self.target_estimator.device = device

    def checkpoint_attributes(self):
        '''
        Return the current checkpoint attributes (dict)
        Checkpoint attributes are used to save and restore the
            model in the middle of training
```

```
        Saves the model state dict, optimizer state dict, and all
            other instance variables
        '''

        return {
            'agent_type': 'DQNAgent',
            'q_estimator': self.q_estimator.checkpoint_attributes
                (),
            'memory': self.memory.checkpoint_attributes(),
            'total_t': self.total_t,
            'train_t': self.train_t,
            'epsilon_start': self.epsilons.min(),
            'epsilon_end': self.epsilons.max(),
            'epsilon_decay_steps': self.epsilon_decay_steps,
            'discount_factor': self.discount_factor,
            'update_target_estimator_every': self.
                update_target_estimator_every,
            'batch_size': self.batch_size,
            'num_actions': self.num_actions,
            'train_every': self.train_every,
            'device': self.device
        }

    @classmethod
    def from_checkpoint(cls, checkpoint):
        '''
        Restore the model from a checkpoint

        Args:
            checkpoint (dict): the checkpoint attributes generated
                by checkpoint_attributes()
        '''

        print("\nINFO - Restoring model from checkpoint...")
        agent_instance = cls(
            replay_memory_size=checkpoint['memory']['memory_size
                '],
            update_target_estimator_every=checkpoint['
                update_target_estimator_every'],
            discount_factor=checkpoint['discount_factor'],
            epsilon_start=checkpoint['epsilon_start'],
            epsilon_end=checkpoint['epsilon_end'],
            epsilon_decay_steps=checkpoint['epsilon_decay_steps'],
            batch_size=checkpoint['batch_size'],
            num_actions=checkpoint['num_actions'],
            device=checkpoint['device'],
            state_shape=checkpoint['q_estimator']['state_shape'],
            mlp_layers=checkpoint['q_estimator']['mlp_layers'],
            train_every=checkpoint['train_every']
        )

        agent_instance.total_t = checkpoint['total_t']
        agent_instance.train_t = checkpoint['train_t']

        agent_instance.q_estimator = Estimator.from_checkpoint(
            checkpoint['q_estimator'])
        agent_instance.target_estimator = deepcopy(agent_instance.
            q_estimator)
```

```
        agent_instance.memory = Memory.from_checkpoint(checkpoint
            ['memory'])


        return agent_instance

    def save_checkpoint(self, path, filename='checkpoint_dqn.pt'):
        ''' Save the model checkpoint (all attributes)

        Args:
            path (str): the path to save the model
        '''
        torch.save(self.checkpoint_attributes(), path + '/' +
            filename)

class Estimator(object):
    '''
    Approximate clone of rlcard.agents.dqn_agent.Estimator that
    uses PyTorch instead of Tensorflow.  All methods input/output
       np.ndarray.

    Q-Value Estimator neural network.
    This network is used for both the Q-Network and the Target
       Network.
    '''

    def __init__(self, num_actions=2, learning_rate=0.001,
       state_shape=None, mlp_layers=None, device=None):
        ''' Initilalize an Estimator object.

        Args:
            num_actions (int): the number output actions
            state_shape (list): the shape of the state space
            mlp_layers (list): size of outputs of mlp layers
            device (torch.device): whether to use cpu or gpu
        '''
        self.num_actions = num_actions
        self.learning_rate=learning_rate
        self.state_shape = state_shape
        self.mlp_layers = mlp_layers
        self.device = device

        # set up Q model and place it in eval mode
        qnet = EstimatorNetwork(num_actions, state_shape,
            mlp_layers)
        qnet = qnet.to(self.device)
        self.qnet = qnet
        self.qnet.eval()

        # initialize the weights using Xavier init
        for p in self.qnet.parameters():
            if len(p.data.shape) > 1:
                nn.init.xavier_uniform_(p.data)

        # set up loss function
        self.mse_loss = nn.MSELoss(reduction='mean')

        # set up optimizer
```

```
        self.optimizer =  torch.optim.Adam(self.qnet.parameters(),
            lr=self.learning_rate)

    def predict_nograd(self, s):
        ''' Predicts action values, but prediction is not included
            in the computation graph.  It is used to predict
                optimal next
            actions in the Double-DQN algorithm.

        Args:
          s (np.ndarray): (batch, state_len)

        Returns:
          np.ndarray of shape (batch_size, NUM_VALID_ACTIONS)
              containing the estimated
          action values.
        '''
        with torch.no_grad():
            s = torch.from_numpy(s).float().to(self.device)
            q_as = self.qnet(s).cpu().numpy()
        return q_as

    def update(self, s, a, y):
        ''' Updates the estimator towards the given targets.
            In this case y is the target-network estimated
            value of the Q-network optimal actions, which
            is labeled y in Algorithm 1 of Minh et al. (2015)

        Args:
          s (np.ndarray): (batch, state_shape) state
              representation
          a (np.ndarray): (batch,) integer sampled actions
          y (np.ndarray): (batch,) value of optimal actions
              according to Q-target

        Returns:
          The calculated loss on the batch.
        '''
        self.optimizer.zero_grad()

        self.qnet.train()

        s = torch.from_numpy(s).float().to(self.device)
        a = torch.from_numpy(a).long().to(self.device)
        y = torch.from_numpy(y).float().to(self.device)

        # (batch, state_shape) -> (batch, num_actions)
        q_as = self.qnet(s)

        # (batch, num_actions) -> (batch, )
        Q = torch.gather(q_as, dim=-1, index=a.unsqueeze(-1)).
            squeeze(-1)

        # update model
        batch_loss = self.mse_loss(Q, y)
        batch_loss.backward()
        self.optimizer.step()
        batch_loss = batch_loss.item()
```

```
        self.qnet.eval()

        return batch_loss

    def checkpoint_attributes(self):
        ''' Return the attributes needed to restore the model from
            a checkpoint
        '''
        return {
            'qnet': self.qnet.state_dict(),
            'optimizer': self.optimizer.state_dict(),
            'num_actions': self.num_actions,
            'learning_rate': self.learning_rate,
            'state_shape': self.state_shape,
            'mlp_layers': self.mlp_layers,
            'device': self.device
        }

    @classmethod
    def from_checkpoint(cls, checkpoint):
        ''' Restore the model from a checkpoint
        '''
        estimator = cls(
            num_actions=checkpoint['num_actions'],
            learning_rate=checkpoint['learning_rate'],
            state_shape=checkpoint['state_shape'],
            mlp_layers=checkpoint['mlp_layers'],
            device=checkpoint['device']
        )

        estimator.qnet.load_state_dict(checkpoint['qnet'])
        estimator.optimizer.load_state_dict(checkpoint['optimizer
            '])
        return estimator


class EstimatorNetwork(nn.Module):
    ''' The function approximation network for Estimator
        It is just a series of tanh layers. All in/out are torch.
            tensor
    '''

    def __init__(self, num_actions=2, state_shape=None, mlp_layers
        =None):
        ''' Initialize the Q network

        Args:
            num_actions (int): number of legal actions
            state_shape (list): shape of state tensor
            mlp_layers (list): output size of each fc layer
        '''
        super(EstimatorNetwork, self).__init__()

        self.num_actions = num_actions
        self.state_shape = state_shape
        self.mlp_layers = mlp_layers

        # build the Q network
        layer_dims = [np.prod(self.state_shape)] + self.mlp_layers
```

```
        fc = [nn.Flatten()]
        fc.append(nn.BatchNorm1d(layer_dims[0]))
        for i in range(len(layer_dims)-1):
            fc.append(nn.Linear(layer_dims[i], layer_dims[i+1],
                bias=True))
            fc.append(nn.Tanh())
        fc.append(nn.Linear(layer_dims[-1], self.num_actions, bias
            =True))
        self.fc_layers = nn.Sequential(*fc)

    def forward(self, s):
        ''' Predict action values

        Args:
            s  (Tensor): (batch, state_shape)
        '''
        return self.fc_layers(s)

class Memory(object):
    ''' Memory for saving transitions
    '''

    def __init__(self, memory_size, batch_size):
        ''' Initialize
        Args:
            memory_size (int): the size of the memroy buffer
        '''
        self.memory_size = memory_size
        self.batch_size = batch_size
        self.memory = []

    def save(self, state, action, reward, next_state,
            legal_actions, done):
        ''' Save transition into memory

        Args:
            state (numpy.array): the current state
            action (int): the performed action ID
            reward (float): the reward received
            next_state (numpy.array): the next state after
                performing the action
            legal_actions (list): the legal actions of the next
                state
            done (boolean): whether the episode is finished
        '''
        if len(self.memory) == self.memory_size:
            self.memory.pop(0)
        transition = Transition(state, action, reward, next_state,
            done, legal_actions)
        self.memory.append(transition)

    def sample(self):
        ''' Sample a minibatch from the replay memory

        Returns:
            state_batch (list): a batch of states
            action_batch (list): a batch of actions
            reward_batch (list): a batch of rewards
            next_state_batch (list): a batch of states
```

```
            done_batch (list): a batch of dones
        '''
        samples = random.sample(self.memory, self.batch_size)
        samples = tuple(zip(*samples))
        return tuple(map(np.array, samples[:-1])) + (samples[-1],)

    def checkpoint_attributes(self):
        ''' Returns the attributes that need to be checkpointed
        '''

        return {
            'memory_size': self.memory_size,
            'batch_size': self.batch_size,
            'memory': self.memory
        }

    @classmethod
    def from_checkpoint(cls, checkpoint):
        '''
        Restores the attributes from the checkpoint

        Args:
            checkpoint (dict): the checkpoint dictionary

        Returns:
            instance (Memory): the restored instance
        '''

        instance = cls(checkpoint['memory_size'], checkpoint['
            batch_size'])
        instance.memory = checkpoint['memory']
        return instance
```

D Reward Progression Graphs

The following section contains reward progression graphs for both DQN and LSTM-VAE DQN agents during training. There are two agents used to determine the effectiveness of each method.

Random: The opposing agent plays perfectly randomly, sampling a random distribution to perform a perfectly random action.

Aggressive ("Maniac"): The opposing agent is likely to take risks and not play "according to the book." The agent is likely to bet extremely large amounts and raise frequently despite a weaker hand. The agent aims to control the pot while forcing opponents into tough decisions [10].

D.1 Reward Progression graph for DQN against Random Agent

The following is the Reward Progression Graph for DQN against Random Agents. The DQN agent was able to obtain an average reward of 1.41.

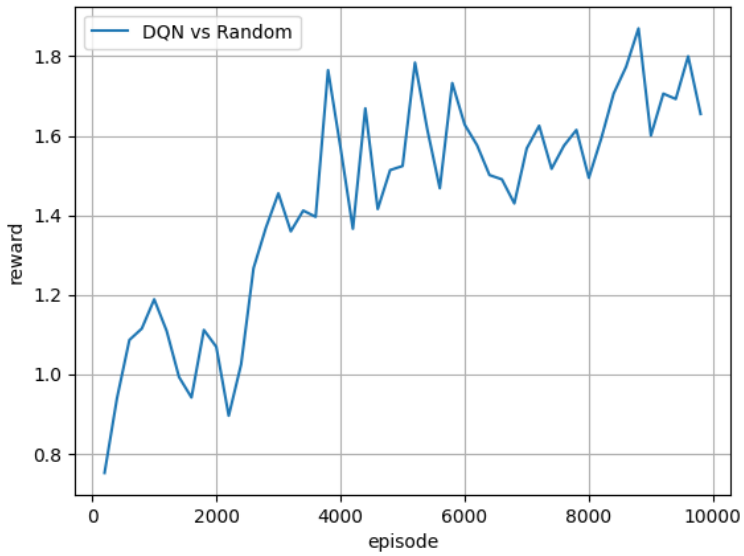

Figure 6: Reward progression for DQN agent in Bluff Game training against Random agents

D.2 Reward Progression graph for DQN against Aggressive Agent

The following is the Reward Progression Graph for DQN against Aggressive Agents. The DQN agent was able to obtain an average reward of -0.33.

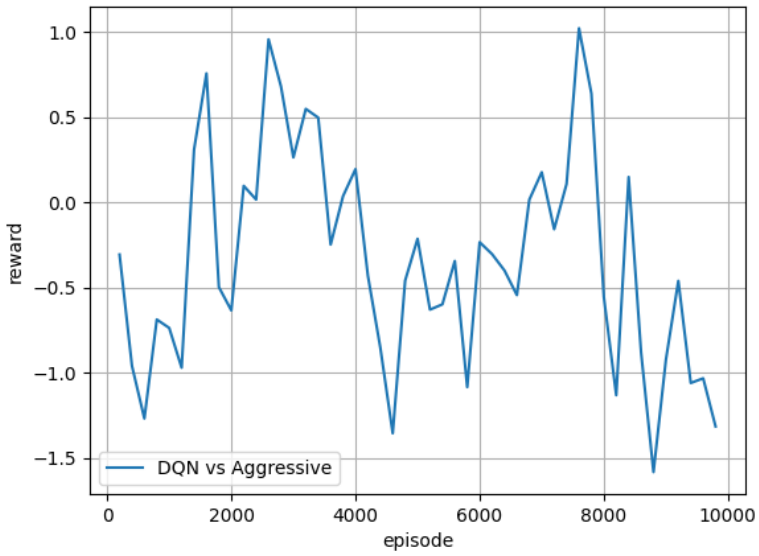

Figure 7: Reward progression for DQN agent in Bluff Game training against Aggressive agents

D.3 Reward Progression graph for LSTM-VAE DQN against Random Agent

The following is the Reward Progression graph for LSTM-VAE DQN against Random Agents. The LSTM-VAE DQN agent was able to obtain an average reward of 1.38

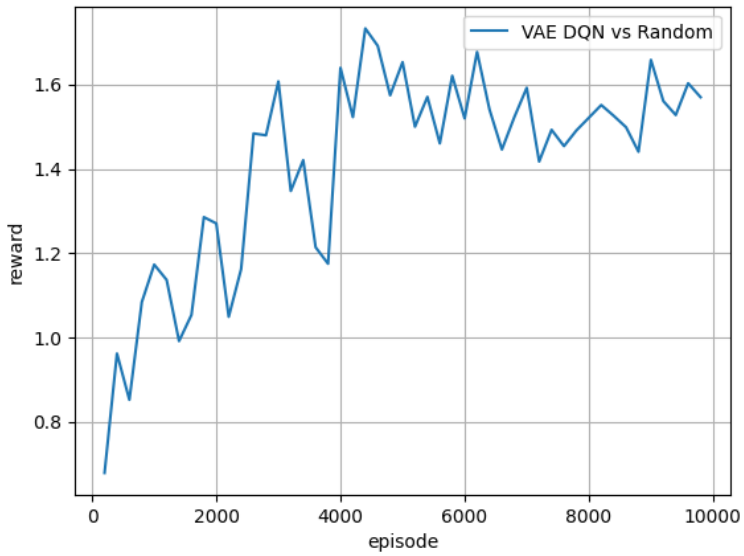

Figure 8: Reward progression for LSTM-VAE DQN agent in Bluff Game training against Random agents

D.4 Reward Progression graph for LSTM-VAE DQN against Aggressive Agent

The following is the Reward Progression graph for LSTM-VAE DQN against Aggressive Agents. The LSTM-VAE DQN agent was able to obtain an average reward of 0.66

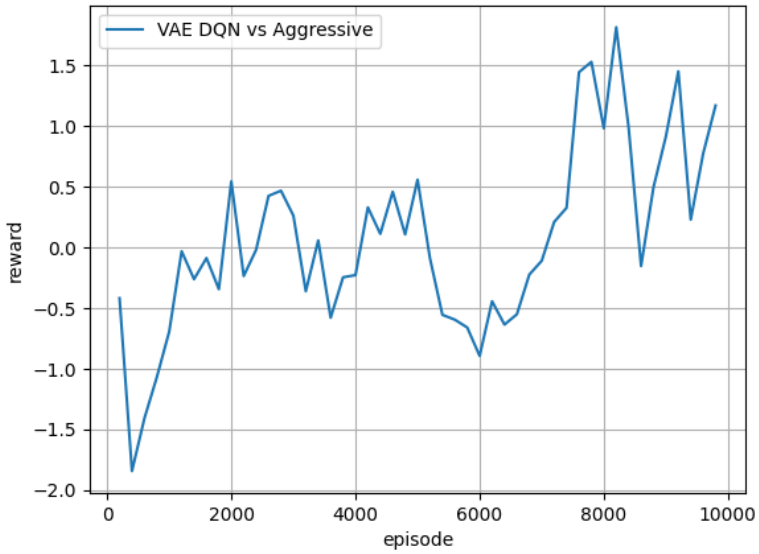

Figure 9: Reward progression for LSTM-VAE DQN agent in Bluff Game training against Aggressive agents

E Hyperparameter Testing

The following section contains graphs for different hyperparameter combinations. A random search was used to test various hyperparameter combinations with the following three yielding the best results.

E.1 Adversarial Hyperparameter Tuning, Hidden Size = 32, Learning Rate = 0.0001

The following is the Reward Progression graph for the LSTM-VAE DQN agent against Random agents with a hidden size of 32 and learning rate of 0.0001. The DQN agent was able to obtain an average reward of -1.32

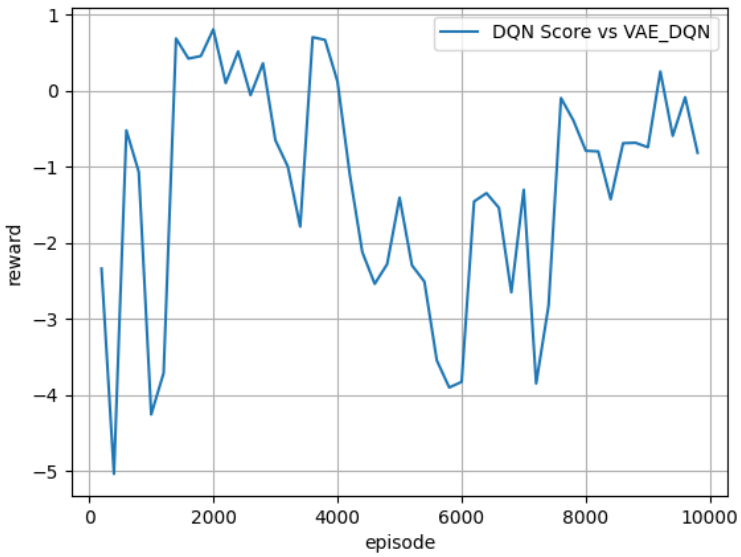

Figure 10: Reward progression for DQN agent in Bluff Game training against LSTM-VAE DQN agent (Hidden Size = 64, Learning Rate = 0.0001)

E.2 Adversarial Hyperparameter Tuning, Hidden Size = 64, Learning Rate = 0.0001

The following is the Reward Progression graph for the LSTM-VAE DQN agent against Random agents with a hidden size of 64 and learning rate of 0.0001. The DQN agent was able to obtain an average reward of -0.85

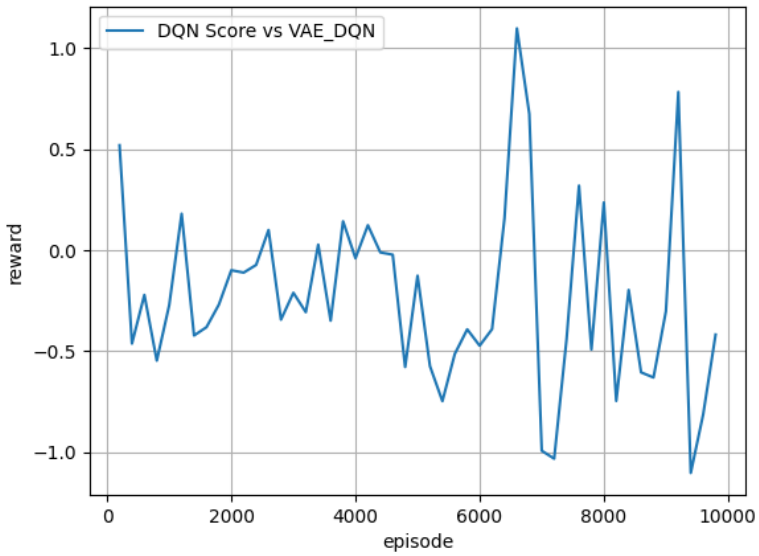

Figure 11: Reward progression for DQN agent in Bluff Game training against LSTM-VAE DQN agent (Hidden Size = 64, Learning Rate = 0.0001)

NeurIPS Paper Checklist

The checklist is designed to encourage best practices for responsible machine learning research, addressing issues of reproducibility, transparency, research ethics, and societal impact. Do not remove the checklist: **The papers not including the checklist will be desk rejected.** The checklist should follow the references and follow the (optional) supplemental material. The checklist does NOT count towards the page limit.

Please read the checklist guidelines carefully for information on how to answer these questions. For each question in the checklist:

- You should answer [Yes] , [No] , or [NA] .
- [NA] means either that the question is Not Applicable for that particular paper or the relevant information is Not Available.
- Please provide a short (1–2 sentence) justification right after your answer (even for NA).

The checklist answers are an integral part of your paper submission. They are visible to the reviewers, area chairs, senior area chairs, and ethics reviewers. You will be asked to also include it (after eventual revisions) with the final version of your paper, and its final version will be published with the paper.

The reviewers of your paper will be asked to use the checklist as one of the factors in their evaluation. While "[Yes] " is generally preferable to "[No] ", it is perfectly acceptable to answer "[No] " provided a proper justification is given (e.g., "error bars are not reported because it would be too computationally expensive" or "we were unable to find the license for the dataset we used"). In general, answering "[No] " or "[NA] " is not grounds for rejection. While the questions are phrased in a binary way, we acknowledge that the true answer is often more nuanced, so please just use your best judgment and write a justification to elaborate. All supporting evidence can appear either in the main paper or the supplemental material, provided in appendix. If you answer [Yes] to a question, in the justification please point to the section(s) where related material for the question can be found.

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- **Delete this instruction block, but keep the section heading "NeurIPS paper checklist"**,
- **Keep the checklist subsection headings, questions/answers and guidelines below.**
- **Do not modify the questions and only use the provided macros for your answers**.

1. **Claims**

   Question: Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope?

   Answer: [Yes]

   Justification: We assert that our primary claim—developing a deep RL agent (Bluff-Bot) capable of learning and adapting to imperfect-information gameplay in Bluff Game—is clearly stated in the introduction and substantiated through our framework description and preliminary experimental results. We justify our contributions by comparing against standard baselines and detailing our modifications to the RLCard toolkit.

2. **Limitations**

   Question: Does the paper discuss the limitations of the work performed by the authors?

   Answer: [Yes]

   Justification: We acknowledge that while our report demonstrates proof-of-concept success with a DQN agent, there are limitations. These include the inherent challenges of deterministic Q-learning in imperfect-information settings and a need for more extensive statistical validation (e.g., error bars, confidence intervals). We plan to address these in future revisions.

3. **Theory Assumptions and Proofs**

Question: For each theoretical result, does the paper provide the full set of assumptions and a complete (and correct) proof?

Answer: [NA]

Justification: Although our work is primarily empirical and does not provide formal proofs, we discuss the theoretical limitations of deterministic Q-learning in approximating Nash equilibrium strategies in imperfect-information games. Our report motivates the need for a probabilistic approach—specifically, an encoder–decoder framework—that better models the distribution of possible states and actions, aligning more closely with the mixed strategies inherent in Nash equilibrium.

4. **Experimental Result Reproducibility**

   Question: Does the paper fully disclose all the information needed to reproduce the main experimental results?

   Answer: [Yes]

   Justification: We describe the environment setup, hyperparameters (e.g., the four-layer MLP with neuron counts of 64, 128, 64, and 32, Tanh activations, epsilon–greedy exploration, etc.), and training protocols in Sections 3.1, 3.2, and Appendices B and C. However, our current results are preliminary, and we plan to include additional run statistics and error measurements in the final submission.

5. **Open access to data and code**

   Question: Does the paper provide open access to the data and code, with sufficient instructions to faithfully reproduce the main experimental results, as described in supplemental material?

   Answer: [Yes]

   Justification: We have included the DQN agent architecture code along with detailed modifications to the RLCard toolkit in the report appendices, notably in Appendix B, which contains the code for the modified game environment and agent training scripts. Moving forward, we plan to upload the complete modified environment files to further enhance reproducibility. Additionally, repository links and comprehensive documentation will be provided as supplementary material.

6. **Experimental Setting/Details**

   Question: Does the paper specify all the training and test details (e.g., data splits, hyperparameters, how they were chosen, type of optimizer, etc.) necessary to understand the results?

   Answer: [Yes]

   Justification: Our report includes detailed descriptions of the virtual game environment, agent architecture, and training setup. While most details are provided, we will add further specifics (such as optimizer settings and complete hyperparameter ranges) in our final version to ensure all experimental protocols are fully reproducible.

7. **Experiment Statistical Significance**

   Question: Does the paper report error bars suitably and correctly defined or other appropriate information about the statistical significance of the experiments?

   Answer: [No]

   Justification: Our preliminary reward graphs demonstrate positive trends; however, we have not yet reported error bars or confidence intervals. In our final submission, we will conduct multiple runs and report appropriate statistical measures to confirm the significance of our results.

8. **Experiments Compute Resources**

Question: For each experiment, does the paper provide sufficient information on the computer resources (type of compute workers, memory, time of execution) needed to reproduce the experiments?

Answer: [No]

Justification: Although we describe the experimental setup and number of episodes, we have not explicitly detailed the compute resources (e.g., GPU/CPU models, memory, training time). We will include these details in the final version.

9. **Code Of Ethics**

Question: Does the research conducted in the paper conform, in every respect, with the NeurIPS Code of Ethics `https://neurips.cc/public/EthicsGuidelines`?

Answer: [Yes]

Justification: Our work adheres to standard ethical guidelines for academic research. As our study is focused on simulation and algorithmic development without any direct human subject impact, it aligns with accepted research ethics practices.

10. **Broader Impacts**

Question: Does the paper discuss both potential positive societal impacts and negative societal impacts of the work performed?

Answer: [No]

Justification: While our paper focuses extensively on the technical development and empirical evaluation of Bluff-Bot in a simulated environment, it does not explicitly discuss the broader societal impacts of our work. We have not yet explored potential risks or benefits (e.g., ethical implications, real-world applicability, or unintended consequences) associated with deploying game-playing AI. In light of this, we plan to evaluate both the potential benefits (such as advancing research in opponent modeling and reinforcement learning) and the risks (such as misuse in contexts like real-world gambling) to fully address the broader impacts of our work.

11. **Safeguards**

Question: Does the paper describe safeguards that have been put in place for responsible release of data or models that have a high risk for misuse (e.g., pretrained language models, image generators, or scraped datasets)?

Answer: [Yes]

Justification: Given that our research is confined to simulated environments and does not involve sensitive real-world data, the risks of misuse are low. Nonetheless, we note that any potential adaptation for real-world applications would require additional safeguards.

12. **Licenses for existing assets**

Question: Are the creators or original owners of assets (e.g., code, data, models), used in the paper, properly credited and are the license and terms of use explicitly mentioned and properly respected?

Answer: [Yes]

Justification: We have built our work on the publicly available RLCard toolkit and other open-source resources. We have cited these assets appropriately and will ensure that all licensing terms are respected when releasing our code and data.

13. **New Assets**

Question: Are new assets introduced in the paper well documented and is the documentation provided alongside the assets?

Answer: [NA]

Justification: Our paper does not introduce new datasets or proprietary assets beyond the modifications we have made to existing tools.

14. **Crowdsourcing and Research with Human Subjects**

Question: For crowdsourcing experiments and research with human subjects, does the paper include the full text of instructions given to participants and screenshots, if applicable, as well as details about compensation (if any)?

Answer: [NA]

Justification: Our research involves algorithm development and simulation only, with no crowdsourced data or human subjects involved.