Credit-cognisant reinforcement learning for multi-agent cooperation

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Abstract—Traditional multi-agent reinforcement learning (MARL) algorithms, such as independent Q-learning, struggle when presented with partially observable scenarios, and where agents are required to develop delicate action sequences. This is often the result of the reward for a good action only being available after other agent’s have taken theirs, and these actions are not credited accordingly. Recurrent neural networks have proven to be a viable solution strategy for solving these types of problems, resulting in significant performance increase when compared to other methods. In this paper, we explore a different approach and focus on the experiences used to update the action-value functions of each agent. We introduce the concept of credit-cognisant rewards (CCRs), which allows an agent to perceive the effect its actions had on the environment as well as on its co-agents. We show that by manipulating these experiences and constructing the reward received within them to include the rewards received by all the agents within the same action sequence, we are able to improve significantly on the performance of independent deep Q-learning as well as deep recurrent Q-learning. We evaluate and test the performance of CCRs when applied to deep reinforcement learning techniques at the hands of a simplified version of the popular card game Hanabi.

Index Terms—Card Games, Machine Learning, Multi-agent Systems, Multi-player Games, Neural Networks, Reinforcement Learning.

I. INTRODUCTION

REINFORCEMENT learning (RL) holds promising potential to address a large variety of problems where artificial agent operation offers a significant improvement over alternative methods [1]. For certain real-world problems, single-agent operation is not optimal (or even possible) and the incorporation of multiple agents would be beneficial (or necessary). Scenarios such as autonomous vehicles navigating terrain [2], guided drone swarms [3], mapping verbal instructions to executable actions [4], or switching of railway lines benefit from the use of multiple agents. RL could help agents to effectively cooperate within these multi-agent scenarios by learning from past and or simulated experiences.

Unfortunately, the introduction of multiple agents into an environment typically increases the complexity of the problem exponentially. It introduces a moving target learning problem [5], since all the agents must learn simultaneously. The reason for this is that each individual agent’s policy changes over time, which in turn causes a non-stationary environment. This could inhibit all the agents from developing effective policies and produce undesired behaviour [5].

One of the most straightforward solutions to multi-agent reinforcement learning (MARL) is the combination of deep Q-networks (DQNs) and independent Q-learning [6], where each agent independently and simultaneously learns its own action-value function (or Q-values) while interacting with the same environment. However, this strategy does not fair well when paired with partial observability [7], [8]. Hausknecht and Stone [9] have shown that recurrent neural networks offer an improved solution to MARL problems containing partial observability. These networks incorporate a built-in short term memory over which experiences are unrolled (or combined to form longer sequences). This is often combined with deep Q-learning’s feed forward neural network to produce deep recurrent Q-learning [9].

In this paper, we specifically focus on turn-based MARL problems containing partial observability, and where a delicate action sequence is required for successful cooperation. We define a delicate action sequence as a set of consecutive actions, where each action is imperative and highly correlated to the others. Changing any one action in such a sequence would make the difference between receiving a reward or not, and the agents will not be able to effectively solve the problem at hand. Most research efforts explore the implementation of advanced algorithms with powerful function approximators to solve similar MARL problems [10], [11].

A popular approach is to use games as a medium for testing and evaluating RL algorithms, where examples include Go [12], Backgammon [13], and Dota 2 [14]. In this paper, we use a simplified version of the popular card game Hanabi, which has recently become an area of interest for testing and developing MARL algorithms [15], as an illustrative example.

A. Related work

Sunehag et al. [16] propose an alternative solution to independent deep Q-learning called value decomposition networks (VDNs). Instead of each agent learning independently, the agents learn a joint action-value function which is equal to a linear combination of each agent’s individual action-value functions [16]. VDNs allow for the automatic decomposition of complex learning problems into local simplified sub-problems for each agent. However, VDNs can only represent

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1Partial observability refers to problems where the full state space is hidden from each individual agent, resulting in each agent having their own unique perspective of the problem.
a limited class of joint action-value functions and do not scale well when increasing the number of agents [11], [16].

Rashid et al. [11] introduce an extension of VDNs called QMIX, allowing agents to cooperate in a more complex environment. They explore and evaluate this method within the context of the video game StarCraft II. QMIX uses a combination of recurrent neural networks and hypernetworks to act as a non-linear combination of each agent’s action-value functions to achieve remarkable performance in this environment. Although remarkable, this approach has high complexity since it involves the combination of multiple networks and a non-linear combination of action-value functions, which can lead to sub-optimal policies [17].

To achieve effective communication between agents within a partially observable environment, Foerster et al. [10] explore the capabilities of multiple deep RL agents and develop two methods called Reinforced Inter-Agent Learning (RIAL) and Differentiable Inter-Agent Learning (DIAL). These agents can directly share weights of their networks via communication, to allow for the development of cooperative policies. Although simpler than QMIX, their research is specifically focused on the communication protocol developed between agents and how they can cooperate effectively through communication.

Another alternative is the distribution of the joint action-value function between agents, proposed by Schneider et al. [18]. This distribution is based on each agent’s predefined contribution within the global reward function. Guestrin et al. [19] further build on this research by introducing coordination graphs that allow for the exploitation of conditional independencies between agents. This approach allows the agents to coordinate their actions more effectively. However, in both cases this requires the agent’s dependencies on each other to be predefined and their influence within the global reward to be known.

Rainbow, introduced by Hessel et al. [20], offers a state-of-the-art solution. It combines various advancements made to deep Q-learning, and has proven to offer significant performance gain when faced with large discrete action spaces [21]. A natural extension of Rainbow to multi-agent systems is the implementation of independent agents (referred to as MARainbow) [22]. Bard et al. [15] explore the capabilities of MARainbow within Hanabi as a preliminary solution strategy. However, Rainbow introduces a plethora of new hyperparameters which can often result in sub-optimal policies [23].

B. Summary of Contributions

We argue that delicate action sequences pose a challenge to the traditional RL update step. We will prove this by implementing tabular RL within a simplified problem, to illustrate the shortcoming of independent Q-learning. To achieve this, we extend existing RL methods to turn-based, partially observable environments using our unifying notation. Using this extension, we introduce our novel contribution, called credit-cognisant rewards (CCRs), and show how it improves on existing RL methods.

The key to CCR is the fact that the reward received for a good action is usually only available after other agents have taken their actions, and that these actions are not credited accordingly. We contrast this to distributed value functions and coordination graphs where the dependencies between agents and their role within the global reward is predefined. We expect our agents to learn these dependencies without requiring predefined knowledge. This is also in contrast to RIAL and DIAL, where agents share network weights directly, and thereby increasing the problem complexity by introducing an additional communication channel between agents. Additionally, our approach does not introduce any new hyperparameters, and acts as a variation to existing methods utilising traditional transition tuple.

Our approach also differs from n-step bootstrapping, which shares similarities, but implements a different concept. We also contrast this to recurrent neural networks where the focus is on architecture design and function approximation, whereas our focus is a fundamental modification of the experiences received by each agent. We compare and evaluate independent Q-learning, independent deep Q-learning and deep recurrent Q-learning along with their CCR variants, to demonstrate the shortcomings of existing methods and illustrate how CCR can lead to improved performance.

C. Paper Outline

To discuss some of the core concepts of RL, we first consider the single agent system with full observability in Section II, and introduce deep reinforcement learning with standard terminology. We then extend these concepts to turn-based MARL containing partial observability with our unifying notation in Section III. This is followed by the introduction and formal definition of credit-cognisant rewards (CCRs) in Section IV. We then introduce our example settings, namely a tabular problem and colourless Hanabi, in Section V and VI. For each example, we discuss the experimental setup for each algorithm, and present and discuss our results.

II. Preliminaries

Reinforcement learning allows agents to develop policies based on past experiences [24]. These policies are usually aimed at maximizing a reward $R$ received from the environment after taking action $A$ within a given state $S$. This results in the transition tuple

$$e = (S_t, A_t, R_{t+1}, S_{t+1})$$  \hspace{1cm} (1)

at timestep $t$ [24]. These transition tuples are used to calculate the value functions which acts as a quantitative measure for the desirability of a state. In tabular methods these values are represented using a lookup-table, while deep RL methods use powerful function approximators to estimate these values.

A. Independent Q-learning

Q-learning is an off-policy, temporal difference (TD) control algorithm that learns the action-value function $Q(S, A)$ by directly approximating the optimal action-value function...
$Q^*(S, A)$, independent of the policy being followed [24]. The update step for the action-value function is defined as

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[ R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t) \right], \quad (2)$$

where $\alpha$ is the learning rate and $\gamma$ the discount factor of future rewards.

In Q-learning the agent selects its actions based on an $\epsilon$-greedy strategy, i.e.,

$$a = \begin{cases} \arg\max_a Q(S_t, a) \quad \text{with probability } 1 - \epsilon \\ \text{random action} \quad \text{with probability } \epsilon \\ \end{cases}, \quad (3)$$

where $\epsilon$ is the exploration rate to account for exploration of the state-space [24]. This can be extended to MARL with independent Q-learning, where each agent has their own action-value function and uses their individual experiences in their update steps [25].

Instead of distinct policies, independent Q-learning agents can make use of a shared policy, especially when the environment contains symmetries [25]. This allows the update step (2) to be updated more frequently by using the experiences of all the independent agents. This has proven to offer significant performance gain and allow agents to learn more effectively [25].

B. N-step Bootstrapping

N-step bootstrapping is a method unifying one-step TD learning and Monte Carlo methods, to allow an agent’s action-values to be bootstrapped over a longer time sequence [24]. In n-step methods, the rewards are constructed over $n$ actions, resulting in the update step

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[ \sum_{i=0}^{n-1} \gamma^i R_{t+1+i} + \gamma^n \max_a Q(S_{t+n}, a) - Q(S_t, A_t) \right]. \quad (4)$$

For $n = 1$, (4) simplifies to (2), and if $n = \infty$ the update step is calculated over the entire episode of experiences (identical to Monte Carlo methods). It is important to note that the update step in (4) can only occur at timestep $t + n$, to ensure that all the rewards are available. This allows an agent to develop improved policies based on more than just one experience, without waiting for the episode to terminate. We will later discuss how this differs from our new variant.

C. Deep Q-learning

Deep Q-learning is an extension of tabular Q-learning where artificial neural networks (referred to as deep Q-networks or DQNs) are used as non-linear function approximators [26]. Unfortunately, RL often becomes unstable or diverges from the desired policy when using non-linear function approximators [26]. To solve this instability, deep Q-learning implements an experience replay memory to store the experiences $e$ [27]. These experiences are usually sampled in random batches $b$ to remove correlation within the observation sequence, thereby smoothing over the changes within the data distribution [26].

Deep Q-learning usually incorporates a policy network and a target network [26]. The policy network is used to select actions and utilises the update step, while the target network serves as a baseline when calculating the TD error. The target network is updated periodically with the policy network to reduce correlation with the target.

The weights of the policy network are updated using backpropagation with the goal of minimizing the TD error, which is defined as

$$L_i(\theta_i) = E_b \left[ (R_{t+1} + \gamma \max_a Q(S_{t+1}, a; \theta_i^\ast) - Q(S_t, A_t; \theta_i))^2 \right], \quad (5)$$

where $\theta_i$ and $\theta_i^\ast$ are the weights of the policy-and target network, respectively, at iteration $i$ [26]. To obtain the update step for the weights of the policy network, the TD error defined in (5) must be differentiated according to the weights to obtain

$$\theta_{i+1} = \theta_i + \alpha \left[ R_{t+1} + \gamma \max_a Q(S_{t+1}, a; \theta_i^\ast) - Q(S_t, A_t; \theta_i) \right] \nabla_{\theta_i} Q(S_t, A_t; \theta_i), \quad (6)$$

which Sutton and Barto [24] refer to as the semi-gradient form of Q-learning [26]. In practice the backpropagation and calculation of the TD error is usually handled by an optimizer, such as the Adam optimizer [28].

Similar to tabular Q-learning, deep Q-learning can be extended to MARL using independent deep Q-learning [6]. However, due to the addition of DQNs and the added complexity of the moving target learning problem, this approach does not have any guarantees of convergence. In spite of this uncertainty, it has a strong track record and has shown some remarkable performance in the game of Pong [6], and is often considered a baseline when measuring the performance of other algorithms.

D. Deep Recurrent Q-Learning

In deep Q-learning, the algorithm performs better with full observability of the environment. However, for MARL problems with partial observability, deep recurrent Q-learning has shown to be a superior alternative [9]. Instead of approximating the action-value function with a fully-connected feed forward neural network, deep recurrent Q-learning adds recurrent layers to the network. These layers can maintain a history of visited states and accumulate observations over time, acting as a built-in memory system [9].

These recurrent layers are typically gated architectures such as long short-term memory (LSTM) [29] or gated recurrent unit (GRU) [30] which allows learning over longer timescales. It introduces a new hyperparameter called the unrolled length $K$, which determines the number of iteration timesteps over which the update step is calculated. This offers remarkable performance gain, and will be considered as a viable alternative solution strategy during our evaluation.

III. Modelling Partial Observability

We now extend independent Q-learning, n-step bootstrapping, and deep Q-learning to include turn-based environments containing partial observability using our unifying notation.
This will allow us to introduce credit-cognisant rewards (CCRs) and show how it builds on these concepts.

A. Transition Tuple

First, we must change the transition tuple in (1) to account for multiple agents by separating their individual states based on their perspectives. These perspectives will be unique due to the partial observability of the problems we consider. Therefore, we can separate the perspectives of each agent \( i \) using

\[
i = t - rP,
\]

where \( P \) is the total number of players within the environment and \( r \) the current round.

Since the problems we consider are turn-based, each action and reward at timestep \( t \) will be associated with agent \( i \) within that round, and does not require discerning based on perspectives. Using this we can extend the transition tuple in (1) to a turn-based multi-agent system with

\[
e = \langle S_i^t, A_i, R_{t+1}, S_i^{t+1} \rangle.
\]

These tuples will be used to update the action-value functions of each agent within the MARL environment. Table I illustrates a typical agent experience when interacting with a turn-based environment containing three agents.

| Time(t) | Round(r) | Agent(i) | State | Action | Reward | New State |
|---------|----------|----------|-------|--------|---------|-----------|
| 0       | 0        | 0        | \( S_0^t \) | \( A_0 \) | \( R_1 \) | \( S_2^t \) |
| 1       | 0        | 1        | \( S_1^t \) | \( A_1 \) | \( R_2 \) | \( S_1^t \) |
| 2       | 0        | 2        | \( S_2^t \) | \( A_2 \) | \( R_3 \) | \( S_2^t \) |
| 3       | 1        | 0        | \( S_1^t \) | \( A_3 \) | \( R_4 \) | \( S_1^t \) |
| 4       | 1        | 1        | \( S_2^t \) | \( A_4 \) | \( R_5 \) | \( S_1^t \) |
| 5       | 1        | 2        | \( S_3^t \) | \( A_5 \) | \( R_6 \) | \( S_2^t \) |
| 6       | 2        | 0        | \( S_0^t \) | \( A_6 \) | \( R_7 \) | \( S_1^t \) |
| \cdots  | \cdots   | \cdots   | \( S_i^t \) | \( A_i \) | \( R_{t+1} \) | \( S_i^{t+1} \) |

This ensures that the policy network is updated using the states and actions of an individual agent based on its perspective. It will follow a similar strategy as Algorithm 1, with the calculation of the TD error and network weights’ backpropagation replacing the update step in line 9.

C. Independent N-step Bootstrapping

We can also extend n-step bootstrapping for turn-based environments containing partial observability using the new transition tuples in (8). This results in the update step

\[
Q(S_i^t, A_i) \leftarrow Q(S_i^t, A_i) + \alpha \left[ R_{t+1} + \gamma \max_a Q(S_{t+1}^i, a) - Q(S_i^t, A_i) \right],
\]

(9)

This ensures that each agent’s update step is constructed over their own experiences, but similar to (2) the agents can utilise a shared policy to increase the overall performance. This results in the algorithm shown in Algorithm 1, where the agents implement an \( \epsilon \)-greedy policy. The experiences resulting from lines 7 and 8 will follow the same structure as the transition tuples illustrated in Table I.

Similarly, we can extend the update step for deep Q-learning (6) using the tuples in (8) to obtain

\[
\theta_{t+1} = \theta_t + \alpha \left[ R_{t+1} + \gamma \max_a Q(S_{t+1}^i, a; \theta_t) - Q(S_i^t, A_i; \theta_t) \right] \nabla_{\theta_t} Q(S_i^t, A_i; \theta_t).
\]

(10)

This ensures that the policy network is updated using the states and actions of an individual agent based on its perspective. It will follow a similar strategy as Algorithm 1, with the calculation of the TD error and network weights’ backpropagation replacing the update step in line 9.

IV. CREDIT-COGNISANT REWARDS

Traditional MARL methods struggle when presented with partial observability, where a delicate action sequence is required for effective cooperation. To overcome this challenge, we introduce a novel approach that incorporates the rewards received by all the agents within a given action sequence. For this purpose, we define the credit-cognisant reward (CCR) as

\[
C_{t+1} = \sum_{k=0}^{P-1} R_{t+1+k}.
\]

(12)
This allows an agent to perceive the effect their action had on the environment as well as on the other agents contained within it, and encourages the development of improved action sequences. It acts as an action-reaction mechanism where an agent observes their immediate reward for taking an action, and incorporates the consecutive agents’ rewards into this immediate reward as a reaction to the first agent’s action.

A. CCR Transition Tuple

We can, therefore, change the multi-agent transition tuple defined in (8) to include the CCR as

\[ e = (S^i_t, A^i_t, C_{t+1}, S^{i+1}_t) \]  

(13)

The next state \( S^{i+1}_t \), typically used in the estimation value, has changed to \( S^{i+1}_t \), i.e., the new state as seen from the current agent’s perspective after the other agents have taken their turns. This allows the other agent’s actions to be seen as part of the ‘environment step’ resulting from action \( A^i_t \), effectively mimicking a single-agent environment interaction.

It is important to note that \( C_{t+1} \) is only available after a timestep of \( t + P \) (or one round), resulting in a delay when updating the action-value functions (similar to n-step).

B. CCR applied to Independent Q-learning

To apply CCRs to independent Q-learning, we must incorporate the new transition tuple (13) into the update step (9) of the action-value function for each agent, resulting in

\[
Q(S^i_t, A^i_t) \leftarrow Q(S^i_t, A^i_t) + \alpha \left[ C_{t+1} + \gamma \max_a Q(S^{i+1}_t, a) - Q(S^i_t, A^i_t) \right]
\]

(14)

This requires that we store each agent’s action and reward within a temporary buffer for each action sequence, to allow the calculation of the CCR for each action after a delay of \( P \). This will result in a delay within the update step of line 9 in the independent Q-learning method found in Algorithm 1, while also introducing the temporary buffer in line 8. Therefore, we now update the algorithm found in Algorithm 1 to produce Algorithm 2, which acts as the algorithm for independent Q-learning with CCR applied. In this algorithm, \( \tau \) represents the time step lagging the current time step \( t \) by the number of players \( P \).

Similar to Algorithm 1, the first few lines act as initialisation of hyperparameters and is identical. When the agents select and execute actions in line 6 and 7, the rewards and new states must be stored within the temporary buffer. As mentioned previously, the calculation of the CCR can only occur after 1 round, and is incorporated into line 8. Line 9 illustrates the lagging time step \( \tau \), which allows for the calculation of the CCRs and updating of the value functions for the current player \( i \) using the rewards of the previous action sequence.

Importantly, lines 17 to 21 illustrate the terminal round calculation, which is considered a special case. The terminal round calculation requires that an agent’s final rewards are calculated based on the rewards received after it took its final action until the terminal state. Additionally, it requires that the update step includes the terminal state as seen by all the agents from their individual perspectives \((S^{i+1}_t)\).

We note that CCR requires the sharing of rewards during training, which in practice is not always feasible. However, the agents can utilize centralized training with decentralized execution allowing for the sharing of reward information in the training phase [31]. During execution the agents act independently without sharing additional information, and act greedily according to their individual action-value functions.

Furthermore, the delay imposed in the update step is only present when training the agents, during execution there is no difference between the original method and its CCR variant. Similar to this discussion, the CCR variant can be extended to any method utilizing the traditional transition tuple.

C. CCR vs N-step Bootstrapping

CCR shares similarities with n-step bootstrapping, but in fact utilises a different concept. The update step defined in (14) illustrates the major differences between n-step bootstrapping and CCRs. The n-step rewards are constructed over \( n \) actions of an individual agent’s experience, e.g., if \( P = 3 \) and \( n = 2 \), then agent 0 will calculate its rewards based on the rewards received for actions \( A_0 \) and \( A_1 \) (see Table I). This allows the agent to learn from rewards that were received on another
agent’s turn as an indirect consequence of its action, as oppose
to its own rewards over multiple actions.

Additionally, CCR does not introduce a new hyperparameter
(unlock n-step bootstrapping) and only acts as a variation to
any MARL method using traditional transition tuples. Another
important difference between n-step bootstrapping and CCRs
is the next state used in the update step. For n-step bootstrapp-
ing the next state is $S_{i+1+(n-1)p}$, as seen in (11), while
CCR uses $S_{i+p}^i$. This reduces the severe shift in an agent’s
perspective as the environment transitions from one state to
the next as a result of each agent taking an action, e.g., the
difference between $S_{i}^0$ and $S_{i}^3$ for agent 0 in our example
mentioned previously. During training and evaluation we will
compare CCRs to n-step bootstrapping to further illustrate the
difference between these two methods.

D. CCR applied to Deep Reinforcement Learning

Similar to tabular methods, when applying CCR to deep
RL it only affects the experiences stored within the replay
memory of each agent. In the case of deep Q-learning,
these experiences will consist of tuples identical to the ones
defined in (13). These experiences are then sampled in random
batches, which is used to calculate the new TD error

$$L_i(\theta_i) = \mathbb{E}_\theta \left[ (C_{i+1} + \gamma \max_a Q(S_{i+1+p}^i, a; \theta_i^-) - Q(S_{i}^i, A_i; \theta_i))^2 \right].$$

(15)

Similar to the TD error defined in (5), we can differentiate
according to the weights of the policy network to obtain the
semi-gradient form of deep Q-learning with CCR applied,

$$\theta_{i+1} = \theta_i + \alpha \left[ C_{i+1} + \gamma \max_a Q(S_{i+1+p}^i, a; \theta_i^-) - Q(S_{i}^i, A_i; \theta_i) \right] \nabla \theta_i Q(S_{i}^i, A_i; \theta_i).$$

(16)

Deep Q-learning with CCR applied will follow a similar
structure as Algorithm 2, with the only difference being the
update steps in line 11 and 20, where the TD error must be
calculated and sent to the optimizer to perform backpropagation.
Additionally, before calculating the TD error, the experiences
containing the CCR must be stored in the experience replay
memory. A similar methodology is used when applying CCR
to deep recurrent Q-learning, and will only affect the experi-
ences stored within the short term memory.

V. A QUINTESSENTIAL EXAMPLE

We test independent Q-learning and its CCR variant within
a simplified scenario with a small state space to show the
fundamental limitation of RL methods, even for the tabular
case. We will then show how our variation improves upon
them. We will discuss the experimental design and briefly
highlight the main results.

The environment is a cooperative two-player card game.
Each player receives 3 cards with rank 1, 2, or 3, but cannot
see their own cards, they can only see the cards of the other
player. In the center is a target card visible to both players,
and the aim of the game is to play a card matching the target
card. On their turn a player can, either play a card from their
hand or hint a card in the other player’s hand. The game ends
as soon as a card is played, and if the card matched the target,
the play was successful and the players receive a score of 1.
Otherwise, the players loose with a score of 0. The solution
to this problem is trivial and only requires two turns. The first
player must hint to the other player which card matches the
target, and on the next turn the player must play that card.
For a discussion on the hyperparameters used in each method see
Table III in Appendix A.

Fig. 1 shows the learning curves for each method over the
course of 25 000 episodes. It is clear that both methods are
capable of solving the problem and achieve a perfect score of
1, but independent Q-learning requires a considerable number
of training steps to do so. Therefore, it is clear that independent
Q-learning agents struggles to learn in this simplified problem.
We can further justify this statement by plotting the number of
steps before the game ended in perfect score, shown in Fig. 2.
From these results, we can see that, although the independent
Q-learning agents are able to solve the problem, they cannot
learn the optimal policy. In contrast, the CCR agents display
significantly faster training capabilities and converges at the
perfect score with the optimal policy.

![Graph showing learning curves for independent Q-learning (QL) and independent Q-learning with CCR applied (QL CCR) with a 100-episodes moving average and standard deviation, averaged over 50 runs per method.](image)

VI. PERFORMANCE EVALUATION USING COLOURLESS
HANABI

To test and evaluate the performance of CCRs when applied
to deep RL, we use a simplified version of the cooperative card
game Hanabi, called colourless Hanabi. Bard et al. [15] pro-
pose Hanabi as a new frontier for the testing and development
of cooperative RL algorithms. It offers an intricate challenge
testing various concepts crucial for successful cooperation.

Using colourless Hanabi we will evaluate the performance
of deep Q-learning, n-step deep Q-learning, CCR applied to
deep Q-learning, deep recurrent Q-learning and CCR applied
Fig. 2. Distribution of the number of steps taken by independent Q-learning (QL) and independent Q-learning with CCR applied (QL CCR) agents over the course of 1 000 evaluation episodes, after training for 100 000 episodes.

to deep recurrent Q-learning. All these methods’ hyperparameters are optimized to ensure the comparison of each method’s best agents. We will first introduce colourless Hanabi and discuss the experimental setup for each method. This is followed by the results for each method’s performance and an evaluation of the learned policies.

A. Colourless Hanabi

Colourless Hanabi is a cooperative two-player card game. The aim of the game is to consecutively stack cards in numerical order from one to five. The deck comprises of 20 cards with a distribution of six 1s, four 2s, four 3s, four 4s, and two 5s. At the start of the game, each player receives five cards randomly from the deck. Similar to the tabular problem, a player cannot see their own cards and can only see those of the other player.

The players take consecutive turns, and on each turn a player can either play, discard, or hint. Hinting involves revealing all the cards in the other player’s hand matching a certain rank. In the centre is a stack where the players must play their cards, and a successful play entails playing a card that follows the current card on top of the stack (starting at 0). If the card played does not follow the current card on the stack, the play was unsuccessful (called a misplay) and the players lose one of their shared life tokens. An example game is shown in Fig. 3.

At the start of the game the players have a shared total of three life tokens and eight hint tokens. If all the hint tokens are depleted, a player cannot take the hint action and must either play or discard a card from their hand. The players are awarded a shared score depending on the number of cards successfully placed on the stack. If the players manage to build the stack to the maximum of 5, the game ends and the players receive a perfect score of 5/5. Alternatively, if the players lose all their life tokens, or if the deck is depleted, the game ends. A discard action, or a misplay, will result in the card being removed from the game. When a player chooses the discard or play action, they draw a new card from the deck to replenish the missing card (which is also hidden from current the player). This problem requires a delicate action sequence to solve. Even if the first action is optimal, it amounts to nothing without the appropriate response. A player requires knowledge that only the other player can give in order to win.

B. Experimental Setup

Before discussing the results, we will briefly highlight the architecture design for each deep RL technique. For a full list of the hyperparameters used in each method see Table III in Appendix A. All the methods received a one-hot encoded tuple shown in Fig. 4 as input to their neural networks.

The deep Q-learning and n-step deep Q-learning solutions use a feed forward neural network as shown in Fig. 4, utilising the ReLU activation functions [32]. Both methods implement the Adam optimizer [28] to calculate the TD error and perform backpropagations to update the network weights. Deep recurrent Q-learning uses a similar architecture as deep Q-learning with two hidden feed forward neural networks, but with the addition of a LSTM recurrent layer before the outputs. It also uses the Adam optimizer to calculate the TD error and implements an unrolled length of 2.

When applying CCR to deep Q-learning and deep recurrent Q-learning, we only change the transition tuples stored within each method’s memory. Although this does not influence the network architecture, the optimal hyperparameters are different, as shown in Table III in Appendix A. During evaluation we compare each method’s 100 episode moving averages and standard deviations, averaged over 20 different runs.

Due to the symmetric nature of the environment, we apply a shared policy strategy for independent deep Q-learning, deep recurrent Q-learning and their CCR variants. As a result, the agents act as copies of each other, similar to a self-play scenario [33]. However, this still restricts learning by
only using individual experiences, i.e., there is no additional sharing of state information between each agent, the agents merely share an action-value function. During evaluation the agents are completely separate, and do not share any additional information.

C. Performance of CCRs

The learning curves for DQN, n-step DQN, and DQN-CCR over the course of 100 000 episodes are shown in Fig. 5. This shows that the DQN agents display an inability to learn within the example setting. The average score achieved never exceeds 1/5 and starts to deteriorate as training continues, with the agents devolving to semi-random behaviour, further demonstrating the agents’ inability to learn delicate action sequences. If instead we use n-step bootstrapping, the performance increases slightly, but the agents still perform inadequately.

DQN-CCR significantly improves the performance of the DQN agents. The agents are able to learn and achieve a near perfect score of 5/5, indicating that they are able to solve the problem. The CCR variant displays a significantly faster steady-state response and improves on the performance of n-step bootstrapping. This illustrates that by incorporating the reward of the other agents into an agent’s return, we are able to encourage the development of delicate action sequences, crucial for solving cooperative tasks.

We continued our investigation and applied recurrent networks to see if it offers any performance gain. Fig. 6 shows the learning curves for DRQN and DRQN-CCR, and compare them to DQN-CCR (from Fig. 5) as a baseline. It is evident that the DRQN agents are able to improve on the performance of the DQN agents, as well as n-step bootstrapping, however, it is still not optimal. DRQN displays a fast steady-state response when compared to n-step bootstrapping, but with a significant amount of standard deviation. This indicates instability within the learnt policies. By applying CCR to DRQN, we are able to further improve on its performance and mitigate its shortcomings. The DRQN-CCR agents are able to achieve a perfect score and display less deviation within the convergent policy. The DQN-CCR agents still displays the best performance, but after enough training episodes, the DRQN-CCR agents achieve a similar steady-state response.

These results show that the DQN agents are not able to learn within this environment and by using recurrent networks, we are able to improve on the performance. However, the agents are not able to achieve a perfect score and therefore do not solve the problem. The results show that by applying CCRs to both cases, we are able to significantly improve on these
shortcomings and the agents are able to solve the problem. From the learning curves in Fig. 6, the DQN-CCR agents perform the best of all the methods. It converges (a) the fastest, and (b) to the perfect score. It also displays less standard deviation, indicating a more stable policy.

D. Learned Policies and Conventions

We next evaluate the learned policies of each method after training for 10,000 episodes. The results are shown in Table II. The oracle is a rule-based agent that is handcrafted to be able to solve colourless Hanabi for the best case scenario, where the deck is perfectly distributed and the need for discarding thereby omitted. This will allow the game to be ended within 10 steps, since a player hints a card and on the next turn that card is played.

From these results we can see that the DQN and n-step DQN agents show the worst performance, with the lowest scores, least number of plays, most discards and the inability to achieve a perfect score. The DRQN agents manage to achieve a higher average score compared to the DQN and n-step DQN agents, but with a high percentage of misplays and the lowest number of hints. When monitoring the DRQN agents’ behaviour we observe a high risk policy, where the agents often take the play action at random and only start to act conservatively when the number of life tokens are low. This, however, is not an ideal policy since it can result in important cards being discarded from the game, and is supported by the agents only managing a success rate of 19.7%. The DQN-CCR and DRQN-CCR agents respectively manage to achieve a perfect score 98.1% and 95.7% of the time. Both methods achieve similar scores, number of plays and percentage of discards indicating that they are able to solve the problem.

We argue that the presented results show that current RL formulations struggle to develop delicate action sequences when they are unable to observe the effect their actions had on the environment, and on other agents. Our results show that by using our variation on the transition tuple for turn-based MARL problems, we are able to significantly improve on the performance of independent Q-learning, independent deep Q-learning and deep recurrent Q-learning. We also illustrate the difference between our novel CCR variant and n-step bootstrapping, which shares similarities, but implements a different concept and produces different results.

VII. Conclusion

We proved that delicate action sequences pose a challenge to existing MARL formulations. Without observing the effect an agent’s action had on the environment as well as its co-agents, can lead to inadequate policy development and inability to cooperate. We proposed a new variant, called credit-cognisant rewards, which addresses these challenges and encourages the development of delicate action sequences by incorporating all the rewards within an action sequence into the immediate reward of an individual agent’s action.

We demonstrated how our CCR variant improved on the performance of independent Q-learning, by producing a faster training time and superior convergent policy. We extended this to colourless Hanabi, which is a simplified version of the cooperative card game Hanabi, and explored the capabilities of independent deep Q-learning and deep recurrent Q-learning. This further justified the shortcomings of existing MARL techniques, and we showed how our CCR variant continues to improve upon them. CCR applied to deep Q-learning produced the best overall performance, with the highest average score and success rate. It also displayed the lowest percentage of misplays and the agents achieved the closest results to the oracle.

Future work can further explore the capabilities of CCRs, and apply it to other value-based and or policy gradient meth-
ods. This could offer additional performance gain and allow for added capabilities of MARL agents, with the end goal of solving more complex problems requiring agent cooperation.

APPENDIX A: HYPERPARAMETERS

Herein follows a list of the hyperparameters used for independent Q-learning, deep Q-learning, n-step deep Q-learning, deep recurrent Q-learning, and their CCR variants shown in Table III. Each method’s hyperparameters were optimized using parameter sweeps, i.e., training each method with various combinations of hyperparameters over the course of multiple runs and selecting the hyperparameters with the best results.

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TABLE III
Table of Hyperparameter Values for Each Method Used in Our Evaluations. Each Hyperparameter Sweep Were Conducted Over 10 Runs Consisting of 50,000 Episodes.

| Hyperparameter | Value | Description |
|----------------|-------|-------------|
| **Independent Q-learning** | | |
| Learning rate $\alpha$ | 0.1 | Learning rate used in Q-learning update step |
| Discount factor $\gamma$ | 0.9 | Discount factor used in Q-learning update step |
| Exploration $\epsilon$ | 0.01 | Value of $\epsilon$ in $\epsilon$-greedy strategy |
| **Independent Q-learning with CCR** | | |
| Learning rate $\alpha$ | 0.01 | Learning rate used in Q-learning update step |
| Discount factor $\gamma$ | 0.01 | Discount factor used in Q-learning update step |
| Exploration $\epsilon$ | 0.01 | Value of $\epsilon$ in $\epsilon$-greedy strategy |
| **Deep Q-learning** | | |
| Learning rate $\alpha$ | 0.0001 | Learning rate used by Adam optimizer |
| Discount factor $\gamma$ | 0.7 | Discount factor used in Q-learning update step |
| Exploration $\epsilon$ | 0.01 | Value of $\epsilon$ in $\epsilon$-greedy strategy |
| Replay memory size | 10,000 | Where experiences are stored to use in the update step |
| Sampling batch size | 64 | Number of experiences randomly sampled from the experience replay memory used in the update step |
| Target network update frequency | 100 | Number of steps before the target network is updated with the policy network |
| **N-Step Deep Q-learning** | | |
| Learning rate $\alpha$ | 0.0001 | Learning rate used by Adam optimizer |
| Discount factor $\gamma$ | 0.3 | Discount factor used in Q-learning update step |
| Exploration $\epsilon$ | 0.01 | Value of $\epsilon$ in $\epsilon$-greedy strategy |
| Replay memory size | 10,000 | Where experiences are stored to use in the update step |
| Sampling batch size | 64 | Number of experiences randomly sampled from the experience replay memory used in the update step |
| Target network update frequency | 100 | Number of steps before the target network is updated with the policy network |
| Step count $n$ | 2 | Number of steps over which the return is constructed |
| **Deep Q-learning with CCR** | | |
| Learning rate $\alpha$ | 0.0001 | Learning rate used by Adam optimizer |
| Discount factor $\gamma$ | 0.5 | Discount factor used in Q-learning update step |
| Exploration $\epsilon$ | 0.01 | Value of $\epsilon$ in $\epsilon$-greedy strategy |
| Short term memory size | 5,000 | Where experiences are stored in the hidden layer to use in the update step |
| Sampling batch size | 32 | Number of experiences randomly sampled from the experience replay memory used in the update step |
| Target network update frequency | 100 | Number of steps before the target network is updated with the policy network |
| Recurrent layer types | LSTM | Type of recurrent layer used in the network architecture |
| Recurrent layer count | 1 | Number of recurrent layers before the output |
| Unrolled length $K$ | 2 | Length of the unrolled experiences to use in the update step |
| Maximum episode length | 50 | Maximum number of steps for an episode to be stored in memory |
| **Deep Recurrent Q-learning** | | |
| Learning rate $\alpha$ | 0.0001 | Learning rate used by Adam optimizer |
| Discount factor $\gamma$ | 0.5 | Discount factor used in Q-learning update step |
| Exploration $\epsilon$ | 0.01 | Value of $\epsilon$ in $\epsilon$-greedy strategy |
| Short term memory size | 5,000 | Where experiences are stored in the hidden layer to use in the update step |
| Sampling batch size | 32 | Number of experiences randomly sampled from the experience replay memory used in the update step |
| Target network update frequency | 100 | Number of steps before the target network is updated with the policy network |
| Recurrent layer types | LSTM | Type of recurrent layer used in the network architecture |
| Recurrent layer count | 1 | Number of recurrent layers before the output |
| Unrolled length $K$ | 2 | Length of the unrolled experiences to use in the update step |
| Maximum episode length | 50 | Maximum number of steps for an episode to be stored in memory |

| Hyperparameter | Value | Description |
|----------------|-------|-------------|
| **Deep Recurrent Q-learning with CCR** | | |
| Learning rate $\alpha$ | 0.0001 | Learning rate used by Adam optimizer |
| Discount factor $\gamma$ | 0.1 | Discount factor used in Q-learning update step |
| Exploration $\epsilon$ | 0.01 | Value of $\epsilon$ in $\epsilon$-greedy strategy |
| Short term memory size | 5,000 | Where experiences are stored in the hidden layer to use in the update step |
| Sampling batch size | 32 | Number of experiences randomly sampled from the experience replay memory used in the update step |
| Target network update frequency | 100 | Number of steps before the target network is updated with the policy network |
| Recurrent layer types | LSTM | Type of recurrent layer used in the network architecture |
| Recurrent layer count | 1 | Number of recurrent layers before the output |
| Unrolled length $K$ | 2 | Length of the unrolled experiences to use in the update step |
| Maximum episode length | 50 | Maximum number of steps for an episode to be stored in memory |