

## Abstract

# Application of Multi-Agent Reinforcement Learning to Dynamic Two-Player Games

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This work is devoted to the study of the application of multi-agent reinforcement learning in dynamic two-player games. It presents a modified bargaining problem — an experimental game from game theory. This game can be considered as a model of many real-world situations where parties negotiate the division of a shared resource. It illustrates the complexity of such negotiations and the importance of taking into account various factors, including current and future benefits, risk, and the influence on the opponent. During the research, an artificial intelligence model was developed that, through simulating bilateral negotiations, effectively solves this problem. The conducted experiments confirmed the practical significance of the model, reflected in the monotonic increase in average reward and the level of agreement between participants. The obtained results can be applied to simulate negotiations and achieve mutually acceptable outcomes.

**Keywords:** Artificial Intelligence · Machine Learning · Neural Networks · Reinforcement Learning · Game Theory · Dynamic Games · Modified Bargaining Problem · Negotiation

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# List of Abbreviations

**AI** Artificial Intelligence.

**ANN** Artificial Neural Network.

**DCC** Deep Continuous Clustering.

**DDPG** Deep Deterministic Policy Gradient.

**DQN** Deep Q-Network.

**DRL** Deep Reinforcement Learning.

**MADDPG** Multi-Agent Deep Deterministic Policy Gradient.

**MARL** Multi-Agent Reinforcement Learning.

**NE** Nash Equilibrium.

**PPO** Proximal Policy Optimization.

**RL** Reinforcement Learning.

**TD-learning** Temporal-Difference Learning.

**WoLF** Win or Learn Fast.

# Chapter 1

## Introduction

*Let us move from the age of confrontation to the age of negotiation...*

*Richard Nixon*

In the modern world, there are many problems that can be solved using artificial intelligence technologies. One such problem is the modeling of games involving multiple agents. This can be useful, for example, in business, where agents may represent different companies. For them, game modeling can serve as a tool for market forecasting, determining competition strategies, and developing marketing policies. In addition, modeling games with multiple agents can be beneficial in many other areas, such as politics and technology. In politics, game modeling can help analyze strategies and interactions between various participants in political processes. It can be used to analyze elections, where different parties and candidates choose their strategies depending on the actions of their competitors. In technology, game modeling can be useful for analyzing market competition and developing new products and services. Companies can model games to determine optimal pricing strategies based on competitors' behavior.

### 1.1 Description of Dynamic Two-Player Games and Multi-Agent Reinforcement Learning

Let us consider two players, denoted as  $A$  and  $B$ . Each player has a set of possible strategies, denoted as  $S_A$  and  $S_B$ , respectively. Player  $A$  selects a strategy  $s_A \in S_A$ , and player  $B$  selects a strategy  $s_B \in S_B$ . The strategy choice of each player depends on the previous moves of both players. The payoff of each player is defined by a utility function, denoted as  $U_A(s_A, s_B)$  for player  $A$  and  $U_B(s_A, s_B)$  for player  $B$ . These utility functions depend on the strategies chosen by both players. The goal of each player is to choose a sequence of strategies that maximizes their expected payoff. In other words, player  $A$  aims to maximize  $U_A(s_A, s_B)$  over all possible  $s_A$ , while player  $B$  aims to maximize  $U_B(s_A, s_B)$  over all possible  $s_B$ .

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As for MARL (Multi-Agent Reinforcement Learning), it is a machine learning approach in which agents learn through interaction with each other and the environment. Each agent receives feedback from the environment in the form of a reward or a penalty for each of its actions. The reward represents the measure of success of an action, while the penalty represents the measure of its failure.

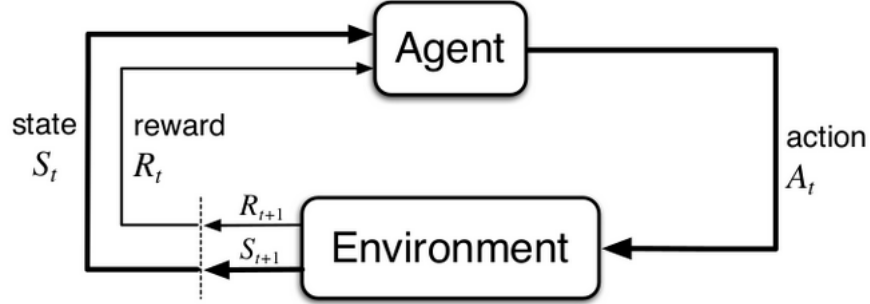


Figure 1.1: Multi-Agent Reinforcement Learning

To model dynamic games using reinforcement learning and subsequently find their solutions, it is necessary to develop algorithms that ensure agent interaction in accordance with specified rules and strategies. The modeling process can begin with the study of a conflict situation intended to be represented as a game, as well as with determining the preferences of the interested parties. The next stage may involve developing strategies and rules. Agents will use strategies to achieve their goals, while the rules will regulate their behavior. Moreover, for effective modeling of multi-agent games, it is important to consider various factors such as the type of game, the number and characteristics of agents, and possible outcomes depending on the strategies chosen by agents. It is also essential to consider potential changes in the game and to adapt strategies and rules accordingly.

## 1.2 Justification of the Topic Choice and Relevance of the Problem

The application of multi-agent reinforcement learning to dynamic two-player games is a relevant and promising research topic. Several arguments justify the choice of this topic and its significance:

1. Multi-agent reinforcement learning is one of the most advanced areas in the field of artificial intelligence. Studying its application in dynamic two-player games may lead to new insights in resolving conflict situations through negotiation.

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2. In real-world scenarios, interaction between agents plays a key role. Research on the application of multi-agent reinforcement learning in dynamic two-player games can help develop new methods and approaches for effective cooperation and competition between agents.
  3. The study of MARL in the context of dynamic two-player games may lead to new applications in various fields such as finance, economics, transportation, robotics, and others. This can contribute to progress in these areas and improve people's quality of life.

Multi-agent reinforcement learning is a relatively new area of research in artificial intelligence that has demonstrated great potential in various tasks. Multi-agent systems are becoming increasingly widespread in many fields, such as robotics, autonomous navigation, finance, gaming, business, politics, and others. In such systems, there is a need to develop efficient learning methods for agents that enable them to adapt to changing conditions and achieve high performance in interactions with other agents and the environment.

### 1.3 Research Goal and Objectives

In addition to describing various MARL algorithms for solving dynamic two-player games, the goal of this work is to develop a new game in game theory — a modified bargaining problem. It will be presented for the first time as an extension of the classical bargaining problem. In this game, participants compete in a non-cooperative interaction aimed at distributing a given shared resource between themselves. A new approach to resource allocation among participants will also be introduced, taking into account each participant's influence on the negotiation process. Based on this approach, an artificial intelligence model capable of solving the modified bargaining problem will be developed. The model will be trained to find optimal strategies, ensure effective communication between participants, and adapt to changing conditions and behaviors of all agents.

Using mathematics and artificial intelligence, this work aims to create a practical tool for solving the following problems:

1. Formalizing completed conflict situations corresponding to the description of this game to determine at which stage the parties failed to reach an agreement and what their losses were.

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2. Formalizing ongoing conflict interactions at early stages of development and proposing optimal outcomes to resolve such situations. Demonstrating that artificial intelligence can be trusted to handle conflict resolution.
  3. Modeling interactions that may potentially cause conflicts in real life. Taking into account the influence of participants on the situation, their power, interests, and time factor, and proposing possible solutions.

The introductory part of the **first chapter** provides general background information. The chapter includes definitions of MARL and dynamic games. Then, the arguments motivating the topic choice and its relevance under current conditions are presented. Finally, the problem to be addressed and the overall objectives of the thesis are formulated.

The **second chapter** analyzes major publications on two-player games and multi-agent reinforcement learning. It reviews key studies that describe various approaches and techniques forming the foundation of modern methods in this field. Additionally, the classical bargaining problem is formally described, and existing approaches to solving it are reviewed in detail.

The **third chapter** formulates the modified bargaining problem and justifies the transition from the classical to the modified version. The final part of the chapter discusses the motivation for applying machine learning methods to solve this problem.

The **fourth chapter** provides a detailed description and comparison of the selected multi-agent reinforcement learning algorithms and their application to the modified bargaining problem. It discusses algorithm selection, training and optimization processes, and justifies their suitability for this task.

The **fifth chapter** presents the results of experiments conducted to evaluate the effectiveness of the developed model in solving the modified bargaining problem. It describes the experimental environment and the dataset used for training and evaluation.

The results of the study are discussed in the final, **sixth chapter**, which also reveals the practical significance and value of the research. This chapter additionally includes recommendations for further development and expansion of the application scope of the obtained results.