Designing a system of multiple, heterogeneous agents that cooperate to achieve a common goal is a difficult task, but it is also a common real-world problem. Multiagent learning addresses this problem by training the team to cooperate through a learning algorithm. However, most traditional approaches treat multiagent learning as a combination of multiple single-agent learning problems. This perspective leads to many inefficiencies in learning such as the problem of reinvention, whereby fundamental skills and policies that all agents should possess must be rediscovered independently for each team member. For example, in soccer, all the players know how to pass and kick the ball, but a traditional algorithm has no way to share such vital information because it has no way to relate the policies of agents to each other.

In this dissertation a new approach to multiagent learning that seeks to address these issues is presented. This approach, called multiagent HyperNEAT, represents teams as a pattern of policies rather than individual agents. The main idea is that an agent's location within a canonical team layout (such as a soccer team at the start of a game) tends to dictate its role within that team, called the policy geometry. For example, as soccer positions move from goal to center they become more offensive and less defensive, a concept that is compactly represented as a pattern.

The first major contribution of this dissertation is a new method for evolving neural network controllers called HyperNEAT, which forms the foundation of the second contribution and primary focus of this work, multiagent HyperNEAT. Multiagent learning in this dissertation is investigated in predator-prey, room-clearing, and patrol domains, providing a real-world context for the approach. Interestingly, because the teams in multiagent HyperNEAT are represented as patterns they can scale up to an infinite number of multiagent policies that can be sampled from the policy geometry as needed. Thus the third contribution is a method for teams trained with multiagent HyperNEAT to dynamically scale their size without further learning. Fourth, the capabilities to both learn and scale in multiagent HyperNEAT are compared to the traditional multiagent SARSA(lamba) approach in a comprehensive study. The fifth contribution is a method for efficiently learning and encoding multiple policies for each agent on a team to facilitate learning in multi-task domains. Finally, because there is significant interest in practical applications of multiagent learning, multiagent HyperNEAT is tested in a real-world military patrolling application with actual Khepera III robots. The ultimate goal is to provide a new perspective on multiagent learning and to demonstrate the practical benefits of training heterogeneous, scalable multiagent teams through generative encoding.