Artificial neural networks (ANNs) are an abstraction of the low-level architecture of biological brains that is often applied in general problem solving and function approximation. Neuroevolution (NE), i.e. the evolution of ANNs, has proven effective at solving problems in a variety of domains. Information from the domain is input to the ANN, which outputs its desired effects. This dissertation presents a new NE algorithm called Hypercube-based NeuroEvolution of Augmenting Topologies (HyperNEAT), based on a novel indirect encoding of ANNs. The key insight in HyperNEAT is to make the algorithm aware of the geometry in which the ANNs are embedded and thereby exploit such domain geometry to evolve ANNs more effectively. The dissertation then focuses on applying HyperNEAT to tactical and strategic decision domains. These domains involve simultaneously considering short-term tactics while also balancing long-term strategies. Board games such as checkers and Go are canonical examples of such domains; however, they also include real-time strategy games and military scenarios. The dissertation details three proposed extensions to HyperNEAT designed to work in tactical and strategic decision domains. The first is an action selector ANN architecture that allows the ANN to indicate its judgments on every possible action all at once. The second technique is called substrate extrapolation. It allows learning basic concepts at a low resolution, and then increasing the resolution to learn more advanced concepts. The final extension is geometric game-tree pruning, whereby HyperNEAT can endow the ANN the ability to focus on specific areas of a domain (such as a checkers board) that deserve more inspection. The culminating contribution is to demonstrate the ability of HyperNEAT with these extensions to play Go, a most challenging game for artificial intelligence.