An important goal for machine learning is to transfer knowledge between tasks. For example, learning to play RoboCup Keepaway should contribute to learning the full game of RoboCup soccer. Often approaches to task transfer focus on transforming the original representation to fit the new task. Such representational transformations are necessary because the target task often requires new state information that was not included in the original representation. In RoboCup Keepaway, changing from the 3 vs. 2 variant of the task to 4 vs. 3 adds state information for each of the new players. In contrast, this dissertation explores the idea that transfer is most effective if the representation is designed to be the same even across different tasks. To this end, (1) the bird's eye view (BEV) representation is introduced, which can represent different tasks on the same two-dimensional map. Because the BEV represents state information associated with positions instead of objects, it can be scaled to more objects without manipulation. In this way, both the 3 vs. 2 and 4 vs. 3 Keepaway tasks can be represented on the same BEV, which is (2) demonstrated in this dissertation.

Yet a challenge for such representation is that a raw two-dimensional map is high-dimensional and unstructured. This dissertation demonstrates how this problem is addressed naturally by the Hypercube-based NeuroEvolution of Augmenting Topologies (HyperNEAT) approach. HyperNEAT evolves an indirect encoding, which compresses the representation by exploiting its geometry. The dissertation then explores further exploiting the power of such encoding, beginning by (3) enhancing the configuration of the BEV with a focus on modularity. The need for further nonlinearity is then (4) investigated through the addition of hidden nodes. Furthermore, (5) the size of the BEV can be manipulated because it is indirectly encoded. Thus the resolution of the BEV, which is dictated by its size, is increased in precision and culminates in a HyperNEAT extension that is expressed at effectively infinite resolution. Additionally, scaling to higher resolutions through gradually increasing the size of the BEV is explored. Finally, (6) the ambitious problem of scaling from the Keepaway task to the Half-field Offense task is investigated with the BEV. Overall, this dissertation demonstrates that advanced representations in conjunction with indirect encoding can contribute to scaling learning techniques to more challenging tasks, such as the Half-field Offense RoboCup soccer domain.