1 Abstract

Games such as go, chess and checkers have multiple equivalent game states. That is, multiple board positions where symmetrical and opposite moves should be made. These equivalences are not exploited by current state of the art neural agents which instead must relearn similar information, wasting computing time. Group equivariant CNNs in existing work create networks which can exploit symmetries to improve learning, however, they lack the expressiveness to correctly reflect the move embeddings necessary for games.

I introduce two methods for creating agents with an innate understanding of these board positions; Game Graph Convolutional Networks (GGCNs) and Finite Group Neural Networks (FGNNs). These are shown to improve the performance of networks playing checkers (draughts), and can be easily adapted to other games.

Additionally, FGNNs can be created from existing network architectures. This includes, for the first time, those with skip connections and arbitrary layer types. I demonstrate that an equivariant version of U-Net (FGNN-U-Net) outperforms the unmodified network in image segmentation.