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Abstract

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Introduction

Being able to transfer previously acquired knowledge to a new domain is one of the hallmarks of human intelligence. Humans are naturally endowed with the ability to extract relevant features from a situation, identify the presence of these features in a novel setting and use previously acquired knowledge to adapt to previously unseen challenges using acquired knowledge. More formally, Perkins (1992) defines transfer of learning as the application of skills, knowledge, and/or attitudes that were learned in one situation to another learning situation. This typically human skill has so far eluded modern AI agents. Deep neural networks for instance can do very well on image recognition tasks and can even reach super-human performance levels on video and strategic board games. Yet they struggle to learn as fast or as efficiently as humans do, and more importantly they have a very limited ability to generalize and transfer knowledge to new domains. (Lake, Ullman, Tenenbaum, & Gershman, 2017) argue that human learning transfer abilities take advantage of important cognitive building blocks such as an abstract representation of concepts underlying tasks and compositionally structured causal models of the environment.

One way to build abstract representations of the environment when the task involves interactions with others is to build a model of the person we are interacting with that may inform what actions they are likely to take next. Once we learn something about them, we can use this knowledge to inform how to best behave in novel situations. This may lead to very efficient generalization of knowledge, even to situations that are dissimilar to the history of interaction, assuming what we have learned about others is an abstract representation that is not too dependent on the environment of the initial interaction. There is evidence that people learn models of their opponents when they play repeated economic games (Stahl & Wilson, 1995), engage in bilateral negotiations (Baarslag, Hendrikx, Hindriks, & Jonker, 2016), or simply try to exploit a non random player in chance games such as

Rock-Paper-Scissors (Weerd, Verbrugge, & Verheij, 2012). In this paper, we are specifically

interested in the way in which people build and use models of their opponent to facilitate

learning transfer, when engaged in situations involving an interaction with strategic

considerations. These situations arise frequently such as in negotiations, auctions, strategic

planning and all other domains in which theory of mind abilities (Woodruff, Sciences, Brain,

& 1978, n.d.) play a role in determining human behaviour. In order to explore learning

transfer in these strategic settings, it is generally useful to study simple games as a model of

more complex interactions. More specifically, we need a framework that allows the study of

whether and how a player takes into consideration, over time, the impact of its current and

future actions on the future actions of the opponent and the future cumulative rewards.

Repeated games, in which players interact repeatedly with the same opponent and have the

ability to learn about the opponent's strategies and preferences (Mertens, 1990) are

particularly adapted to the task of opponent modelling.

Early literature on learning transfer in games has mostly focused on measuring the

proportion of people who play normatively optimal (Nash Equilibria) or salient actions (e.g

Risk Dominance) in later games, having had experience with a similar game environment

previously. For instance, Ho, Camerer, & Weigelt (1998) measure transfer as the proportion

of players who choose the Nash Equilibrium in later p-beauty contest games, after training

on similar games. They find there is no evidence of immediate transfer (Nash equilibrium

play in the first round of the new game) but positive structural learning transfer as shown by

the faster convergence to equilibrium play by experienced vs non experienced players. (**???**)

test learning transfer in players exposed to two games with multiple equilibria sequentially

and explore the ability of players to coordinate their actions to choose a particular

equilibrium in subsequent games having reached it in prior ones. They distinguish between

games that are similar in a purely descriptive way, meaning similar choice labels, identity of

players, format and number of action choices; and games that are similar in a strategic sense,

meaning similar payoffs from combination of actions, identical equilibrium properties or

significant social characteristics of payoffs such as possibility of punishment, need for fairness and cooperative vs competitive settings. They find that transfer of learning (successful coordination) occurs more readily in the presence of both descriptive and strategic similarity. If the games were only strategically similar, then the transfer was much weaker.

Juvina, Saleem, Martin, Gonzalez, & Lebiere (2013) made a similar distinction between what they deemed surface and deep similarities and find that both contribute to positive learning transfer. However, they show that surface similarity is not necessary for deep transfer and can either aid or block this type of transfer depending on whether it leads to congruent or incongruent actions in later games. In a series of experiments using economic signalling games (Cooper & Kagel, 2003, 2008) the researchers found that participants who have learned to play according to Nash Equilibrium in one game can transfer this to subsequent games, even though the actions consistent with Nash Equilibrium in later games are different. They show that this transfer is driven by the emergence of sophisticated players who are able to represent the strategic implications of their actions and reason about the consequences of changed opponent payoffs.

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