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ScienceDirect

Cognitive Systems Research 42 (2017) 1–22

Cognitive Systems RESEARCH

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Heterogeneity in generalized reinforcement learning and its relation to cognitive ability

Action editor: Sebastien Helie

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Received 3 April 2016; received in revised form 5 November 2016; accepted 8 November 2016
Available online 19 November 2016

Abstract

In this paper, we study the connections between working memory capacity (WMC) and learning in the context of economic guessing games. We apply a generalized version of reinforcement learning, popularly known as the experience-weighted attraction (EWA) learning model, which has a connection to specific cognitive constructs, such as memory decay, the depreciation of past experience, counterfactual thinking, and choice intensity. Through the estimates of the model, we examine behavioral differences among individuals due to different levels of WMC. In accordance with 'Miller's magic number', which is the constraint of working memory capacity, we consider two different sizes (granularities) of strategy space: one is larger (finer) and one is smaller (coarser). We find that constraining the EWA models by using levels (granules) within the limits of working memory allows for a better characterization of the data based on individual differences in WMC. Using this level-reinforcement version of EWA learning, also referred to as the EWA rule learning model, we find that working memory capacity can significantly affect learning behavior. Our likelihood ratio test rejects the null that subjects with high WMC and subjects with low WMC follow the same EWA learning model. In addition, the parameter corresponding to 'counterfactual thinking ability' is found to be reduced when working memory capacity is low.
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Keywords: Generalized reinforcement learning; Experience-weighted attraction learning; Cognitive ability; Granularity

1. Introduction: motivation and literature review

The purpose of this paper is twofold. First, it is a follow-up study to the research on *individual differences in learning* observed in the laboratory of games and markets and characterized by various empirical (parametric) learning models (see Section 1.1). In this literature, learning heterogeneity can be represented by the diversity of the estimates of the models when they are applied to observations associated with different individual subjects or different groups of subjects. Among many possible parametric learning models, *generalized reinforcement learning*, or more popularly known as *experience-weighted attraction (EWA) learning*, is the one strongly motivated by psychology (Camerer & Ho, 1999); hence, it provides us with a natural wonder regarding the possible psychological underpinnings of the observed individual differences in learning. The strength of EWA modeling is that its parameters infer multiple cognitive constructs, such as memory decay, counterfactual thinking, and choice intensity, any of which may be sensitive to individual differences in strategic learning.

In pursuing this line of reasoning, this paper examines two hypotheses related to the effects of working memory capacity on learning, one more general and the other more

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http://dx.doi.org/10.1016/j.cogsys.2016.11.001
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focused. The general one is termed the *working memory hypothesis for individual differences in learning*, and the focused one is termed the *working memory hypothesis for individual differences in counterfactual thinking ability*. The first hypothesis, also referred to as the maintained hypothesis, states that subjects with different WMC do not share the same generalized reinforcement learning model. By pinning down one possible source of the above difference, the second hypothesis further states that subjects with different WMC differ in their counterfactual thinking ability, a specific behavioral parameter of the EWA learning model; in particular, as motivated by the literature to be reviewed in Section 2.2, the hypothesis assumes a positive relationship between WMC and counterfactual thinking ability.

Second, an unintended realization from our work is that the learning model is sensitive to the size (cardinality, granularity) of the set of alternatives (choices, strategies, actions, chunks, and so on). We find that the psychological underpinning can be sensibly identified only when the size (cardinality) is small or, at least, not overwhelmingly large. This constraint may be related to Miller's (1956) concept of limited short-term or working memory capacity (Section 1.2).

In this regard, this paper suggests that the generalized reinforcement learning model can be constrained by reducing its strategy space to the number of items defined by the limits of working memory. Constraining the EWA models by using levels (granules) within the limits of working memory allows for a better characterization of the data based on individual differences in WMC, and by using this constrained version of EWA learning, we find that working memory capacity can significantly affect learning behavior. Our likelihood ratio test rejects the null that subjects with high WMC and subjects with low WMC follow the same EWA learning model; hence, the working memory hypothesis for individual differences in learning is well supported. In addition, under the same constrained version of EWA learning, we find that 'counterfactual thinking ability' is significantly reduced when WMC is moderately low or very low; nevertheless, in the reverse direction, 'counterfactual thinking ability' is not significantly increased with moderately high or very high WMC. Hence, our second hypothesis is only weakly supported.

1.1. Individual differences in learning

In recent years, behavioral heterogeneity has not only been identified in game experiments, but has also been related to subjects' cognitive ability. In particular, recent studies have placed emphasis on the correspondence between cognitive ability and strategic sophistication, such as inductive reasoning, iterated dominance, and level-k thinking (Brañas-Garza, García-Muñoz, & González, 2012; Burnham, Cesarini, Johannesson, Lichtenstein, & Wallace, 2009; Devetag & Warglien, 2003; Rydval, Ortmann, & Ostatnicky, 2009; Schnusenberg & Gallo, 2011). Within the extensive literature on those behavioral heterogeneities and their possible cognitive correlates, relatively little research has focused on *learning*, and there have been few attempts to establish a direct relationship between cognitive ability and learning.

This deficit may be partially attributed to the *convergence hypothesis*, i.e., the behavioral heterogeneity observed in initial periods of an experiment, if any, may be temporal after subjects become more experienced. Some early studies involving independent measures of cognitive ability have also shown that even though cognitive ability is correlated with the behavioral heterogeneity in the one-shot guessing game, also known as the beauty contest game (BCG), if the game is played repeatedly this correlation is no longer significant (Burnham et al., 2009; Schnusenberg & Gallo, 2011).

Nevertheless, the convergence property does not guarantee a unique path toward the equilibrium, and one large body of the literature in economics examines the so-called *out-of-equilibrium dynamics*. Hence, the relevance of cognitive ability to individual differences in learning can still be an issue from the perspective of the transition dynamics of the games or markets. By applying individual learning models, several studies have identified individual differences in learning in games (Ho, Wang, & Camerer, 2008) and in markets (Chen & Hsieh, 2011; Hommes, 2011). In addition, there are also experimental studies showing that learning is not independent of cognitive ability (Casari, Ham, & Kagel, 2007).

In the context of a guessing game (beauty contest experiment), Gill and Prowse (2012) found that cognitive ability may positively affect learning in that subjects with higher cognitive ability may learn more actively than subjects with lower cognitive ability and hence, in the end, their performance gap will become even more significant than that at the initial time.

Chen, Du, and Yang (2014) conducted six series of 15- to 20-person beauty contest experiments, and examined the guessing behavior of a set of 108 subjects involved in these experiments. They found a significant correlation between guessing performance and WMC. They also performed regression analysis and found that WMC positively affects reasoning depth. Through a game of up to 10 rounds, the performance gap between the high WMC group and the low WMC group was found to shrink but still existed significantly. They further applied the level-k reasoning model (see Section 3.3) to examine subjects' guessing behavior from round to round. It was found that subjects with high WMC tended to guess with a higher level of reasoning than subjects with low WMC, specifically in the initial periods. Through the analysis of the estimated Markov transition matrix among different levels of reasoning, they further found that the subjects with high WMC had a dynamic behavioral pattern that was different from those with low WMC, which may indicate the possible effect of WMC on learning.

However, neither the level-k reasoning model nor the Markov transition model applied in Chen et al. (2014)

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