When Big Data Fails! Relative success of adaptive agents using coarse-grained information to compete for limited resources

V. Sasidharan, Appilineni Kushal, and Sitabhra Sinha

1 The Institute of Mathematical Sciences, CIT Campus, Taramani, Chennai 600113, India.
2 Indian Institute of Science, C V Raman Road, Bangalore 560012, India.

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Agents in a population often coordinate their actions with that of their neighbors resulting in striking forms, such as in swarming and flocking [1, 2]. Typically, in such cases, individuals use information obtained from their local environment to adjust their actions in order to achieve some desired objective [3–6]. Emergent coordination is therefore crucially dependent on the information acquired by an agent and its ability to process it appropriately, which determines its future course of action. Often the objectives of different agents in a system may not be compatible with each other, for instance when they are competing for a limited resource. Examples of such situations are abundant in nature, where individuals vie for food, shelter and mating opportunities. Even in our more complex social environment, we regularly come across instances of such competition, e.g., people trying to choose the least congested route through an urban road network or anticipating whether the relative demand for a financial asset will increase, so as to profit by buying or selling it at the present [7]. In these settings, individuals may use strategies which project information about past experiences to make decisions about the future course of action [8–10]. Conventional wisdom suggests that the relative success of an agent in meeting its objective (i.e., gaining access to the scarce resource) would increase with the quality and quantity of available data that would form the basis for its decisions. Indeed the recent excitement about “big data” is partially based on the premise that access to more and better information provides a competitive advantage [11].

In this paper we show that agents using quantitatively more data that is also finely resolved (and hence also qualitatively superior) may not actually do better - and in fact lead to significantly worse payoffs - in situations where they are competing with agents that have access to less, as well as more coarse-grained, information. This surprising result arises from emergent coordination in the collective activity of agents who use information of a particular quality (i.e., level of coarse-graining) leading to macroscopic patterns of behavior that may be discernible from the data only at a different level of coarse-graining. Thus, if there are other agents in the population who have access to information about the system this at latter coarse-grained level, they can potentially exploit this predictability to their advantage. We show this using a model of preferential access to a limited resource. This comprises a complex adaptive system of agents, each attempting to maximize their payoffs. The agents are distinguished in terms of the quality and quantity of information that they use to choose between several possible options. The setting allows us to vary the composition of the population in terms of the different types of agents, each of whom exclusively uses one of two types of historical data about the system that represent the two extremes of coarse-graining. We show that the relation between information asymmetry and the performance of agents is a complex one, depending on the relative fraction of the population that each type of agents constitute. Thus, the utility of “big-data” is contingent upon the precise nature of the ecosystem comprising all its competitors that an agent is located in. The premise that more and better information will automatically result in better performance, e.g., by improving predictive power, therefore needs to be treated with caution. This is especially true for competitive situations where adaptation through learning is involved that are ubiquitous in systems around us, such as financial markets [12, 13].

To investigate how information asymmetry between agents affects their performance, specifically when different agents use information at diverse levels of coarse-graining, we focus on a complex adaptive system where agents compete for a limited resource. Here the heterogeneous agents use the different types of information that they have access to for the same purpose, viz., to have preferential access to the resource. In particular, we use the paradigm of the Minority Game (MG) [14, 16], which has all the ingredients to address the above question in a quantitative manner. In addition, it has the advan-
tage that the classical version, in which agents use information only at a single level of coarse-graining, is well-understood and can be used as a benchmark for the more complex situation that is investigated here. We consider a population of an odd number $N$ of agents who independently and simultaneously choose between two options (A and B, say) in each round. The option that is chosen by fewer agents is considered the better choice (outcome) in each round and leads to a higher payoff (say, 1), while those who had chosen the alternative receive a lower payoff (say, 0).

We assume that the population consists of different types of agents distinguished in terms of the data that they have access to, which is coarse-grained to different levels (Fig. 1). The level of coarse-graining $k$ ($2 \leq k \leq N + 1$) is defined in terms of the extent to which an agent can resolve the number of agents ($N_A$, say) opting for a particular choice (A). For example, an agent with $k = 2$, the coarsest level of resolution, can only distinguish between $N_A > N/2$ and $N_A < N/2$ (i.e., whether $A$ was chosen by the majority or not) in a particular round. Conversely, the finest level of resolution corresponds to $k = N + 1$, for which an agent can determine the exact number of agents $N_A$ opting for $A$ in a round. Any value of $k$ between these two extremes represents intermediate levels of coarse-graining where the agent can only distinguish whether, in each round, $N_A$ belongs to any one of the intervals $[iN/k, (i + 1)N/k]$ where $i = 0, \ldots, k - 1$. The agents of each type use the appropriately coarse-grained data to determine their choice of action in the next round. For clarity we focus on the interaction between only two types of agents corresponding to the extremes of coarse-graining, viz., $k = 2$ (which we designate as Type 1 agents) and $k = N + 1$ (Type 2 agents). The memory length of each type of agent indicates the number of past rounds whose information they retain, and is denoted by $m_1$ ($m_2$) for Type 1 (Type 2) agent. Each agent uses strategies that map the information about past actions ($m_1$ bits for Type 1 agent, $m_2 \log_2(N + 1)$ bits for Type 2 agent) to the choice of action in the next round (i.e., A or B). Each agent initially chooses at random a small sample of strategies (e.g., of size 2 as here) from the set of all possible strategies, which is of size $2^{m_1}$ for a Type 1 agent and $2^{(N+1)m_2}$ for a Type 2 agent. At each round, an agent scores the strategies according to the potential payoffs that would have been obtained by using them in the previous rounds (feedback), and uses the one having the highest score.

In order to study how the relative performance of agents in choosing their optimal future action is affected when different agents have access to data with different levels of coarse-graining (and therefore, qualitatively distinct information), we first focus on the simplest case of a single Type 1 agent with memory length $m_1$ interacting with a population of $N - 1$ Type 2 agents with memory length $m_2$. Note that both types of agents use the different information available to them (representing the two extremes of coarse-graining) with the identical aim of predicting the outcome in the next round. One may naively expect that agent(s) having more information at their disposal (e.g., as measured in units of bits) will have an advantage over the other type of agents. Consequently, it would have been expected that when the number of bits, $m_1$, in the information accessible to the Type 1 agents is less than $m_2 \log_2(N + 1)$, the corresponding quantity for the Type 2 agents, then the latter would have obtained a relatively higher payoff. This would also be in accordance with the intuitive notion that the highly resolved detailed data of Type 2 agents is qualitatively better than the low-resolution outcome data of Type 1 agents. However, the mean payoffs of the two types of agents shown in Fig. 2 for different memory lengths $m_1$ and population sizes $N$ reveals that the actual behavior is more complex.

The most surprising outcome for the case when the Type 2 agents have memory length $m_2 = 1$ (Fig. 2) is that the Type 1 agent is able to acquire a relatively higher payoff at low values of $m_1$ even though the information

![Figure 1: A schematic representation of a complex adaptive system comprising N agents that are competing for a limited resource. Every agent has to choose between two possible actions (A or B) at each round, with the option chosen by the lesser number of agents being the better choice (outcome) in that round. The agents decide on their choice using strategies based on information about the previous m rounds’ collective choice dynamics, which could result in the system being in one of k possible states (2 ≤ k ≤ N + 1, depending on the level of coarse-graining) at each round. Here agents have been distinguished into two classes (Types 1 and 2) according to the two extreme levels of coarse-grained information, i.e., $k = 2$ and $k = N + 1$, respectively, that they have access to. After each round t, the detailed information about the total number of agents choosing a specific action A (say), $N_t^A$, that is accessed only by Type 2 agents, as well as, binary information, viz., the choice of the minority (A or B) which is accessed only by Type 1 agents, are added to the history of outcomes. The information about the outcome is also used as feedback for adaptive selection of strategies by the agents.](image)
As there is no predictability in the time-series on average receive essentially the same payoff as the rest available to the Type 1 agent that it can exploit, it will distinguish from agents randomly choosing between they can outperform Type 2 agents with possible for these mutually competing individuals to decrease the population of Type 2 agents. However, as we shall see, the collective action of any one type of agents may result in predictable patterns at the other level of coarse-graining and hence observable only to these other agents. This “useful” information content above the noise level can be quantified by measuring the predictability of a particular choice (say A) being the outcome in a particular round, given the history of past outcomes. This history can be either the binary sequence of outcomes A,B or the detailed time-series of the number of agents \( \{N_1^A\} \) choosing a particular option A, the former (latter) being accessible only to a Type 1 (Type 2) agent. We therefore define two distinct information measures, viz., \( H_1 = \sum u_{L_{bin}} P(u_{L_{bin}}) |P(A|u_{L_{bin}}) - (1/2)|^2 \), and \( H_2 = \sum u_{L_{det}} P(u_{L_{det}}) |P(A|u_{L_{det}}) - (1/2)|^2 \). Here, \( u_{L_{bin}} \) is the binary sequence of outcomes for the previous \( L_{bin} \) rounds while \( u_{L_{det}} \) is the sequence of integers, each lying between 0 and \( N \), representing the number of agents choosing A in the previous \( L_{det} \) rounds. The probability with which a particular sequence of \( L \) successive outcomes is observed is denoted as \( P(u_{L}) \), while \( P(A|u_{L}) \) represents the conditional probability that the outcome A follows the sequence \( u_{L} \).

We first consider the case of a population comprising only Type 2 agents having memory length \( m_2 \). The collective behavior of such agents generates a history of binary outcomes whose information content \( H_1 \) is shown in Fig. 3 (a) for \( m_2 = 1 \) and 2. Note that this information cannot be used by the Type 2 agents themselves, whose strategies are based on \( u_{L_{det}} \), but is accessible in principle to a hypothetical Type 1 agent whose strategies use \( u_{L_{bin}} \). We observe that \( H_1 \) increases with the length of the binary sequence, \( L_{bin} \), over the range of sequence lengths considered here, with \( H_1 = 0 \) when the history is restricted to the immediately preceding round, i.e., \( L_{bin} = 1 \). Thus, if a Type 1 agent with memory length \( m_1 \) is introduced into this population, it can make use of the predictability present in the binary sequence accessible to it when \( m_1 > 1 \). As \( m_1 \) increases, the num-

![Figure 2: Average payoffs](https://example.com/figure2.png)
predictability present in becomes progressively less likely that the agent will ran-

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= 2, as is indeed confirmed by Fig 2.

We next consider the other extreme case represented

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Type 1 agent memory m

Figure 3: (a) Information content H1 of the binary sequence containing the history of outcomes for a game involving only Type 2 agents shown as a function of the sequence length L_{bin}.

(b) Information content of the binary sequence, H1, and that of the time series containing detailed information (exact number opting for a particular choice) of sequence length L_{det} = 1. H2, for a game involving only Type 1 agents, shown as a function of the memory length m_1 of the agents. The number of agents considered in both (a) and (b) is N = 255. Results shown are averaged over 100 realizations.

ber of possible strategies that can be used by the Type 1 agent increases exponentially (= 2^{m_1}). It therefore becomes progressively less likely that the agent will randomly pick the strategy that can optimally exploit the predictability present in u_{L_{bin}}. This implies that the highest payoff of Type 1 agent is achieved for the lowest value of m_1 having non-zero information content, i.e., m_1 = 2, as is indeed confirmed by Fig 2.

We next consider the other extreme case represented by a population comprising only Type 1 agents having memory length m_1. This situation has been studied earlier in the context of understanding how the collective behavior of such agents undergoes a phase transition as m_1 is varied [18, 19], where the focus is on the information content H_1 of the binary sequence of outcomes available to these agents [18, 22]. Here our focus is instead on the information content H_2 of the detailed time-series u_{L_{det}}, recording the number of agents choosing a particular option (shown in Fig. 3 (b) for L_{det} = 1). It is important to note that the latter information cannot be used by the Type 1 agents whose interactions produce it, as their strategies are based on u_{L_{bin}}. However, it is accessible to a hypothetical Type 2 agent with an appropriate memory length, viz., m_2 = L_{det}. We observe that H_2 is non-zero even when H_1 = 0 at low values of the memory length m_1. This indicates that the detailed history u_{L_{det}} contains potential predictability that can be exploited by a Type 2 agent. Thus, both cases of homogeneous agent type populations considered above demonstrate that the collective behavior of agents having access to information coarse-grained at a specific level can give rise to some amount of predictability that can be perceived only in the information available at a different level of coarse-graining.

The above arguments explain the performance of a single agent of one type interacting with a population consisting exclusively of agents of the other type. However, in reality, the number of each type of agents having access to data at different levels of coarse-graining can be arbitrary. We shall now, therefore, consider the situation where the relative fraction of the two types of agents present in the population is varied between the two extreme cases considered earlier. The important effect of introducing more than one agent of a specific type into the population is that effective coordination between these agents can emerge, resulting in enhanced payoffs for them.

We gradually vary the fraction f_1 of Type 1 agents in a population of total size N comprising agents of both Types 1 and 2. Fig. 4 shows the average payoffs P_1, P_2 for agents of each type respectively, for different values of f_1 and memory length m_1 of Type 1 agents, keeping the memory length of Type 2 agents fixed [viz., m_2 = 1 (a) and m_2 = 2 (b)]. As shown earlier for the case of a single Type 1 agent in a population of Type 2 agents, here also we see that Type 1 agents can outperform Type 2 agents even when the quantity of information (measured in bits) available to the former is much less than that for the latter. This is particularly striking when the memory length m_1 of Type 1 agents is low, i.e., information content of each is m_1 bits ≪ m_2 log_2(N + 1) bits, which is the information content of a Type 2 agent. Fig. 4 shows that, in this low m_1 regime, Type 1 agents when present in small numbers (i.e., low f_1) can receive higher payoffs than the Type 2 agents who form the bulk of the population. We expect the situation that we considered earlier, viz., a single Type 1 agent playing against N − 1 Type 2 agents, to occur when f_1 → 0. Thus, we expect the Type 1 agent to achieve best performance (i.e., maximum payoff) for a memory size m_1 = 2 which is indeed observed. On the other hand, as f_1 → 1 the setting is that of a conventional MG between Type 1 agents where the maximum payoff occurs for m_1 = 0, as is also seen. Indeed, for any fraction 0 < f_1 < 1 of Type 1 agents, their best performance is achieved for a memory size m_1 = 2 and log_2(0.337N) [indicated by the broken curves in Fig. 4]. Thus, having multiple Type 1 agents in the population can help them achieve a higher payoff than they are capable of by playing singly against a population of Type 2 agents, suggesting an important role of emergent coordination among a group of competing agents who are distinguished by the nature of information available to them.

A simple qualitative argument for this locus of maximum payoffs for Type 1 agents in the (m_1, f_1) parameter
The relatively higher payoff of Type 1 agent (with low memory length) compared to Type 2 agents, despite the latter having quantitatively more information for decision-making, is thus an extremely surprising outcome that emerges from the collective dynamics of interactions between agents with access to information coarse-grained at different levels.

Let us now consider the performance of the Type 2 agents. When playing against Type 1 agents with low memory length $m_1$, Type 2 agents achieve their highest payoff when $f_1 \to 1$, i.e., when they are present in extremely small numbers in the population. In other words, to achieve the best performance out of availability of detailed data, it is important to have the size of the group to which this data is available as small as possible in this regime of low $m_1$. As more agents have access to this data (i.e., decreasing $f_1$), their payoff is eroded until they actually perform worse than those having coarser-grained data, i.e., Type 1 agents. Thus, access to more and better data is not by itself a determining factor for success in a complex adaptive situation.

As the memory length $m_1$ of the Type 1 agents increases, the optimal population fraction at which Type 2 agents achieve the highest payoff decreases from the neighborhood of $f_1 = 1$. In fact, in the case of Type 2 agents having memory length $m_2 = 2$ (the optimal memory length for a population exclusively composed of such agents), their best performance is achieved as $f_1 \to 0$. Thus, in this high $m_1$ regime ($m_1 \geq 6$ for the case of $m_2 = 2$), Type 2 agents achieve high payoffs by dominating the population. By contrast, Type 1 agents do better than Type 2 agents for large $f_1$ as a result of emergent coordination within their group. Indeed, in this regime, for any given $m_1$ the payoff of Type 1 agents increases with $f_1$. Thus, the outcome is not symmetric for agents having access to information at the two extreme levels of coarse-graining. Note that as $m_1$ is increased more and more, the strategy space for Type 1 agents become so large that the action of the agents essentially resemble randomly choosing between the two options. If $m_1$ is also sufficiently large ($> 2$), both types of agents achieve similar payoffs, equal to that obtained by a random choice strategy (see Supplementary Information).

To conclude, we have shown that information asymmetry among agents in a complex adaptive system can have surprising consequences. Specifically, in a system where agents compete for a limited resource using strategies based on information about the collective behavior in previous interactions, asymmetry arising from individuals having access only to data coarse-grained to different levels can result in agents with more and better data performing worse than others under certain circumstances. Such counter-intuitive effects arise from predictable patterns emerging in the collective information about the system at a certain level of coarse-graining and thus discernible only to agents privy to that level. This provides them a competitive advantage when the pop-
ulation is dominated by agents of a different type who do not have access to the coarse-graining level at which such patterns generated by their own collective activity are apparent. The relation between the relative performance of the different types of agents and the nature of information asymmetry is therefore crucially dependent on the exact composition of the population to which they belong. Our results imply that striving to acquire and process ever increasing quantities of data in the hope of making more accurate predictions in complex adaptive systems, such as financial markets, may sometimes be counter-productive. While concerns about the potential pitfalls of “big data” have been voiced earlier [22], we provide possibly the first rigorous demonstration using a quantitative model of how such a failure can come about. The insights gained from our study are quite general and should apply to the broader context of strategic interactions between a large number of adaptive agents.

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* Electronic address: sasidevan@gmail.com
† Electronic address: akushalstar@gmail.com
‡ Electronic address: sitabhra@imsc.res.in
[1] C. Castellano, S. Fortunato and V. Loreto, Rev. Mod. Phys. 81, 591 (2009).
[2] F. Vanni, M. Lukovic and P. Grigolini, Phys. Rev. Lett. 107, 078103 (2011).
[3] M. A. Nowak and R. M. May, Nature (Lond.) 359, 826 (1992).
[4] I. Couzin, Nature (Lond.) 445, 715 (2007).
[5] D. J. G. Pearce, A. M. Miller, G. Rowlands and M. S. Turner, Proc. Natl. Acad. Sci. USA 111, 10422 (2014).
[6] F. L. Pinheiro, F. C. Santos and J. M. Pacheco, Phys. Rev. Lett. 116, 128702 (2016).
[7] D. Challet, A. Chessa, M. Marsili and Y-C. Zhang, Quant. Fin. 1, 168 (2001).
[8] H. Simon, Quart. J. Economics 69, 99 (1955).
[9] W. B. Arthur, Am. Econ. Rev. 84, 406 (1994).
[10] W. B. Arthur, Science 284, 107 (1999).
[11] C. A. Mattmann, Nature (Lond.) 493, 473 (2013).
[12] M. Potters, R. Cont and J. Bouchaud, EPL 41, 239 (2007).
[13] S. Sinha, A. Chatterjee, A. Chakraborti and B. K. Chakrabarti, Econophysics: An introduction (Wiley-VCH, Weinheim, 2010).
[14] D. Challet and Y-C. Zhang, Physica A 246, 407 (1997).
[15] E. Moro, in Advances in Condensed Matter and Statistical Mechanics (Eds. E. Korutcheva and R. Cuerno) (Nova Science Publishers, New York, 2004).
[16] D. Challet, M. Marsili and Y-C. Zhang, Minority Games: Interacting agents in financial markets (Oxford University Press, Oxford, 2005).
[17] V. Sasidevan, J. Stat. Mech. 6, 073405 (2016).
[18] D. Challet and Y-C. Zhang, Physica A 256, 514 (1998).
[19] D. Challet, M. Marsili and R. Zecchina, Phys. Rev. Lett. 84, 1824 (2000).
[20] D. Challet and M. Marsili, Phys Rev. E 60, R6271 (1999).
[21] N. J. P. Hui, D. Zheng and M. Hart, J. Phys. A 32, L427 (1999).
[22] D. Challet, M. Marsili and Y-C. Zhang, Physica A 276, 284 (2000).
[23] N. Silver, The Signal and the Noise (Penguin, New York, 2012).
SUPPLEMENTARY INFORMATION

Figure S1: Average payoffs $P_1, P_2$ of Type 1 and Type 2 agents (respectively) shown as a function of the memory length $m_1$ of a single Type 1 agent interacting with $N - 1$ Type 2 agents with memory length $m_2 = 2$ for different population sizes $N$. Note that when the lone Type 1 agent does not have any relative advantage over the Type 2 agents. However, it still receives its highest payoff when $m_1 = 2$ (as in Fig. 2 for $m_2 = 1$). Payoffs are averaged over $10^4$ iterations in the steady state and over 100 different realizations.

Figure S2: Average payoffs $P_1, P_2$ of Type 1 and Type 2 agents (respectively) shown as a function of the memory length $m_1$ of a population of $N - 1$ Type 1 agents interacting with a single Type 2 agent with memory length $m_2 = 1$ for different values of $N$. Note that the lone Type 2 agent enjoys a significant advantage over the rest of the population for low values of $m_1$. The trend of the payoff of the Type 2 agent as a function of $m_1$ appears to mirror that of the Type 1 agents. Payoffs are averaged over $10^4$ iterations in the steady state and over 100 different realizations. A similar profile is seen when the memory length of the Type 2 agents is $m_2 = 2$. 
Figure S3: The average payoffs $P_1, P_2$ of Type 1 (shown in blue) and Type 2 agents (red) comprising a population of size $N (=255)$ for different population fractions $f_1$ and memory length $m_1$ of Type 1 agents. As Type 2 agents with sufficiently large memory length ($m_2 > 2$) effectively use random choice strategy \[17\], here the Type 2 agents are assumed to be randomly choosing between the two possible options. The contours separate the regions in the $(m_1, f_1)$ parameter space where Type 1 agents have a relative advantage over Type 2 agents and vice versa. The broken curve represents the optimal population fraction $f_1^*$ of Type 1 agents with a given memory length $m_1$ at which they receive the highest payoff. The dotted curve is the value of $m_1$ at which $Nf_1$ Type 1 agents are expected to have maximum payoff in absence of any Type 2 agents. Payoffs are averaged over $10^4$ iterations in the steady state and over 100 different realizations.