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Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 28(28)

ISSN
1069-7977

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Publication Date
2006

Peer reviewed

How to Learn Good Cue Orders: When Social Learning Benefits Simple Heuristics

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Abstract

Take The Best (TTB) is a simple one-reason decision-making strategy that searches through cues in the order of cue validities. Interestingly, this heuristic performs comparably to, or even better than, more complex information-demanding strategies such as multiple regression. The question of how a cue ordering is learned, however, has been only recently addressed by Dieckmann and Todd (2004). Surprisingly, these authors showed that learning cue orders through feedback—by updating cue validities—leads to a slow convergence to the ecological cue validities. Various other simple learning algorithms do not provide good results either. In the present paper, we provide a solution to this problem. Specifically, in a series of computer simulations, we show that simple social rules such as "imitate the successful" help to overcome the limitations of individual learning reported by Dieckmann and Todd (2004). Thus, the dilemma of individual learning can be collectively solved. In line with the spirit of bounded rationality, we found that several simple social rules performed comparably to, or better than computationally demanding social rules. We relate our results to previous findings on bounded rationality in the social context.

Fast and Frugal Heuristics

In our everyday lives, we make decisions frequently. However, the information we need for that might not always be available, and it might not be possible to consider all alternatives as fully as we would wish because of our limitations in time and cognitive processing power, and the complexity of the environment. How do we make such decisions? One recent approach, promoted by the Center for Adaptive Behavior and Cognition (ABC; Gigerenzer, Todd, & the ABC Research Group, 1999; Todd & Gigerenzer, 2000) suggests that in these situations, people use *fast and frugal heuristics*, that is, simple but nevertheless fairly accurate strategies that use a minimum of information. These heuristics enable organisms to make smart choices quickly under limitations of time and cognitive processing by exploiting the way information is structured in the environment (Martignon & Hoffrage, 2002). The ecological rationality view of decision making as promoted by Gigerenzer et al. (1999; see also Simon, 1990) thus brings the two elements—mind and environment—together, focusing on how minds with limited capacities are adapted to their environments and how the environments in which we make decisions shape our strategies, a concept known as *bounded rationality*.

One fast and frugal heuristic is *Take The Best* (TTB; Gigerenzer & Goldstein, 1996). This heuristic is designed for forced-choice paired comparisons. That is, it can be used to infer which of two alternatives, described on several dichotomous cues, has a higher value on a quantitative criterion, such as which of two cities has a higher population based on cues such as whether they have a university.

As a step-by-step algorithm, TTB is constructed from *building blocks* of information gathering and processing to generate a decision. More specifically, it has a *search rule*, which prescribes the order in which to search for information (TTB looks up cues sequentially in the order of the *cue validities*—the probability that a cue will lead to the correct decision given that it discriminates between the alternatives; Martignon & Hoffrage, 2002); a *stopping rule*, describing when the search is to be stopped (TTB stops after the first discriminating cue); and a *decision rule* for how to use the available information to make a decision (TTB chooses the alternative favored by the first discriminating cue and ignores the rest of the cues. TTB is thus called one-reason decision making).

The efficiency of TTB consists in its surprising performance relative to its extreme simplicity. For instance, Gigerenzer and Goldstein (1996) tested the performance of TTB with more savvy strategies such as multiple regression using the German cities data set, which consists of the 83 German cities that had more than 100,000 inhabitants at the time. These cities were described on nine cues, such as whether a city has a university or whether it is on an intercity train line. Gigerenzer and Goldstein (1996) found that the performance of TTB came close to or even outperformed multiple regression in cross-validation. [1] Czerlinski, Gigerenzer, and Goldstein (1999) further demonstrated the superiority of TTB across a wide range of real-world environments.

The Problem: Individual Learning of Cue Orders Is Very Slow

The accuracy of a strategy depends critically on the order in which cues are searched in the environment. Note that in the German cities data set, there are 9! (i.e., 362,880) possible cue orders. Therefore, finding the best cue order is computationally intractable (Martignon & Hoffrage, 2002). In this data set, the best cue order achieves an accuracy of 75.8%. TTB, which searches through cues in the order of the cue validities calculated using the 83 cities in the German cities data set, achieves an accuracy of 74.2%. Surprisingly, only *1.8%* (i.e., 7,421) of the cue orders achieve a higher performance than TTB. The mean of the distribution of the accuracy of all possible cue orderings in the German cities data set (i.e., 70%) corresponds to the expected performance of the Minimalist, a one-reason decision-making heuristic that searches through cues in a random order (Gigerenzer & Goldstein, 1996). This indicates that TTB achieves an impressive performance.

How can an individual learn a good cue order if cue validities are not available beforehand? One could assume that people could use TTB and update a cue order by using only the cues they searched. That is, one could assume that a cue ordering by validity can be acquired by learning-while-doing. This question has been only recently addressed by Dieckmann and Todd (2004) in a series of computer simulations. These authors evaluated the performance of a variety of simple learning algorithms for ordering cues in the forced-choice paired comparison task for which TTB was designed. These algorithms update cue orderings on a trial-by-trial basis (Bentley & McGeoch, 1985).

The accuracy of the cue orderings resulting from the application of simple learning algorithms was tested using the German cities data set. Specifically, each algorithm started with a random cue ordering and searched one cue at a time until it found a cue that discriminated between the alternatives, which was then used to make the decision (i.e., the algorithm chose the alternative favored by the first discriminating cue). After each decision, feedback was provided and the cue ordering was updated. Decisions were made repeatedly through one hundred pair comparisons.

Which simple learning algorithms did Dieckmann and Todd (2004) consider in their simulations? They evaluated the validity, tally, swap, and tally swap learning algorithms. The *validity algorithm* keeps two pieces of information for each cue: a count of all discriminations made by a cue up to a certain trial, and a count of all the correct decisions. The validity of each cue was then computed by dividing the number of current correct decisions by the number of current discriminations.[2] The *tally algorithm* simply counts the number of correct decisions made by a cue up to a certain trial minus the number of incorrect decisions (=tally). The *swap algorithm* moves a cue up one position in the cue order after a correct decision, and down if the decision was wrong. Finally, the *tally swap* algorithm makes swapping contingent on whether or not a cue has a higher tally than a neighboring cue.

Dieckmann and Todd (2004) tested the offline accuracy and frugality of the learned cue orderings at each trial, for the total set of pair comparisons (i.e., 3,403 pairs of 83 cities). Their results showed that the performance of these algorithms soon rose above that achieved by Minimalist, which searches through cues in a random order (see Figure 1).

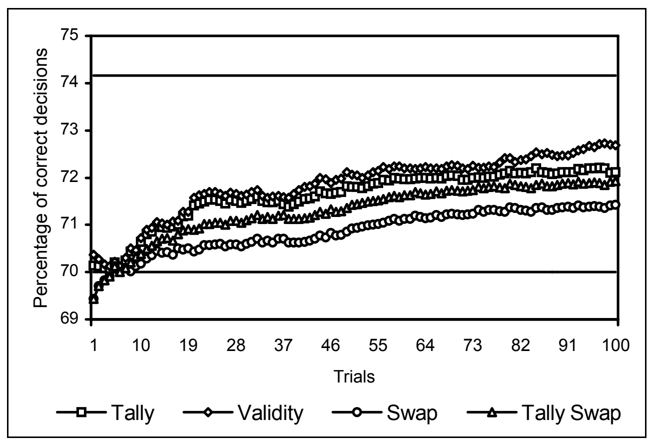

Figure 1. Mean performance of the four learning algorithms in Dieckmann and Todd's (2004) simulations. The bottom straight line shows the performance of Minimalist (random cue orders). The top straight line shows the performance of TTB (ecological cue validities).

Surprisingly, none of these learning algorithms reached the benchmark performance of TTB based on the ecological cue validities (upper line in Figure 1). Even after obtaining feedback for 100 pair comparisons, they all fell well behind. These simulations showed that updating cue validities through feedback leads to a slow convergence to the ecological cue validities, at least after the first 100 pair

[1] Cross-validation refers to the accuracy of a decision strategy that is fitted to one half of a data set (training set) and tested on the other half (test set).

[2] Note that the difference between TTB and a one-reason decision-making strategy that uses the validity learning algorithm is that the first computes cue validities beforehand using all objects and cues in the environment, whereas the second acquires knowledge about cue validity on a trial-by-trial basis using only information about the first discriminating cue that is looked up. Therefore, these strategies do not necessarily have to arrive at the same cue ordering.

comparisons. Various other learning algorithms reported by Dieckmann and Todd (2004) did not provide better results either.

Can Social Learning Resolve the Limitations of Individual Learning?

The simple learning algorithms we mentioned above suffer from a serious and frequent problem in the literature of reinforcement learning (e.g., Sutton & Barto, 1998; see also Einhorn, 1980): the trade-off between exploration and exploitation of the information in the environment. Specifically, to be fast and frugal, the learning algorithms considered by Dieckmann and Todd (2004) do not search for all the available cues in the environment but instead stop search after the first discriminating cue. Exploitation of the environment, therefore, is an important constraint that significantly reduces performance (i.e., if all the cues were looked up, these algorithms would soon achieve the performance of the ecological cue validities). Yet, an exhaustive exploration of all the cues in a real world environment not only decreases speed and frugality but is often impossible. Thus, the trade-off between exploration and exploitation seems to be an essential problem for these learning algorithms for ordering cues as long as they simultaneously pursue speed, frugality, and accuracy in performance.

In contrast to laboratory tasks, in real-world environments we often exchange reports of our experiences with other individuals. Consider once again the question of which of two cities has a higher population; rather than collecting information individually, we might discuss with other people what the relevant cues are. Thus, people could learn to order cues not only individually but also socially by exchanging information. Our argument is that the exchange of information can help boundedly rational individuals to solve the problem of learning good cue orders without impairing speed and frugality.

From a theoretical point of view, collective information sharing can be modeled as rules that define how people update cue orders on the basis of those of others. These rules might differ both in simplicity and accuracy. For instance, a complex social rule (the average rule) implies exchanging knowledge about subjective cue validities with other individuals, then computing the mean value across all individuals for each cue to arrive at a new cue order. In contrast, the majority rule is an example of a less demanding way to come up with new cue orders: Individuals simply vote for the cue that they consider best, second best, and so on.

Along these lines, Hastie and Kameda (2005) recently compared the performance accuracy of several social rules in group decision making. Interestingly, they found that very simple social rules performed comparably to much more demanding rules. Bearing this in mind, in the following we investigate, by means of a simulation study, whether social rules can help to overcome the slow progress in individual learning of a good cue order.

Simulation Study

We conducted a series of computer simulations in which we evaluated the success of several *social rules* (see Hastie & Kameda, 2005, for a review) when they were implemented in two of the simple learning algorithms for ordering cues considered by Dieckmann and Todd (2004). The two algorithms chosen were validity and tally swap. The former defines cue orderings of TTB and performed best in Figure 1. The latter was reported in an experiment by Dieckmann and Todd (2006) to capture the participants' behavior best. We tested the simple social rules using the German cities data set (Gigerenzer & Goldstein, 1996). As we mentioned above, the German cities data set consisted of the 83 German cities that had more than 100,000 inhabitants. In our simulation study, the task was to infer which of two cities has a higher population. For this inference, several cues could be considered (e.g., whether the city is the national capital).

Basic Setting of the Simulations

The key feature of our simulations was that a group of individuals exchanged information about the cue orders that they learned independently. Specifically, they started from random cue orderings and went through a subset of pair comparisons in which they derived and updated such random cue orders with feedback. In the basic simulation, groups of ten individuals went through a set of five pair comparisons. They all used the same learning algorithm but received a different set of five pair comparisons. Consequently, after this individual learning experience, each group member came up with a different cue order.

All group members then exchanged information about their cue orders and used a social rule to arrive at a single *social cue order*. In a further subset of five trials, group members started looking cues up in the social cue order instead of the random one. This social cue order was subsequently updated through individual learning. The process of social exchange and individual learning took place repeatedly every five trials and for up to one hundred pair comparisons.

Social Rules

In the simulations, we investigated the following five social rules:

1. The *average rule*: Each group member estimates the validity (or tally) of each cue, and the group computes the mean value across all members for that cue.
2. The *Borda rule*: Each group member ranks all cues according to their validities (or tallies). The value assigned to each cue is the sum of the members' rank order for that cue.
3. The *majority rule*: Each member assigns one vote to the cue with the highest validity (or tally), and the cue that receives the most votes is selected. This process is repeated for all the cues.

4. The *Condorcet rule*: All comparisons between two cues are kept. The cue that wins all comparisons in each cue order position is the Condorcet winner.

5. The *imitate the most successful rule* (also known as the *best member rule*): The cue order of the group member who achieved the highest accuracy in the last five trials is used by all members of the group. Note that *imitate the most successful* is the simplest rule. In contrast to the rest of the social rules, it does not involve the aggregation of social information. Individuals using such a rule just have to find out who performed best in the last five trials and imitate that group member.

During a set of five trials, all the group members kept count of the number of correct decisions and the total number of discriminations made by each cue. These accounts were subsequently updated when individuals arrived at a social cue order. Specifically, those individuals who used the average rule replaced the accounts of each cue by the corresponding values averaged across all group members. Individuals using the rest of the social rules estimated both accounts drawing random values for a uniform distribution with the following constraints: (1) the range of the distribution was determined by the maximum and minimum values stored in the previous trial, and (2) the final values had to conform to the social cue order.

Results of the Basic Simulation

Figure 2 shows the performance of the five social rules averaged across 1000 runs when they were implemented in the *validity* learning algorithm. For comparison, we further added the performance of individual learning according to validity (solid jagged line), TTB (upper straight line), and *Minimalist* (lower straight line).

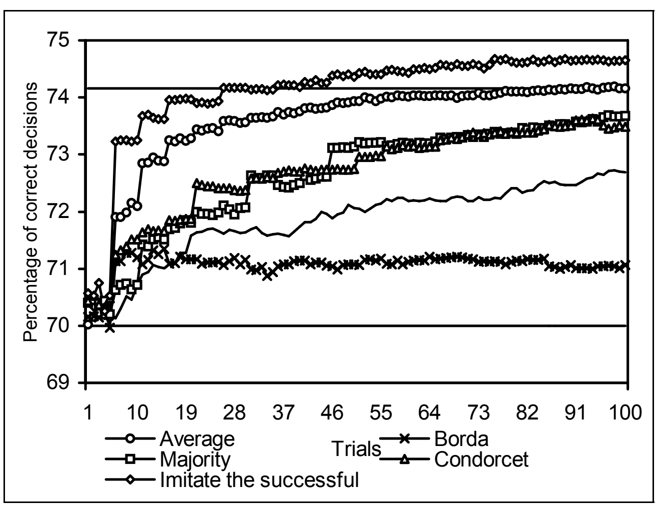

Figure 2. Mean performance of the five social rules when implemented in the validity learning algorithm.

Results showed that the complex average rule matched the performance of TTB after 100 pair comparisons. The majority and Condorcet rules, which are computationally less demanding, performed comparably, placing behind the average rule. The Borda rule fell behind the rest of the social rules. It did not achieve the accuracy that the individual learning algorithm did, but its performance was better than that of random order. Interestingly, the "imitate the most successful" rule beat the rest of the social rules we considered and even TTB.

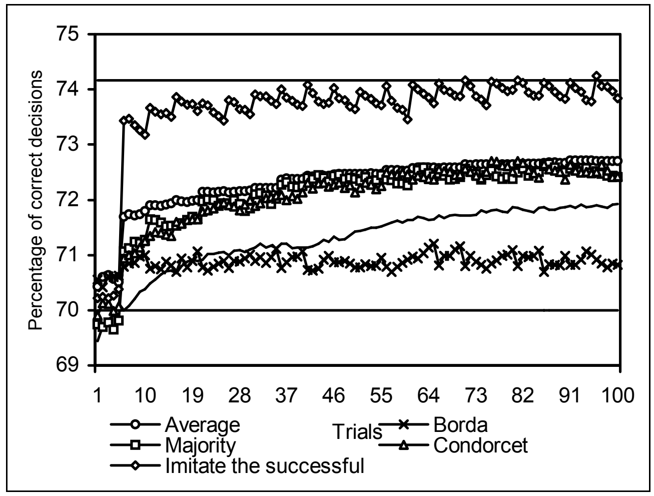

Figure 3. Mean performance of the five social rules when implemented in the tally swap learning algorithm.

How frugal were these rules? Table 1 shows the mean number of cues looked up in 100 trials for all the social rules. Note that all social rules, except "average," were comparable to and more frugal than TTB, which looked up 4.23 cues on average. However, all these rules were less frugal than Minimalist, which looked up 3.34 cues on average.

Table 1. Averaged number of cues looked up in 100 trials for the five social rules.

	Validity algorithm	Tally swap algorithm
Individual	3.2	3.13
Average	3.94	2.96
Borda	3.35	3.19
Majority	3.50	2.99
Condorcet	3.35	3.03
Imitate the successful	3.53	3.26

What is the consequence when individual learning by validity is replaced by the tally swap algorithm? Some of the previous findings were replicated (see Figure 3). For comparison, we also added the performance of individual learning according to tally swap (solid jagged line), TTB (upper straight line), and *Minimalist* (lower straight line). The average, majority, and Condorcet rules outperformed individual learning using tally swap. However, they still lagged behind the performance of the ecological cue validity order. Again, the Borda rule performed worse than individual learning, but still better than the random order. The accuracy of the “imitate the most successful” rule when implemented in the tally swap learning algorithm matched that of TTB. Yet one characteristic distinguished it from validity learning: After each social exchange, there was a decline in performance, and the average performance was not as high as when individuals updated cue orders by validity. Furthermore, all these social rules were comparable in frugality (see Table 1). In fact, they all were more frugal than the TTB and Minimalist.

Why did the cue orders resulting from the application of some of these social rules perform so well? Why did some of them perform better than others? To answer these questions, we analyzed the accuracy of the social cue orders obtained by each social rule for both the validity and tally swap learning algorithms. We gathered 20,000 cue orders that each social rule produced until the 100th trial. Then, we classified them depending on whether they achieved a better performance than (1) the ecological cue validities order (i.e., TTB), (2) individual learning according to the corresponding learning algorithm, (3) the random order (i.e., Minimalist), or (4) whether their performance was even worse than the random order (see Figure 4).

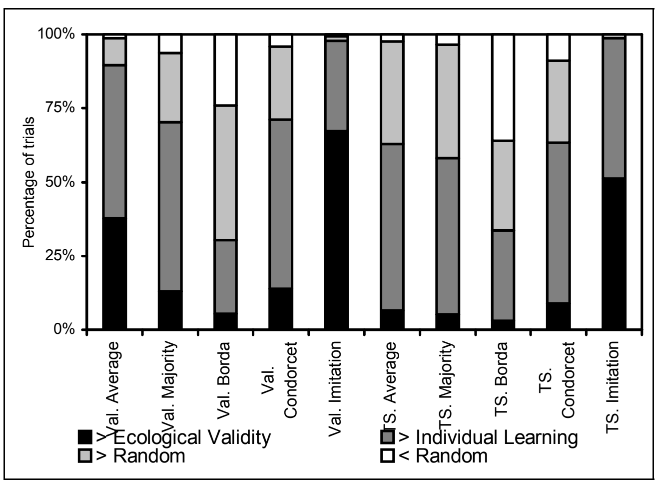

Figure 4. Performance of the five social rules relative to three criterions: the ecological cue validities order, individual learning, and the random order.

Interestingly, results showed that the cue orders produced by the “imitate the most successful” rule were more accurate than the ecological cue validities order in more than 50% of occasions. This result was found for both validity and tally swap. Note that, as we mentioned above, in the German cities data set, there are 9! (i.e., 362,880) possible cue orders, and only 1.8% (i.e., 7,421) of them perform better than the ecological cue validity order does. Furthermore, the rest of the social rules apart from Borda generally came up with cue orders that achieved a better performance than individual learning but worse than the ecological cue validities order. Finally, most of the cue orders produced by the Borda rule achieved a performance that was worse than individual learning.

Sensitivity Analyses

In an extended set of simulations, we modified several parameters of the basic simulation. More specifically, we focused on the number of individuals who exchange information to arrive at a social cue order (i.e., the group size), and the number of trials in which individuals learned independently before exchanging information (i.e., the frequency of social information exchange). In these extended simulations, we focused on three of the social rules (i.e., average, majority, and imitate the most successful). We examined the performance and frugality of these rules for four different group sizes (2, 10, 25, and 100 individuals), and three different frequencies of social information exchange (5, 25, and 50 trials).

The general conclusion from these extended simulations is that the more individuals are included in the group, the higher the group’s accuracy, regardless of the social rule and the individual learning algorithm they used. The increase in accuracy from 5 to 25 individuals was larger than from 25 to 100. Furthermore, the lower the frequency of exchanging social information, the lower the performance was in the long run. Again, the combination of “imitate the most successful” and the validity learning algorithm proved to be an effective way to resolve the problem of slow individual learning. For instance, when 10 individuals exchanged information on just one occasion (after 50 trials), this was sufficient to achieve the accuracy of the ecological cue validity order.

To achieve the performance of TTB, it is not necessary to exchange information with a large group of individuals. Frequent exchange, or the aggregation of social information (as would be required, for instance, in the average rule), is not necessary either. In summary, the superiority of the “imitate the most successful” rule, observed in the basic simulation, remained stable with an increasing number of individuals in the group, even when the number of social exchange opportunities was reduced. Briefly, the results of the basic simulation were strengthened.

Conclusions

The results of our simulations support the hypothesis that very simple social rules are able to improve the performance of simple algorithms for ordering cues. Specifically, all social rules we considered (except the Borda rule) outperformed individual learning. Even more interestingly, the “imitate the most successful” rule beat more computationally demanding social rules, such as the average or majority. Furthermore, it not only solved the problem of slow individual learning, but also performed even better than TTB using the ecological cue validity order did. In everyday life, aggregation of information can be difficult, requiring demanding computations; cognitively simple strategies are a viable alternative.

As mentioned above, finding the best cue order becomes computationally intractable as the number of available cues in the environment increases. One solution to this problem is to rely on simple learning algorithms for ordering cues. However, as Dieckmann and Todd (2004) showed, updating a cue order in a trial-by-trial basis leads to a slow convergence to the ecological cue validities. We showed that the limitation of the individual learning algorithms considered by Dieckmann and Todd (2004) could be resolved at a group level. That is, higher performance could be achieved by very simple social rules. These results suggest a promising avenue for future research on bounded social rationality (see Gigerenzer et al., 1999).

For the sake of simplicity, in the current computer simulations we mimicked a situation of group discussion. However, this might be troublesome in real-world group discussion because communication and coordination require a huge effort, especially when aggregating complex information such as cue orders. The discussions of a group of people who report cue orders sequentially and aggregate them with a certain protocol, such as majority rule, could also be cumbersome. Rather, in the real world, a single person could easily come up with a single cue order (i.e., a social cue order) when listening to other people's opinions. In such a situation, we believe that the "imitate the most successful" rule would also work well.

Our basic results are in line with findings by Hastie and Kameda (2005). By means of computer simulations and using forced-choice tasks, they investigated how the members of a group who made decisions individually arrived at a collective decision. In contrast, we focused on how individuals exchanging information about individually learned cue orders arrive at a social cue order. The results of Hastie and Kameda (2005) are focused on the social learning of "decisions." In contrast, our results are focused on the social learning of the "information" individuals use to make decisions. Despite theses differences, both studies found that cognitively simple social rules perform comparably to cognitively more demanding rules, such as the average rule. However, the impressive performance of the "imitate the most successful" rule is unique in our study. The performance of this rule in Hastie and Kameda's (2005) study was worse than those of the majority and average rules in most cases. In future research, we will investigate the reasons for this seemingly contradictory finding, and also study the generalizability of our results to other learning situations.

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