the corresponding results bear little relation to graphs that arise in real-life situations, where edges are characteristically added with some dependence on edges that are already present.

A more interesting class of networks, which has received much recent interest, are so-called "small networks" in which most nodes are not directly connected to each other, but can be reached from every other by a small number of hops. This sort of network is often explained in the popular literature via the "Kevin Bacon Game" in which the nodes are actors and the edges connecting them represent their having appeared in the same movie. The question is then posed of how many edges one must follow (how many nodes one must hop between) to get from Kevin Bacon to any given actor. Each actor then gets a "Bacon number" which represents how many hops away from Kevin Bacon they are. Remarkably, most successful actors have a Bacon number less than or equal to 5. Such networks, in the context of the four-quadrant human decision-making map (Behrens & Sporns 2012), would represent a trend toward the east – more sociality, and more chances to connect lead naturally to such networks. Such networks have many interesting properties including a tendency to have a small number of nodes with very high degrees of connectivity – something that can be looked for in (big) data. Similar patterns appear in anatomical connections in the brain (Sporns et al. 2002) and in synchronization networks of cortical neurons (Yu et al. 2008).

Various mechanisms can give rise to such networks, the most popular being the Watts-Strogatz (W-S) mechanism (Watts & Strogatz 1998), which is constructed by iteratively rewiring a pre-existing graph (something which might be expected to model evolution on a pre-existing network), and the Barabási–Albert (BA) model (Barabási & Albert 1999), which is based on the notion of preferential attachment, where new nodes are added with connections made preferably to those which already are more connected. The BA model, for example, has been used to model the World Wide Web (www) where one might well expect that more people would add new links to a more popular (more linked to) site than to one less used. A general review can be found in Albert and Barabási (2002).

The BA model also gives rise to an interesting distinction from the W-S mechanism in that it gives rise to power-law or "scale-free" networks where the number of nodes with some number of connections depends as a power of that number. This gives rise to long-tailed distributions (Behrens & Sporns 2012). Indeed, this behavior is found by Bentley et al. in their Figure 1 (target article, sect. 2). Again, this sort of behavior can be sought in big datasets and can give valuable information about the possible origin of a given network configuration. So far we have assumed a deviation from randomness (an appearance of structure) due to fairly deterministic processes where, even if edges appear randomly, their probabilities depend deterministically on other factors. Relatively little is known if one weakens this dependence by the addition of random noise.

As an aside, we note that the north–south axis is described as "the extent to which there is a transparent correspondence between an individual's decision and the consequence of that decision" (target article, sect. 2, para. 4). If we interpret this as a weakening of a direct cause-effect relationship, we suggest that this might indeed be modeled as noise – something that has been much less studied in the physics community, yet which could surely be added to models which have been considered, in some cases perhaps analytically, but also certainly via computer simulations. Spin-glasses are often used to model network dynamics (Binder & Young 1986) where a temperature-like parameter represents noise, but this work tends to be done to represent correlations between activities at nodes rather than on the dynamics which drives the formation of edges – that is, the structure of the network itself.

Big-data approaches from the social sciences are already motivating significant new developments in characterizing brain networks. Over recent years, connectomic analyses of brain activity in large datasets have elucidated the network architecture of the brain (Behrens & Sporns 2012; Sporns 2012; Supekar & Menon 2012) and identified fundamental principles of the brain's graphical organization (Bullmore & Sporns 2012). New approaches promise to shed light on brain networks implicated during specific cognitive tasks, such as altered network interrelationships during volition regulation of emotion (Sripada et al. 2013). Such brain mechanisms involved in specific cognitive tasks might ultimately be helpful in understanding brain–behavior responses to real and increasingly social stimuli – for example, parents responding to baby-cries (Swain & Lorberbaum 2008; Swain et al. 2004; 2011), the complex array of social responses involved in parenting (Swain 2011) – and to broader societally directed behaviors such as altruism (Swain et al. 2012). Such approaches may be helpful in understanding underlying mechanisms of psychiatric disorders such as obsessive-compulsive disorder (Leckman et al. 2004; Mayes et al. 2005), generalized social anxiety, and autism that involve pervasively abnormal functioning in social domains.

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Mapping collective emotions to make sense of collective behavior

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Abstract: While Bentley et al.'s model is very appealing, in this commentary we argue that researchers interested in big data and collective behavior, including the way humans make decisions, must account for the emotional factor. We investigate how daily choice of activities is influenced by emotions. Results indicate that mood significantly predicts people's decisions about what to do next, stressing the importance of emotional state on decision-making.

Bentley et al. propose that decision-making can be understood along two dimensions. The first dimension represents the degree to which an agent makes a decision independently versus one that is socially influenced. The second dimension represents the degree of transparency in the payoffs and risks associated with the decisions agents make. While Bentley et al.'s model is very appealing, we argue that emotions, a key element to understand the way humans make decisions, are missing.

From early theorizing by William James, to Antonio Damasio's work on somatic markers, decades of research consistently have shown that emotions play a central role in the decision-making process (see, e.g., Bechara & Damasio 2005; Loewenstein 2000). For instance, in economic decisions, fear leads to risk-averse choices, whereas anger leads to risk-seeking choices

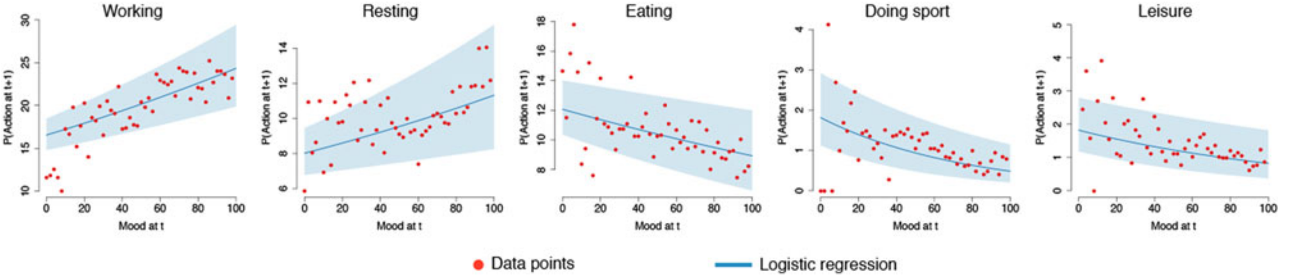

Figure 1 (Taquet et al.). Five activities are significantly predicted by mood. The figure presents the data in red (aggregated by mood in bins of 2 levels: 0–1, 2–3, … , 99–100) and the corresponding logistic curve in blue, corrected for mood at time $t+1$ and the interaction between mood at time t and time between tests. The shaded area corresponds to two standard errors above and two standard errors below the curve. A color version of this image is available at http://dx.doi.org/10.1017/S0140525X1300191X.

(Lerner & Keltner 2001). In medical decisions, positive affect improves physicians' clinical reasoning and diagnosis (Estrada et al. 1997). In ethical decisions, social emotions such as guilt can lead individuals to choose ethically (Steenhaut & Van Kenhove 2006). These studies, among many others, strongly demonstrate that emotions shape most of our decisions. Researchers in microeconomics, health, or ethics are already taking emotions into account. It is now time for big-data and collective behavior researchers to recognize the importance of the emotional factor in the decision-making process.

In this commentary, we illustrate the importance of emotions to predict people's behavior using the example of a big dataset derived from an ongoing large-scale smartphone-based, experience-sampling project (available at: http://58sec.fr/). Specifically, we show that the happiness that individuals experience at time t reliably predicts the type of activities they choose to engage in at time $t+1$.

Subjects voluntarily enroll in the experiment by downloading and installing the mobile application "58sec". They are then presented with questionnaires at random times throughout the day – henceforth referred to as *tests*. Random sampling is ensured through a notification system that does not require users to be connected to the Internet. The minimum time between two tests is set to one hour to avoid large artifactual auto-correlations between answers to the same question in consecutive tests. At each test, participants are asked to rate their current mood on a scale from 0 (very unhappy) to 100 (very happy) and to report which activity they are currently engaged in, among other questions. Activities can be selected from a list of 25 non-mutually exclusive choices that, among other activities, include doing sports, working, resting, praying/meditating, shopping, and commuting.

To illustrate the dynamic between emotion and decision-making, we randomly selected 5,000 people from our database and investigated how their daily choice of activities (e.g., whether one decides to spend the evening working out or watching TV) is influenced by their emotion. Specifically, we tested how much mood reported within one test (time t) predicts the activity reported within the next test (time $t+1$). For each possible activity, a logistic regression model is fitted for the probability of the activity (dependent variable) as a function of previously reported mood (independent variable). Mood at time t may be correlated to mood at time $t+1$, which itself correlates with the activity at time $t+1$. To cross out this indirect effect of emotion on decision, mood at time $t+1$ is included in the model as a covariate. Emotions closer in time to a decision may better predict its outcome. To capture this notion, we included an interaction term between the (random) time between the two tests and mood at time t.

Big datasets allow many variables to be compared simultaneously without diluting the effect of interest in the correction required to account for the multiple comparisons. For the same underlying effect size, the p-value will indeed decrease as the number of data points increase. More data points therefore reduce the number of Type II errors (false negatives), for a constant Type I error rate (false findings). Accordingly, the threshold on the p-value can be reduced from its typical value (e.g., 0.05) to also decrease the number of findings that are false. In this study, we set the significance threshold at $p < 0.001$ to increase the confidence in our findings.

Significance testing was carried out on the coefficient ($\text{Beta}_{\text{pred}}$) of mood at time t in the prediction of each action at time $t+1$. The resulting 25 p-values were corrected for multiple comparisons using Bonferroni correction. Each of the 5,000 subjects participated in an average of 13.1 tests. Those subjects who participated in only one test were discarded since their test results did not convey information about the prediction of emotion on decision. This gave rise to a total of 59,663 data points from which the logistic regression could be fitted.

Five activities were significantly predicted by mood at the $p = 0.001$ threshold after Bonferroni correction (Fig. 1): working ($\text{Beta}_{\text{pred}} = 0.48$, $p < 10^{-12}$), resting ($\text{Beta}_{\text{pred}} = 0.38$, $p < 2 \times 10^{-4}$), eating ($\text{Beta}_{\text{pred}} = -0.34$, $p < 5 \times 10^{-4}$), doing sports ($\text{Beta}_{\text{pred}} = -1.3$, $p < 10^{-9}$), and leisure ($\text{Beta}_{\text{pred}} = -0.81$, $p < 3 \times 10^{-4}$). These results indicate that mood significantly predicts people's decisions about what to do next, stressing the importance of emotion on decision-making.

Big data and large-scale experience sampling through pervasive technologies offer unprecedented opportunities to understand collective behaviors. Such methods are particularly suited to study collective behavior as its causes often involve complex interactions between sensitive variables. One archetypal example of such collective behavior is decision-making which involves independence of the agent, transparency of the payoffs, and emotional state.

Conformity under uncertainty: Reliance on gender stereotypes in online hiring decisions

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Abstract: We apply Bentley et al.'s theoretical framework to better understand gender discrimination in online labor markets. Although such settings are designed to encourage employer behavior in the

different domains of human decision making. In what follows, we argue that this map fails to capture the relationship between social influence and payoff transparency.

Bentley et al. have interpreted their model as a "principal-components representation" (target article Abstract), which assumes that two axes are orthogonal to each other. However, it is well documented in social psychological literature that social influence and payoff transparency influence each other to a great extent. When two parameters are correlated with each other, one axis should not be perpendicular to the other axis (DeVellis 2012, p. 142). Thus, the map as well as the formula at the start of section 2 should be revised to accommodate the hypothesized angle that represents the covariance of the two key parameters. Even though Bentley et al. did acknowledge this interaction in some places (e.g., "Intuitively, what is happening here is a pile-up of correlated behaviors caused by the interaction of social influences coupled with strong enough intensity of choice"; target article, sect. 2.2.1, para. 2), when they compare their map to a Google map (sect. 1, para. 6), they run the risk of misleading the readers into believing that the two axes are perpendicular to each other.

Decision-making is a dynamic process in which transparency and social influence invariably interact with each other. Under social influence, even the most transparent decision-making task becomes ambiguous. For example, in a classic conformity experiment (Asch 1951), participants were instructed to complete a perceptual task in which they had to match the length of a given line with one of three comparison lines. Although the correct judgments were easy to make, 75% of the participants made an incorrect judgment in at least one trial when all the confederates gave the same wrong answer. Thus, social influence can mask even the most transparent decision. Under social influence, even simple tasks like line comparisons are not as transparent as when there is no social influence (Asch 1951; 1952; 1956). Moreover, other studies have shown that social influence could change one's cost–benefit estimation of a decision (Louis et al. 2005).

On the other hand, people are more likely to seek social influence when facing opaque decisions than when facing transparent decisions (Deutsch & Gerard 1955; Stasser & Davis 1981). Deutsch and Gerard (1955) also asked participants to compare lines just like Ash did in the aforementioned study. In half of the trials (visual condition), the lines were physically present when participants and confederates made their judgments. Thus, in this condition, the decisions are fairly transparent. However, in the other condition, the lines disappeared before the participants had the opportunity to make judgments; hence, the decisions depended on memories and were less transparent than decisions in the first condition. Results showed that participants in the second condition were more likely to conform to social influence than those in the first condition.

When people have little knowledge about what to base their decisions on, it is helpful to imitate the successful judgments or to average the judgments of others to exploit the "wisdom of crowds" (Gigerenzer & Gaissmaier 2011). Findings from neural imaging researches support this claim by showing that social information processing and decision making have shared neural substrates (Tomlin et al. 2013). Opaque decisions drive people to seek social influence.

We recently conducted a survey (Zhou 2013) to examine whether transparency and social influence correlate with each other in daily decision making. We asked 55 participants to think about one upcoming decision they have to make in real life. Participants wrote down keywords best describing this decision. Next, participants rated how transparent the decision payoff is to them and how much social influence they are under in making the decision on an 11-point scale (0 = not at all; 10 = very much). The order of these two questions was counterbalanced so that half of the participants rated the transparency first and half of them rated the social influence first. Regardless of which question was asked first, social influence and payoff transparency turned out to be negatively correlated, ($r(53) = -.71$, $p < .0005$). These results support our argument that social influence and transparency interact with each other to a great degree and cannot be considered as independent dimensions.

In conclusion, we agree that Bentley et al. have provided a comprehensive map to evaluate collective behaviors in the big-data era. We also agree that this map will lead to new promising hypotheses on human decision making. However, Bentley et al. have not represented the interaction of the two axes on their map in a precise manner that would reflect the factual nature of the interaction. The accurate depiction of the covariance of social influence and payoff transparency is critical because it exerts direct impact on decision making in the digital age. The map proposed in the target article would function more quantitatively and accurately if it were revised taking the interaction between the two dimensions into account.

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Authors' Response

More on maps, terrains, and behaviors

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Abstract: In a recent *New York Times* column (April 15, 2013), David Brooks discussed how the big-data agenda lacks a coherent framework of social theory – a deficiency that the Bentley, O'Brien, and Brock (henceforth BOB) model was meant to overcome. Or, stated less pretentiously, the model was meant as a first step in that direction – a map that hopefully would serve as a minimal, practical, and accessible framework that behavioral scientists could use to analyze big data. Rather than treating big data as a record of, and also a predictor of, where and when certain behaviors might take place, the BOB model is interested in what big data reveal about *how* decisions are being made, how collective behavior evolves from daily to decadal time scales, and how this varies across communities.

R1. Introduction

We are encouraged and inspired by the rich variety of commentaries, noting that, in general, commentators found something useful in our map of decision making. **MacCoun**, for example, points out his similar model for binary decisions; **Durlauf** appreciates its elegance in simplicity; **Ross** discusses how economics has already explored the four quadrants of our map; and **Uhlmann & Silberzahn** apply the map quadrants to gender bias in a big-data study of employment search patterns. A good number of commentators even propose their own adaptation of the map quadrants, often as an added dimension, including emotion (**Buck**; **García, Torralba, & González** [**García et al.**]; **Ruths & Shultz**; **Taquet, Quoidbach, de Montjoye, & Desseilles** [**Taquet et al.**]), network structure (**Fortunato, Saramäki, & Onnela** [**Fortunato et al.**]; **Swain, Sripada, & Swain** [**Swain et al.**]), social-learning biases (**Le Mens**; **Mesoudi**; **Pfister & Böhm**), and cultural conception of time (**Norgate, Davies, Speed, Cherrett, & Dickinson** [**Norgate et al.**]). Others sought refinement of either the *east–west* dimension (**O'Donnell, Falk, & Konrath** [**O'Donnell et al.**]; **Le Mens**) or the *north–south* dimension (**Spurrett**). Several contributed very useful ways forward in mapping the terrain of the map in considerably more detail (**Analytis, Moussaïd, Artinger, Kämmer, & Gigerenzer** [**Analytis et al.**]; **Christen & Brugger**; **Hopfensitz, Lorini, & Moisan** [**Hopfensitz et al.**]; **Keane & Gerow**; **Le Mens**; **McCain & Hamilton**; **Moat, Preis, Olivola, Liu, & Chater** [**Moat et al.**]; **Reader & Leris**). Objections to our map include oversimplification (**Godzińska & Wróbel**; **Reader & Leris**) and misrepresentation of the orthogonality of its axes (**Bookstein**; **O'Donnell et al.**; **Zhou, Xie, & Ye** [**Zhou et al.**]).

Our response has three parts: the map, its terrain, and some speculation about mapping the effect of big data on collective behavior, including the kinds of self-aware "looping" effects discussed by **Christen & Brugger**; **Fan & Suchow**; **O'Donnell et al.**; **Roesch, Stahl, & Gaber** (**Roesch et al.**); and **Schmidt**.

R2. The map

The theory used as the foundation for the BOB map – discrete choice – is extremely broad (Ben-Akiva et al. 2012), and the map is a tool to help behavioral scientists navigate the large research terrain of its many applications. The map is intended to facilitate interdisciplinary communication and insights across different phenomena and different scales of analysis, from big-data statistics to qualitative observation at the individual scale. As **Ruths & Shultz** put it, the problem is highly dimensional, and the BOB map provides a framework on which future work can productively build. **Spurrett** takes us to task for fuzzy definitions of transparency and payoffs, but we think this flexibility is necessary to get people to use it as a basis for interdisciplinary communication and big-picture research, along the way making their own adaptations and modifications. To communicate with a business audience or public policymakers, for example, the north–south axis might be presented as extending from few choices in the north to many overwhelming choices in the south. Alternatively, as **Buck** advocates, the north–south axis might instead extend from "rational" to "emotional," whereas in discrete-choice economics it would be called the "intensity of choice." As we specify below, it all corresponds to closely related formulations mathematically.

These different shades of interpretation may provide multiple proxies to be measured in big data, which **Godzińska & Wróbel** rightly call for. For it the map to be applicable to decision making, anywhere from prehistory to the era of big data, we need a minimalist structure that allows for added elements such as emotions collected through surveys or text mining, different concepts of time, kinship or other cultural constructions recorded in anthropology, or the millennia of material culture in the archaeological record. Consider the vast range of scales from the population-level patterns in big-data studies of language use in online social media to the activity within individual brains. The spirit of our map is to use big data to generate hypotheses that are then tested by other means (including qualitative) at the individual/group level, which **Godzińska & Wróbel** invite us to consider, or even the level of neurobiology discussed by **O'Donnell et al.** We agree with **Le Mens** and with **Roesch et al.** that future uses of big data will include more sensitive measurements and more varied sources of information as the brain–computer interface develops. The BOB map provides a means of bridging scales of time and population. As **Keane & Gerow** and **Roesch et al.** point out, big-data literature puts a microscope on individuals but often underplays the complex distributional effects and dynamics that are visible at this large scale but also require a time depth.

Ross misunderstood us when he stated that we were relegating all economics to the northwest quadrant; we were putting only *Homo economicus* there. We actually see most of behavioral economics as lying just east of the northwest quadrant. Nevertheless, while we were careful not to map whole disciplines or individual researchers into the quadrants, we recognize that the bulk of literature in any one (sub)discipline tends to gravitate toward one of the quadrants.

Godzińska & Wróbel also see the map as too simplified to capture the essence of decision making, but most commentators accepted our invitation to fill in the map. The engagement of responders and the diversity of proposals to adapt the map help justify its simplicity, as **Durlauf** and **MacCoun** discuss. Even if a more complicated shape, such as the globe or tetrahedron suggested by **Bookstein**, could better capture certain interrelations, the cost would be the interdisciplinary common ground, and few in the *BBS* community would adopt these more complicated heuristic models. Furthermore, a more complicated geometry might make things worse by assuming too much. In other words, Bookstein rightly reminds us that "the map is not the territory." We agree; the simple geometry is deliberate so that few would make this mistake. The simple two-dimensional form invites others to apply it or even modify it to suit their interests.

Together with **Bookstein**, **Zhou et al.** and **Godzińska & Wróbel** object to the "structuralist" dichotomy we have implied by the orthogonal axes, maintaining that transparency itself is socially influenced. **Reader & Leris** usefully caution against treating payoff transparency as a single entity, reminding us that transparency and the costs of decision making likely determine whether social or individual information is used. **Zhou et al.** present survey results in which social influence correlates with payoff transparency. We do not dispute either that b_t and J_t may correlate, or that in discrete-choice theory covariates that go into determining social influence and payoff transparency may indeed be correlated. We doubt, however, that the correlation will be the same in all cases, and one can easily envision situations where the two are anti-correlated or uncorrelated. Rather than assume some fixed correlation, the map is intended to represent how these shifts in decision making happen in any possible direction rather than just on fixed diagonals of assumed covariance.

R2.1. Customizing the map

So far, we have explored the map as we presented it, but as we noted earlier, we welcome the proposals to customize the map with added dimensions. **Norgate et al.** suggest that a crucial added dimension would represent the continuum between perception of "clock time" versus "event time," noting that the big-data era may be shifting societies from clock time back to event time, which presumably is at the primordial end of the spectrum. This relates the transition of our digital era to the classic anthropological formulation of a prehistoric transition from immediate return (hunter–gatherer) to "delayed return" (e.g., agricultural) societies. More generally, it fits very well into the discussion of forward-looking agents, which we discuss in the following section. **Norgate et al.** point out the existence of cultures with an identifiable time orientation toward the future, which **Moat et al.** have shown in their big-data studies (e.g., Preis et al. 2012; 2013) to have economic advantages.

Several commentators emphasize the relevance of emotions in decision making. We confess we had considered emotions to be a proximate cause of a decision, but the arguments of **Buck**, **García et al.**, **Ruths & Shultz**, and **Taquet et al.** are compelling concerning the fundamental importance of emotions to decision making. There are several ways of introducing emotions. One is to integrate them as a third dimension to the map, as proposed by García et al. Alternatively, emotion could be treated as another covariate in dynamic extensions of discrete-choice theory, which can accommodate such forms of decision making (Ben-Akiva et al. 2012). Perhaps most intriguing is the suggestion by Buck to modify the north–south dimension in order to reflect emotions directly, so that the continuum ranges from purely emotional decision making (rather than opaque) in the south to purely rational (rather than transparent) in the north. In fact, if emotions can be used as a proxy for transparency or intensity of choice, then this presents a complementary means of measuring latitude on the map. This could be calibrated through various big-data measures of emotions, such as the smartphone self-assessments that Taquet et al. discuss (and which they correlate with decisions), or the frequencies of word stems on large sources of language use such as Twitter or Google's Ngram viewer (Acerbi et al. 2013; Lampos & Cristianini 2012; Tausczik & Pennebaker 2010).

We attempted to relate the map to generalized network structures in our Figure 8, and **Fortunato et al.** have proposed adding network structure as a third dimension, from highly clustered to fully connected networks – a dimension that is central to the famous small-world network formulation of Watts and Strogatz (1998). **Swain et al.** speculate that the east–west dimension might offer important insights into the dynamics of neural connectivity in small-world properties of brain networks implicated during emotion, social stimuli, social anxiety, and autism. Because small-world networks have been investigated, both within the brain and between brains, network theory provides another unifying framework, as indeed networks have much to say about the short-tailed versus long-tailed distributions we discuss in reference to the map. Fortunato et al. point out that the collective outcome depends on social-network structure the more that agents stick to their choice rather than perpetually updating. This updating is nearly equivalent to adding noise and moving southward on the map, and as we suggested in Figure 8, specific network structure is probably more important in the northeast than in the southeast.

R3. The terrain

Several commentators contributed useful ways forward in mapping the terrain of the map in more detail. This could be through measurement – such as sophisticated data extraction (**Moat et al.**) or subtle changes in distributions (**Keane & Gerow**) – or through multistage decision models (**Analytis et al.**; **Hopfensitz et al.**; **McCain & Hamilton**), or through the remarkably simple addition of "contour lines" (**Christen & Brugger**). We see the computer simulation by Analytis et al. as consistent with the predictions of our map: We just need to reverse the columns of their figure such that their "popularity-cue heuristic" model and its associated uniform distributions is in the west and their "popularity-set heuristic" model is in the east. In their two-stage decision model, each agent first eliminates the majority (e.g., 90%) of options. Agents following the popularity-set heuristic then choose among the shortlisted items through social influence, with probability proportional to popularity. This leads to just the kind of right-skewed distributions that we would expect in the east. Because agents choose the best from among only a 10% random sample, rather than from among all samples, the popularity-cue heuristic yields a more uniform distribution, consistent with the noisy southwest. In other words, the shortlisting stage of the popularity-cue heuristic is random selection, that is, pure southwest ($b = 0$).

Similarly, any social influence under the popularity-cue heuristic is fairly weak because it is activated only after shortlisting and only as a "fourth attribute" among three other attributes that remain reflective of quality. This repeated 10% random-sampling process weakens the tracking of quality, and as a result, the popularity of choices increases slowly in the direction toward the item of highest quality (from 0 to 100). Referring to the concern of **Roesch et al.** about rate of change, the popularity cue may only gradually sort out the best choices from the worst. Perhaps after more time steps, the gradient would be steeper from the worst to best (item 1 to item 100). We might therefore categorize the popularity-cue heuristic as being in the southwest quadrant as a result of the random sampling in step one, but in the northeast quarter of that quadrant because of the transparency ($b > 0$) and weak social influence in step two.

Like **Analytis et al.**, who consider a two-stage process, **Hopfensitz et al.** also study games that have multiple stages. These games may be usefully studied in the extended BOB framework of our response here by modeling them as nested Logit Quantal response games where the first nest is the set of games one chooses to play in the first period, and the second nest is the set of strategies of the game chosen in the first period. The analog of (b, J) would be (b, J) for the choice of game in the first period and (b', J') for the second-period strategy choice of the game played in the second period. The choice of game in the first period includes the "game" of an "outside option" as in the commentary by Hopfensitz et al. Future research in multistage games proposed by Hopfensitz et al. is promising.

Similarly, **McCain & Hamilton** convince us that including social interactions and quantal responses at each stage is an exciting agenda for future research. McCain & Hamilton raise the interesting question of what happens if (b, J) vary across quadrants of the map in the context of anti-coordination games (Bramoullé 2007). Imagine there is a stoplight that has a large but finite penalty if you run a red light, and imagine their Drive On game being played by a pair of players with foggy glasses (a small b). When $b = 0$, each player plays "go" with probability 1/2 and plays "wait" with probability 1/2, and the probability of a crash is 1/4. But when b is infinite, the player facing a red light waits and traffic proceeds ideally.

We have emphasized that the J_t parameter is an attempt to capture social influences, especially those types of influence that possess a "social multiplier" of policy relevance, which was stressed by Manski (1993) as being different from "spurious social effects" (Shalizi & Thomas 2010). Like **Mesoudi** and **Le Mens**, **Ruths & Shultz** are unsatisfied with the way we lump together all social-learning biases into the east. The map does, however, roughly cover the intensity of social tie tracked along the north–south dimension in the east. This makes it relevant to Granovetter's (1973) strong versus weak social ties and how the strength of these ties correlates with emotional closeness (e.g., Hill & Dunbar 2003) – issues to which **O'Donnell et al.** refer. Hence, the north–south dimension does distinguish between the adaptive ratchet in the northeast, where social learning adaptively focuses on the most useful role models, and unbiased imitation in the southeast.

The Arab Spring, mentioned by **Roesch et al.** and **O'Donnell et al.** may be an example of the ambiguity of the effect of social media. When Gladwell (2010) pointed out "why the revolution will not be tweeted" – coincidentally just weeks before the Arab Spring uprising – he meant that revolutions require the strong social influence of the northeast, such as face-to-face interaction, rather than the weak ties of social media in the southeast. Social media are good for retrieving stolen cell phones left in cabs but not for carrying out revolutions, the success of which relies on organized hierarchy, not on here-today-gone-tomorrow social networks.

We are very aware that, as **Ruths & Shultz** point out, sigmoidal adoption curves may indicate social learning but that other models of independent learning (the simplest assuming a normal distribution of independent response times) can produce the same result (e.g., Bentley et al. 2012; Brock & Durlauf 2010; Hoppitt et al. 2010; Shultz 2003). This is why we propose *distributions* as a primary pattern for estimating J along the east–west axis of social influence. This tool can be refined, and we agree completely with **Keane & Gerow** that exploring the dynamics of how diagnostic popularity distributions change through time would refine the geography of our map within each quadrant. **Fortunato et al.** describe their insight from the precise popularity distribution of Wikipedia pages, and Keane & Gerow provide a nice example of how Zipf's Law in verb-phrase popularity became more "winner take all" among financial-media coverage as the stock-market crisis unfolded. **Roesch et al.** suggest that we could use "the velocity of change of decisions" and plot "vectors" on the map to show which way things are moving (vector direction) and at what rate (vector magnitude).

Although distributions are used to characterize the east–west axis, we agree with **Analytis et al.** that distributions may not be particularly diagnostic of transparency along the north–south axis. This is determined by the parameter b, which is sometimes called the "intensity of choice." It measures the level of noisiness in choice – for example, when $b = 0$, noise in choice is so large that choice is completely random over the choice set. When $b = \infty$, transparency in the relative values of the payoffs to each choice is so high that there is no doubt whatsoever which choice yields the highest payoff. The intensity of choice, b_t, is a precise and useful way to model the concept of "transparency" at each date t, where (1) $b_t = 0$ corresponds to the lowest level of transparency and the farthest south on our map, and (2) $b_t = \infty$ corresponds to the highest level of transparency and the farthest north on our map. We realize that this modeling and conceptualization of "transparency" will not capture all useful interpretations, but we believe that it does capture a useful subset and makes a useful linkage to the very large and successful discrete-choice literature (Ben-Akiva et al. 2012).

The north–south axis (the b_t axis) is a useful way of looking at the gain in precision of predicting the future using big-data sets. Prediction requires an expectation by forward-looking agents, and this applies to social transparency, as we discuss below regarding the fascinating future of "looping," to use the term of **Christen & Brugger**. By linking our approach to some classes of social interactions games, for instance, **Hofensitz et al.** suggest that the impact of social ties will be different in the north than in the south. We use their suggestions as an opportunity to explain the theory behind our Equation 1 of BOB, which lies in the domain of logistic quantal response games and quantal response (Nash) equilibria (McKelvey & Palfrey 1995) and has been extended to include social interactions and covariates (Blume et al. 2011; Brock & Durlauf 2001a; 2006). Let there be G groups with I players in each group. We can think of I as being a large number so that the law of large numbers gives a good approximation in what follows. Assume the groups are disjoint, that is, non-overlapping, for simplicity. As a stochastic best-reply function for player i at date t, consider the following modification of BOB's Equation 1 for a representative group g. The probability, $P_{itg}(k)$, that player i in group g chooses k is then

$$P_{itg}(k) = \frac{1}{z_{itg}} e^{b_t U\left(x_{iktg}, J_t \bar{P}^{e}_{itg}(k)\right)} \tag{1.1}$$

where i, k, and g take the integer index values from 1 to I, N_t, and G, respectively. The expected value, $\bar{P}^{e}_{itg}(k)$, denotes the belief, that is, the point expectation, that player i in group g holds on the average probability that k is chosen within his or her group.

Suppose point expectations are homogeneous for all players in all G groups – that is, assume $\bar{P}^{e}_{itg}(k) = \bar{P}_t(k)$. Then we have, further assuming that all covariate vectors are homogeneous across all players and all groups,

$$P_t(k) = P_{it}(k) = \frac{1}{z_t} e^{b_t U\left(x_{kt}, J_t \bar{P}_t(k)\right)}. \qquad (1.2)$$

The fixed point $\bar{P}^*(k) = k$ of Equation 1.2, which we might consider a "norm" of collective behavior, has been more formally labeled as a "logistic quantal response equilibrium with social interactions" (Blume et al. 2011; Brock & Durlauf 2001b; 2006; McKelvey & Palfrey 1995). For example, say person i has both individual preferences concerning choice k and forward-looking expectations concerning the popularity of choice k. Combining these influences as $a_k + c_k{}'X_i + d_k{}'\bar{X}_g + J_k\bar{P}_g(k)$, the probability that person i will choose item k is given by

$$P(k) = P_i(k) = \frac{1}{z_g} e^{b\left(a_k + c_k' X_i + d_k' \bar{X}_g + J_k \bar{P}_g(k)\right)}. \qquad (1.3)$$

In Equation 1.3, each player i has a covariate vector, X_i, and $\bar{X}_g$ denotes the average covariate vector averaged over players in i's group g. A fixed point of Equation 1.3 is a generalization of Nash equilibrium for discrete-choice games, and multiple Nash equilibria may arise when $b \geq 0$ and $J_k \geq 0$ for all k choices (Brock & Durlauf 2006).

At the extreme north of our map, $b = \infty$, and there can be many fixed points when the Js are positive. A full analysis is beyond the scope of our response here (see Brock & Durlauf 2006), but if we consider just the binary case, with $N = 2$ (Brock & Durlauf 2001a), we can fully characterize the set of fixed points for the case $J_1 = J_2 = J$. For the case of non-negative social interactions, $J \geq 0$, there can be three equilibria in many cases when $bJ > 1$ (e.g., in the northeast), if the difference among payoffs is not too large. **MacCoun**'s framework is similarly based on binary decisions; hence his "balance of pressures" (BOP) model and the BOB model apply to the kinds of tipping points and "voter" outcomes that MacCoun mentions, including threshold effects.

Another good representation of the north–south axis is "noise," as suggested by **Swain et al.** with noise increasing as we move south. This noise dimension is what the social-physics literature of fairly deterministic "preferential attachment" network models has yet to engage with. As a case in point, **Fortunato et al.** argue that in a fully connected network, the random imitation of the southeast and popularity-based choice of the northeast (we actually map conformity in the equatorial east) are the same, through preferential attachment. But this neglects the greater degree of random noise as we move south, and hence the noise in choice popularity. Whereas the highly right-skewed distribution does not change much moving down the eastern edge of the map, as **Analytis et al.** also mention, the dynamics do change. This is the point of our Figure 2b.

To explore what happens with the greater noise in the south, let us examine equilibria for the extreme south, where $b = 0$. We have $P(k) = 1/N$, where N is the number of possible choices, that is, all players are just making choices at random, with the probability of each choice equal to $1/N$. When we are in the deep south, where b approaches 0, we see that no matter how strong social ties are, that is, no matter how large J is, there is only one equilibrium. However, when we are in the extreme north, where b is very large, there will be, in many cases, three equilibria in the extreme northeast but only one equilibrium in the extreme northwest. In the extreme southeast, where J is very large, a small value of b can still satisfy $bJ > 1$, so multiple equilibria can easily occur.

R4. The future of big data

The southeast is where we find the unpredictability of success that Watts, Salganik, and colleagues have revealingly demonstrated over the years (e.g., Salganik et al. 2006; Watts & Hasker 2006). This underlies our main question concerning big data: Will the popularity of crowd sourcing soon undo itself, decreasing b through information overload while simultaneously increasing social awareness of the crowd, J, and hence move online society toward the southeast? Slow movement of the key parameters (b,J) from west to east and from north to south, but especially from northwest to southeast, can easily produce behavior such as bifurcations and phase transitions, as unique equilibria morph into multiple equilibria (Berry et al. 1995; Brock & Durlauf 2001a; 2006). Hence, **Moat et al.**, who describe remarkable discoveries of the predictive nature of big data, may soon need to consider future increases in social-interaction effects as those predictive methods become commonplace.

We are grateful to **Christen & Brugger** for contributing a historical perspective through their invocation of Hacking's (1992; 1995) principle of "looping," in which the identification of a phenomenon then feeds into the phenomenon itself. This is exactly why we believe that as predictive as big data might be at the moment, as soon as everyone becomes aware of these predictive algorithms, the competition to outpredict your competitor – whether in fashion, business, or the like – will tend to increase the unpredictability, much like what we see in the stock market. For example, whereas natural systems tend to exhibit early warning systems before critical transitions, financial systems are much more elusive (Scheffer et al. 2012).

Fan & Suchow propose that self-awareness can lead a group to seek out new knowledge and reposition itself on the map. They propose that motivation to solve a problem is a key variable driving groups northward on the map. We are not sure that the crowd can guide its own trajectory, however. We all seek to head north, but as **Schmidt** points out, the onslaught of big data may break lots of compasses, given that practically any opinion on any issue from climate change to genetically modified foods to measles vaccines and evolution can be found online. As Schmidt points out, even human identity becomes ambiguous as each person's digital shadow grows with multiple memberships, enrollments, sign-ups, connections, and so on. Intriguingly, Schmidt proposes that the southeast may subdue the data deluge "through a global relativity," while at the same time making the problem worse through collective behaviors. Schmidt rightly asks whether any of us can be experts anymore, which poses the compelling question of what happens if we were to crowd-source all our decisions, as is already explored in current science fiction. Schmidt suggests this may already be happening in medicine, perhaps the most information-deluged science, where the diagnosis of newly named syndromes has been rising dramatically in a way that is clustered in time and space, suggestive of the southeast.

As **O'Donnell et al.** point out, the neural systems for self-knowledge are involved in social cognition. In fact,

Christen & Brugger add self-reflection to the list of suggested third dimensions to the map because social influence depends on the models people have of themselves and what drives their behavior (e.g., a conscious effort to be a nonconformist) and, of course, whether one is aware of this self-reflection (buck the nonconformist trend by being ironically conformist, for example). This looping can go on forever, reminiscent of what Yogi Berra once said about a popular Italian restaurant in St. Louis: "No one goes there anymore. It's too crowded."

As agents compete to outpredict each other, we enter **Mesoudi**'s discussion of adaptive landscapes (see also Mesoudi 2010; Mesoudi & O'Brien 2008a; 2008b). Anderson et al. (1992) give us a formula for this:

$$E\max_{i\varepsilon\{1,2,\ldots,N_t\}}\{\tilde{U}\} = \frac{1}{b_t}\ln\Big(\sum\nolimits_{i=1}^{N_t} e^{b_t U_i}\Big) \tag{1.4}$$

which relates to ideas and techniques from entropy maximization in Bayesian statistics – tools from mean-field theory that allow us to approximate more complicated social networks, economics, and finance (Ben-Akiva et al. 2012; Brock 1993; Hommes 2013). Note that as $b_t \to \infty$ from south to north, this landscape function converges to $U_{i^*}, i^* = \operatorname{argmax}_k\{U_k\}$ and hence the landscape of Equation 1.4 moves toward a spiked, or so-called "Mount Fuji," shape on the space of choices, $\{1, 2, \ldots, N_t\}$. In contrast, moving from west to east, as J_t increases, multiple equilibria become possible so the landscape becomes more "rugged," and the potential for instability grows. Generally speaking, instabilities in collective dynamics will be north of the "equator," and the northeast especially is where instabilities and emergent bifurcations could link to studies of early warning signals (Scheffer et al. 2012).

Roesch et al. mention the "exponential velocity" of change with access to new technology, but we need to be careful about *tempo* versus *mode* of change, which might lead us to ask whether the current rate of change is any more "exponential" than in the early twentieth century, with most technologies taking off in the same sigmoidal form (Bentley & O'Brien 2012; O'Brien & Bentley 2011). Rather than accelerating change, in some cases increasing access to crowd-sourced data may lead to stasis, especially if accurate popularity statistics are approached with a conformity bias.

On an adaptive fitness landscape, such as what **Mesoudi** describes, there are different ways to avoid getting stuck on a low peak when higher peaks are nearby. The most straightforward is a global view of the landscape from the authoritative vantage of a "control tower," which is the beauty of the Sixth Sense Transport system that **Norgate et al.** have developed for mitigating traffic problems. Without this kind of top-down control, the other means is an optimal balance of information producers and information scroungers, as Mesoudi would describe it (see also Mesoudi 2008), or a balance of "exploration and exploitation," in the more business-like language of Axelrod and Cohen (1999).

On our map, this means an optimal, situation-specific balance of noise (the opposite of transparency) and social influence. Clearly, the balance is critical. **Norgate et al.** point out that "increased imitation can be desirable," and **Zhou et al.** note that when people have little knowledge on which to base their decisions, it is helpful to imitate the successful judgments, or to average the judgments, of others. But under a deluge of information, imitation might also bring about the kind of "pluralistic ignorance" that **Christen & Brugger** suggest could stabilize social dynamics in a suboptimal state. Crowd-sourcing may even preserve an undesirable status quo. As **Uhlmann & Silberzahn** discuss, we assume that the best person for the job gets hired – the northwest – but actual online hiring decisions tend to drift southeast, as information overload leads employers to rely on gender stereotypes as a shortcut decision strategy.

As a result, noise can be a means of (unintentionally) exploring the landscape, as nicely shown by **Hopfensitz et al.** with their game involving ambiguous payoffs (less-transparent payoffs in our language) and strong social interactions, which can yield a more efficient outcome than the same game with less of those aspects in the north. Noise in the dynamics of the game can lead to coordination equilibrium with a higher level of social welfare when multiple Nash equilibria are present in coordination games (Kandori et al. 1993). Hopfensitz et al. formulate their first game so that each player who has ties to another player chooses his or her strategy to maximize a combined utility that is a weighted sum of his own selfish interest and the joint interest of the two players. If the function U in BOB's Equation 1 is replaced by the Hofensitz et al. function, and $b = 0$, then the players will choose their strategies randomly with equal probability, and yet, as Hopfensitz et al. point out, this may yield a higher average welfare than in the case where b is large.

O'Donnell et al. and **Pfister & Böhm** both object to the idea of "independence" as a possibility for human beings, whose minds are social, even when physically alone. They point to neuroimaging studies that show humans are prone to adopt ideas that they may think are becoming more popular (see also Berger & Le Mens 2009; Berger & Milkman 2012; Gureckis & Goldstone 2009), even if they happen to be alone at the time. As O'Donnell et al. note, the neural systems for self-knowledge are involved in social cognition, and social inclusion versus rejection involves the same areas of the brain as physical pleasure and pain. As compelling as the evidence for the "social brain" may be, this is more of a semantic issue for us, to be plotted on the map using data at the scale of individuals or populations.

As **Moat et al.** correctly point out, we were not generous enough to the new big-data sciences of predicting near-future behavior based on recent past behavior. **Roesch et al.** and Moat et al. report on the incredible progress in data generation concerning individual behaviors correlated with all the other geolocated measures one can derive such as ambient temperature, noise level, luminance information, and energy consumption. Our review was only the tip of the iceberg in terms of big-data studies aimed at forecasting future behavior such as financial and commercial activity, economic trends, epidemics, and even crime. As behavioral scientists, we are in awe of the developments in e-commerce, such as recommendation systems in retail applications. As a clarification, we would see computer algorithms recommending products or services as *probably* qualifying as social influence, even if the recommendation algorithms are using social information to act on people who may be alone at their computers (an ambiguity raised by **O'Donnell et al.**).

Predicting the near future by extrapolating the recent past is a huge advantage of big data, especially because it does not require deep understanding of the causality behind behaviors in terms of decision making. Causality is enigmatic in the same way that social diffusion (northeast) can be so difficult to distinguish from (northwest) homophily (Aral et al. 2009), but for prediction and intervention, this may make little difference. The prescription is to intervene at the point of highest activity, with or without knowledge of its cause. **Moat et al.** make the important point that not only can big data assist in "predicting the present" (Choi & Varian 2012), but it can also play a major role in predicting the future – for example, in the trading-strategy-returns studies that they cite.

Although our map is an extremely coarse-grained approximation of the highly dimensioned correlation and prediction studies that **Moat et al.** cite, we show here how the b_t index of "transparency" relates to those studies. Note that

$$\ln\left(\frac{P_t(k)}{P_t(N_t)}\right) = b_t\,(U_{kt} - U_{N_t,t}). \tag{1.5}$$

In applications of discrete-choice theory to correlation and prediction, the Us are parameterized as functions of observable covariates and parameters and taken to datasets for hypothesis formulation, estimation of parameters, and testing of hypotheses. This activity includes correlation studies and prediction studies. If $b_t = 0$, the differences in the estimated values of the Us give no information as to the observed frequencies of choices between choice k and choice N_t at date t. In this case, the covariates give no information on predicting the present or the future. More concretely in the Preis et al. (2013) study that **Moat et al.** cite, we could think of big-data sets from Google Trends as a way of not only improving the specification of the Us in Equation 1.5, but also of increasing the size of b_t relative to previous studies.

To be sure, this may soon be less painstaking with better data and algorithms based on pioneering studies by Aral and Walker (2012) and others, at which point the map will be even more appropriate because measuring the east–west dimension might be routine. Mapping the nature of decisions is crucial because big data will soon be part of our decisions rather than an independent measure of them. **Roesch et al**. mention Project Glass (Google Inc. 2012) and the ubiquity of big data in daily activities, although we note that still only about a third of the world's population has Internet access. As the growing public familiarity with big-data patterns feeds into the decisions themselves (**Christen & Brugger**; **Fan & Suchow**; **Schmidt**), will big data still be as predictive (**Moat et al.**), or are we heading toward a situation, as with financial markets, where everyone is trying to outpredict everyone else? How will collective behavior change as we all become omniscient about global trends in those very behaviors? **Buck** is correct to discuss McLuhan's (1964) "medium is the message" philosophy, which underlies our basic question of how big data will *change* behavior and not merely record it objectively.

In conclusion, we again want to thank all the commentators for providing us much more in the way of excellent proposals for modifying and extending the BOB map into areas that we could not have anticipated. Our only regret is not having the time and the space to respond to the comments in the terms they deserve. We hope both our target article and the accompanying commentaries will inspire other behavioral scientists with an interest in decision making to use the discussions as launching pads for their own work. We very much look forward to what those others have to say.

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[The letters "a" and "r" before author's initials stand for target article and response references, respectively]

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