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.
in the curve. A color version of this image is available at http://dx.doi.org/10.1017/S0140525X1300191X.

mood at time \( t \) term between the (random) time between the two tests and mood at time \( t \) to mood at time \( t \) bins of 2 levels: 0 and 1. To cross out this indirect effect of emotion on decision, \( p_{t+1} \) is included in the model as a covariate. 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.

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correlation between answers to the same question in consecutive tests. At each test, participants are asked to rate their correlation between answers to the same question in consecutive tests. At each test, participants are asked to rate their

auto-correlations between answers to the same question in consecutive tests. At each test, participants are asked to rate their

mood (independent variable). Mood at time \( t \) significantly predicted by mood. The significant Type I error rate (false positives), 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 (Beta 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 (Beta pred = 0.48, \( p < 10^{-15} \)), resting (Beta pred = 0.38, \( p < 2 \times 10^{-4} \)), eating (Beta pred = −0.34, \( p < 5 \times 10^{-4} \)), doing sports (Beta pred = −1.3, \( p < 10^{-30} \)), and leisure (Beta pred = −0.81, \( p < 3 \times 10^{-3} \)). 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.