Using Big Data Methods to Analyze the Matching Law Relative to Performance for all Members of a Population

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Abstract:

The generalized matching equation (GME) has been used to describe the behavior of individual organisms in operant chambers, artificial environments, and nonlaboratory human settings. Most of these analyses have used a handful of participants with the aim of determining how well the GME describes choice in the experimental arrangement or how some experimental manipulation influences estimated parameters. No known studies have fit the GME to the behavior of all individuals in a population and how those parameters align with performance. This is likely because the population-level data was not available or because time and computational constraints made population-level analyses prohibitive. In this study, we demonstrate how big data methods can be combined with the GME to: (1) identify the events likely to serve as reinforcement; (2) estimate GME parameters; and (3) associate the estimated parameters with often-used metrics of performance. Importantly, 1-3 were accomplished for every one of *NNNN* individuals within the targeted population. The results suggest different individuals were more sensitive to different degrees of environmental change following behavior. [*Something about pitching performance. Something about the main takeaway.*]

Keywords: matching law; big data analytics; baseball;

**Using Big Data to Analyze the Matching Law for All Members in a Population**

Introduce choice and matching.

Matching in laboratory settings.

Matching in nonlaboratory settings.

General characteristics of matching studies – small *n*, yes GME works, yes in some contexts. Limitations to these approaches. Absurd to think the reinforcers for one apply to all.

Why the above limitations exist.

Big data methodologies solve those limitations.

Why big data methodologies might tell us something new. Different reinforcers for different people. Analyze sports performance and how GME parameters associate. Analyze how individual fits in a population of behavior/performance ~ game theory, information theory.

Why big data methodologies may help move operant quantitative models into more applied relevance.

The purpose of this study was to demonstrate how combining big data methodologies with one operant quantitative model may help make the model more practically applicable. Specifically, we sought to demonstrate how big data methodologies allow researchers and practitioners to: (1) identify the likely environmental changes that are controlling individual responding; (2) associate each individual’s GME parameters with overall performance; and (3) leverage information about one individual’s behavior relative to the population to strategize behavior change.

**Methods**

**Data.** The data were obtained from [*website*] by using the available dropdown menus to include all information about the game context, pitch type, pitch characteristics, and pitch outcome for every pitcher in MLB during the 2016-2019 Major League Baseball (MLB) seasons. These seasons were chosen because [*reason*]. All data can be found in the “./MLB Data/Team Data/” folder at Cox (2020).

**Quantitative Model.** We used the generalized matching equation (GME; Baum, 1974) to describe each pitcher’s allocation of pitches to the different pitch types. The GME can be written as:

. (Equation 1)

In this equation, *Bi* refers to the behavior of interest (i.e., the specific pitch type we might focus on), *Bo* refers to all other behaviors (i.e., all other pitch types thrown by that pitcher), *Ri*and *Ro* refer to the reinforcement contacted by *Bi* and *Bo*, respectively. And, *a* and *b* are estimated free parameters where *a* refers to the organism’s sensitivity to changing reinforcement schedules and *b* refers to the organism’s bias toward *Bi* or toward *Bo* that is not captured by the measured reinforcement schedules. Based on past research by Cox et al. (2017) and Falligant et al. (2020), *Bi* was always the count of pitches per game that were of the fastball variety (e.g., four-seam fastball, two-seam fastball) and *Bo* was always the count of pitches per game that were of any other pitch type (e.g., curveball, slider, eephus).

Past research that has examined matching of pitch type in baseball contexts has used strikes/outs as the reinforcers in Equation 1. However, it is possible that different pitchers are sensitive to more subtle changes in game states than simple strikes and outs. For example, throwing a strike on the first pitch to the first batter in an inning is unlikely to have a large impact on the outcome of the game when it is the first inning and the score is 0-to-0. However, throwing a strike on the first pitch to the first batter in an inning is more likely to impact the outcome of the game when it is the last inning and the pitcher’s team is winning by one run. Stated differently, contacting strikes or outs for throwing a pitch might be more or less meaningful depending on the context of the game in a manner akin to changing the amount of reinforcement delivered following a level press by rats in an operant chamber (e.g., *citations*).

To quantify the importance of different game states, baseball analysts have developed a metric termed run expectancy 24 (RE24). [*Description of* *RE24*]. RE24 only accounts for the position of runners on the bases and the number of outs recorded to that point in the inning. It is possible that pitchers are sensitive to changing counts on the batter (number of balls and strikes). Combining the logic of RE24 with the addition of count, we can create RE288 to refer to the unique 288 possible combinations of position of runners on the bases, number of outs recorded to that point in the inning, and the current count on the hitter.

For the present analysis, we wanted to determine whether pitchers independently differed in their overall sensitivity of different outcomes following their pitches. Thus, for every pitcher, we fit the GME once using strikes/outs as the assumed reinforcer to replicate past research, once using change in RE24 as the assumed reinforcer, and once using change in RE288 as the assumed reinforcer. Here, the assumption is that the assumed reinforcer that us likely to be maintaining a pitcher’s individual responding is identified by a better fit of the GME to the pitcher’s data (i.e., *R*2 closer to 1.0).

**Calculating Different Reinforcers**. To use strikes/outs as the assumed reinforcers, we counted the number of times per game that each pitch type resulted in a called or swinging strike, or the number of times that each pitch type was put into play and resulted in an out. The number of strikes/outs contacted in a game following a fastball were summed to create *Ri*, and the number of strikes/outs contacted in a game following all other pitches were summed to create *Ro*.

To use RE24 as the assumed reinforcers, we [*where did we get this again?*]. To quantify the “amount” of assumed reinforcer following a pitch, we subtracted the RE24 value after a pitch was thrown from the RE24 value before the pitch was thrown. Thus, a positive RE24 change score reflected an improvement in the game context (potential reinforcer), a negative RE24 change score reflected a worsening of the game context (potential punisher), and a change score of zero reflected no change in the game context. Because Equation 1 only includes reinforcement, only positive RE24 change scores were summed to quantify *Ri* and *Ro* using RE24 as the assumed reinforcer. *Ri* was the summed positive RE24 change scores per game following all fastballs thrown. And, *Ro* was the summed RE24 change scores per game following all other pitches.

No known RE288 tables were available for this analysis. As a result, we combined all the data from the 2016-2019 seasons into a single dataframe consisting of 2,891,247observations. We then labeled every pitch with a corresponding game state number between 1 and 288 (see *Appendix A* for game state labels). Once labeled, we calculated the number of runs that were scored after each pitch was thrown up until the end of that inning. Finally, we calculated the average number of runs scored until the end of an inning for each of the 288 different game states which became the RE288 value used for the analyses in this study. To quantify the “amount” of assumed reinforcer following a pitch, we subtracted the RE288 value after a pitch was thrown from the RE24 value before the pitch was thrown. Similar to RE24, a positive RE288 change score reflected an improvement in the game context (potential reinforcer), a negative RE288 change score reflected a worsening in the game context (potential punisher), and a change score of zero reflected no change in game context. As with RE24, only positive RE288 change scores per game were summed to quantify *Ri* and *Ro* for fastballs and all other pitches, respectively.

Python notebooks containing the code used to create RE288 are located in the “Python\_Scripts\_Notebooks” folder at Cox (2020). Additionally, the final dataframe that contains all data related to the game context, pitch type and characteristics, pitch outcomes, RE24 change score, RE288, and RE288 change score can be found in the “./MLB Data/” folder at Cox (2020).

**GME Scripts and Computational Environment.** Words.

**Analyses.** Words.

**Results**

**Identifying Likely Reinforcer.** Words.

**Population Parameters and Pitching Performance.** Words.

**Leveraging Reinforcers and Location in Population for the Individual.** Words.

**Discussion**

Words.

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