Bayesian Model for Characteristics of Physical Activities

Which Activities are Most Conducive to Flow?

Joshua N. Pritikin

Virginia Commonwealth University

Contact Information:
Virginia Institute for Psychiatric and Behavioral Genetics
800 E Leigh St, Biotech One, Suite 1-133
Richmond, VA 23219 USA

Phone: +1 (804) 601 6384
Email: jpritikin@pobox.com

Introduction

- *Flow* is a state in which an individual is completely immersed in an activity without reflective self-consciousness but with a deep sense of control.
- Preconditions of the flow state are thought to include skills-demands compatibility, clear goals, and immediate feedback [2].
- Previous work has often assumed an idiosyncratic relationship between a person and the activities that that person is intrinsically motivated to engage in.
- Some activities may be more conducive to flow than other activities if we regard personal preference as error.

Objectives

1. Explore characteristics of physical activities thought to be related to flow
2. Provide a data exploration tool to facilitate custom activity rankings according to personal preference
3. Develop an exploratory factor model for flow
4. Generate testable hypotheses
5. Develop new manipulations to induce the flow state

Method

Cross-sectional data are collected online via a brief survey. The public at large is invited to participate. A participant is asked to identify two physical activities. Twenty items ask for a relative ranking on particular characteristics. For example, suppose a participant chose *running* and *golf*. To assess the *predictability* characteristic, an item asks "How predictable is the action?" with response choices: (a) "Golf is much more predictable than running." (b) "Golf is somewhat more predictable than running." (c) "Both offer roughly equal predictability." (d) "Running is somewhat more predictable than golf." or (e) "Running is much more predictable than golf." In addition to clear goals and immediate feedback, an assortment of other likely flow preconditions were included [3, 4, 5]. A complete list of prompts follow with the facet name in parentheses:

1. How much skill is required? (skill)
2. How predictable is the action? (predict)
3. To what extent do you find new and fresh experiences during the activity? (novelty)
4. To what extent are there opportunities to express creativity during the activity? (creative)
5. How complex is the action and the environment in which it takes place? (complex)
6. How clear and straightforward are the short-term rules and goals? (goal1)
7. How quickly do you know whether what you wanted to accomplish in the short term was successful? (feedback1)
8. How clear and straightforward are the long-term rules and goals? (goal2)
9. How quickly do you know whether what you wanted to accomplish in the long term was successful? (feedback2)
10. Does your extraneous mental chatter temporarily shut down during the activity? (chatter)
11. How much time do you feel like is spent waiting for the next step in the activity? (waiting)
12. How much of your body is involved in the activity? Is it full-body or only part of your body? (body)
13. How much control do you feel like you can exert over your performance? (control)
14. During the activity, to what extent do you feel like you are in the present moment? (present)
15. How spontaneous is your action? (spont)
16. During the activity, how important does the activity feel? (stakes)
17. To what extent do you care about how others judge your performance? (evaluated)
18. After engaging in the physical activity, to what extent do you feel great? (reward)
19. What is the risk of minor physical injury (more than just muscle soreness)? (injury1)
20. What is the risk of serious physical injury? (injury2)

Subjects

55 distinct activities. $N = 205$, but 15 comparisons contributed by repeated participation. USA (63%), Germany (14%), and United Kingdom (9%). 67% female. 63% 25 or fewer years old.

Relative to Absolute Rankings

Since the set of physical activities a is open-ended, there will always be some activities with insufficient information. Bayesian priors are used to stabilize parameter estimates [1]. We describe an initial model that treats each characteristic as mostly independent. Latent absolute rankings θ are obtained for each combination of activity and characteristic. Each characteristic c has its own discrimination parameter α. Given thresholds τ_1 and τ_2, the probability of activities $x \in a$ and $y \in a$ receiving relative rating r is modeled as,

$$\Sigma_\theta \sim \mathrm{lkj\_corr\_cholesky}(2.0) \tag{1}$$

$$\theta_a \sim \mathrm{multi\_normal\_cholesky}(0, \Sigma_\theta) \tag{2}$$

$$\tau_1, \tau_2 \sim \mathrm{normal}(0.0, 5.0) \tag{3}$$

$$\alpha_c \sim \mathrm{lognormal}(1.0, 1.0) \tag{4}$$

$$g \equiv \begin{pmatrix} 0.0 \\ \alpha_c(\theta_x - \theta_y) & -(\tau_1 + \tau_2) \\ \alpha_c(\theta_x - \theta_y) & -\tau_1 \\ \alpha_c(\theta_x - \theta_y) & +\tau_1 \\ \alpha_c(\theta_x - \theta_y) & +\tau_1 + \tau_2 \end{pmatrix} \tag{5}$$

$$h_n = \sum_{k=1}^{n} g_k \tag{6}$$

$$r \sim \mathrm{CategoricalLogit}(h). \tag{7}$$

Results

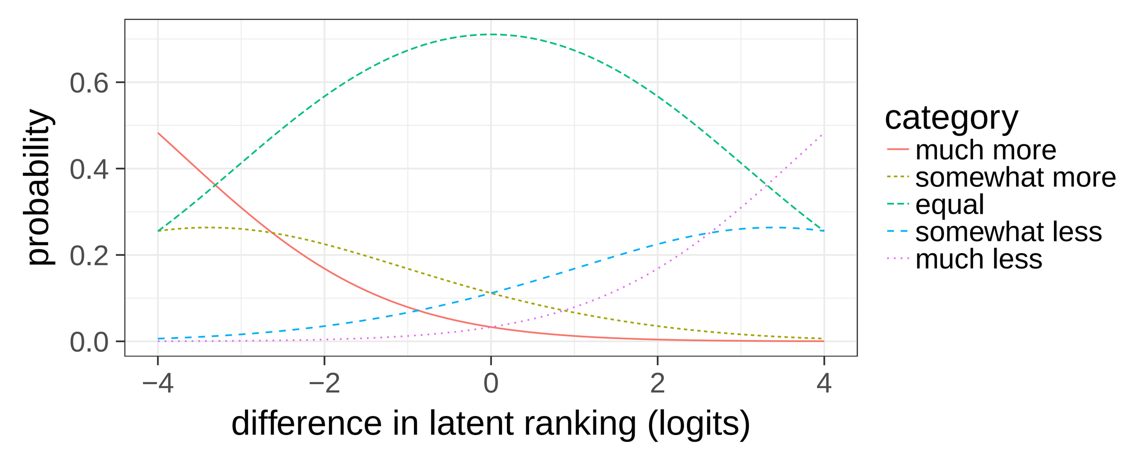

Figure 1: Category response curves conditional on difference in latent absolute ranking $(\theta_x - \theta_y)$ for $\alpha = 0.46$. The *somewhat* response options were endorsed infrequently.

The posterior was summarized by mean point estimates. Thresholds 1 and 2 were estimated at -1.85 and 0.63, respectively. This resulted in a response curve exhibited in Figure 1. Actual α values ranged from 0.36 to 0.66. Of 55 activities, 32 were excluded to due low connectivity (activities compared with less than 3 other activities) leaving 23 well-connected activities. Rankings can be explored by listing the activities at the extremes in each facet (Table 1).

facet	least	2nd least	2nd most	most
reward	walking	basketball	snow skiing	mountain biking
body	walking	baseball	mountain biking	rugby
goal2	football	ultimate frisbee	snow skiing	swimming
feedback2	ultimate frisbee	walking	snow skiing	rugby
present	weightlifting	running	snow skiing	mountain biking
skill	walking	running	snow skiing	lacrosse
control	baseball	football	mountain biking	weightlifting
injury1	walking	swimming	mountain biking	rugby
stakes	walking	cycling	snow skiing	lacrosse
injury2	walking	swimming	snow skiing	rugby
predict	lacrosse	rugby	running	walking
novelty	swimming	walking	lacrosse	rugby
goal1	football	volleyball	running	swimming
creative	running	swimming	lacrosse	rugby
complex	walking	running	rugby	lacrosse
feedback1	walking	cycling	tennis	rugby
evaluated	walking	swimming	rugby	lacrosse
spont	basketball	football	walking	aerobic exercise
chatter	walking	baseball	hatha yoga	mountain biking
waiting	walking	aerobic exercise	lacrosse	snow skiing

Table 1: Most and least ranking activities by facet ordered from most to least discriminating.

As can be seen from the Table 1, rankings do not well reflect intuition and it is too early to make any interpretations. However, we exhibit the facet correlation matrix in Figure 2 and can point out a few tentative conclusions. Skill and complexity are correlated 0.52. Predictability is correlated -0.37 with the risk of serious injury.

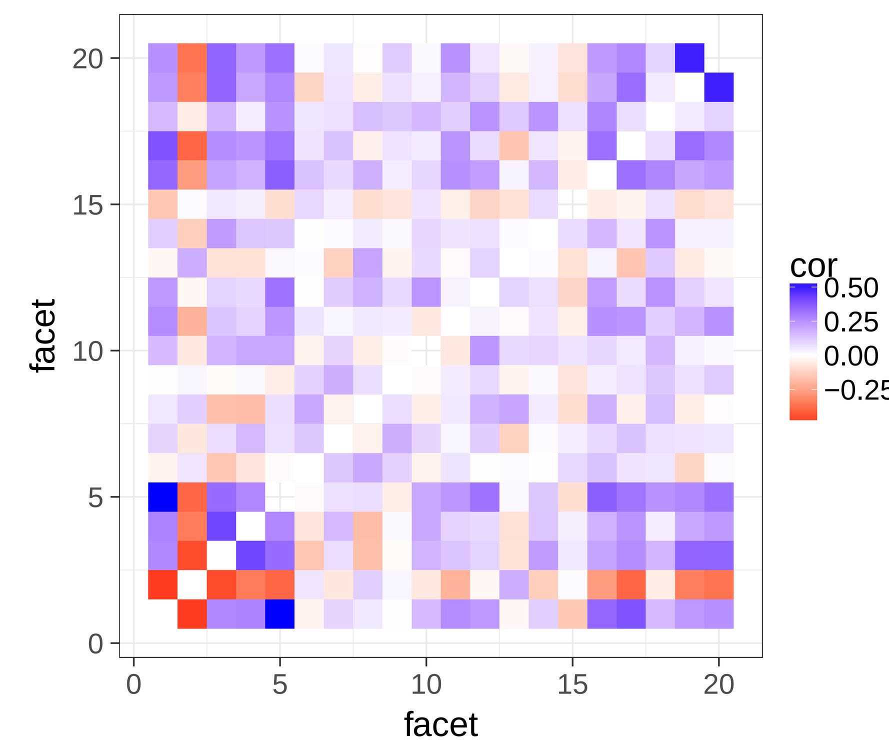

Figure 2: Correlation between facets ($\Sigma_\theta \Sigma_\theta^T$).

Discussion

- Using cross-sectional data, physical activities can be ranked against each other on a variety of flow-related characteristics.
- Preliminary results available for exploration, `http://exuberant-island.surge.sh/rcpa/`
- Much more data is needed. How to get it without compromising quality? Collaborators sought.
- Once data collection is complete, anonymized data and data analysis scripts will be placed in the public domain.
- Guided by flow theory, a exploratory factor model will be developed to rank activities with respect to how conducive the activity is to flow.
- External validity can be examined by comparing rankings with the actual measured prevalence of flow experienced by participants while involved in activities.

References

[1] Bob Carpenter, Andrew Gelman, Matt Hoffman, Daniel Lee, Ben Goodrich, Michael Betancourt, Michael A Brubaker, Jiqiang Guo, Peter Li, and Allen Riddell. Stan: A probabilistic programming language. *Journal of Statistical Software*, 20:1–37, 2016.

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[4] Keith Sawyer. *Group genius: The creative power of collaboration*. Basic Books, 2007.

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