**The influence of salience and surprise in mental model building and updating**

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* People build models that they use to interpret events. When these models no longer predict environment, models need to be updated.
* How does the surprise of an event influence updating?
* Characterizing surprise is difficult because it’s relative to what a person expects. How do you characterize participant expectations?
* Nassar tried, and did an interesting job, but the model is still limited.
* We expand on this model to explore the role of change surprise on updating.

**Experiment 1**

* Experiment 1 set to a) validate our new task, b) find conditions in which updating performance may differ.

**Methods**

*Participants*

A total of 26 undergraduates (DEMOGRAPHICS) from the University of Waterloo participated in Experiment 1a and b for course credit. The experimental protocol was approved by the University of Waterloo’s Office of Research Ethics and all participants gave informed written consent.

*Task environment*

Participants were exposed to a computerized version of the game “Plinko” (a game featured on the American game show *The Price is Right*). The entire task environment was programmed in Python using the PsychoPy library (Peirce, 2009). In our game a red ball would fall through a pyramid of pegs and land in one of 40 possible slots located side by side below the pegs. The pyramid consisted of 29 rows of black pegs that increased in number from the top to the bottom of the pyramid (i.e., the top row contained 1 peg and the bottom row contained 29 pegs). A rectangle was located below the 40 slots spanning their width. Participants were instructed to make their responses in this space (FIGURE).

Participants were informed that a ball would fall through a series of pegs and that their goal was to accurately predict the likelihood that a ball would fall in any of the 40 slots on future trials. Participants adjusted bars under each slot in the space below the pyramid to represent their likelihood estimations. Bars were drawn using the computer mouse: the height of the bars could be adjusted by holding down the left mouse button and changing the position of the cursor. The height of the bar would match the position of the cursor within the limits of the rectangle below the slots. Participants could also erase any single bar by right clicking with the cursor on the bar they wished to delete, or by clicking the backspace key to delete all bars on screen. The bars were not assigned any value; participants were simply told that taller bars represented a higher probability that a ball would fall in a slot, shorter bars a lower probability, and no bars represented zero probability. Participants were informed that they had the option of adjusting their bars at the start of every trial and that they had to have bars on screen before proceeding with the trial. This instruction was applied at the start of the task – that is, participants had to indicate their likelihood estimates before seeing the first ball drop. Participants were encouraged to be as accurate as possible with their estimates. Once participants had indicated their likelihood estimates, they pressed the spacebar to proceed with the trial (FIGURE).

*Ball distributions and condition instructions*

Participants in both conditions were exposed to four distributions of ball drops that changed every 100 trials throughout the task. The sequences of ball drops were generated by randomly selecting integers between 1 and 40 from specific probability distributions: 1) a Gaussian distribution with a mean of X and standard deviation of X (wide Gaussian), 2) a Gaussian distribution with a mean of X and standard deviation of X (narrow Gaussian), 3) a bimodal distribution generated by mixing two Gaussians with different means (X and X respectively) and the same standard deviation of X (bimodal), and 4) a Weibull distribution with a shape parameter of X and scale parameter of X (skewed). The resulting sequences of integers determined the slots in which the ball fell on each trial, with slot 1 representing the slot farthest to the left and slot 40 representing the slot farthest to the right. Participants in both conditions were exposed to the same order of distributions: wide Gaussian first, narrow Gaussian second, bimodal third, and skewed last. Every participant was also exposed to the exact same sequence of ball drops within each distribution.

In Experiment 1a, 10 participants (DEMOGRAPHICS) were exposed to each distribution in separate blocks. Participants would complete our Plinko task for each block and be given an accuracy score at the end of the block that reflected how accurately they had estimated the actual distribution of ball drops (the measure we used for accuracy is explained below). Participants would then press a computer key whenever they were ready to begin the next block. At the start of each block, the bars were reset and the participant would need to redraw his/her bars on screen to start the trial. In Experiment 1b, 16 participants (DEMOGRAPHICS) were exposed to the same order of ball drops, but were not given any breaks or accuracy feedback between each of the distributions.

*Measuring participant accuracy*

In order to compare the participants’ bars with the distribution of ball drops, we normalized the participant bars by dividing the area of each bar (in pixels) by the total area covered by bars in all slots on screen. This normalization provides a discrete probability distribution for each participant on each trial that sums to 1 over all slots. We then characterized participant performance by measuring how accurately participant estimated the distributions of ball drops they were exposed to. Accuracy (*A*) was computer as the sum of overlap between the probability assigned to each slot (*i*) of a participant’s distribution (*D­­p*) compared to the actual discrete distribution of ball drops they were attempting to estimate (*Dc*):

|  |  |  |
| --- | --- | --- |
|  |  | (1) |

where *n* represents the number of slots being estimated.

*Measuring surprise between participant expectations and ball distributions*

We computed

**Results**

*Participants can use the bars effectively to represent different distributions*

The main goal of Experiment 1 was to demonstrate that participants could use our task to effectively approximate different probability distributions. Participants in the break condition were able to use the bars to accurately approximate