Speed-Accuracy Tradeoff in a Random Dot-Motion Experiment

Grace Dalton

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Abstract

This study explores the speed-accuracy tradeoff using the hierarchical EZ diffusion model to understand decision-making processes. It uses a random dot-motion experiment with 43 participants to test how instructions to prioritize speed or accuracy influence decision behavior. The data analysis involves estimating parameters like drift rate, boundary separation, and non-decision time at both individual and group levels. The results found no significant difference in boundary separation between speed and accuracy conditions, suggesting a lack of a speed-accuracy tradeoff, but highlighting the impact of individual differences. The study underscores the need for further research to better understand and compare how cautious subjects are when given different instructions.

Introduction

The EZ diffusion model helps researchers understand the underlying cognitive processes involved in decision making. By analyzing the tradeoff between speed and accuracy, researchers can gain insight into how individuals prioritize quick responses versus accurate ones under different conditions. This research will examine if the speed-accuracy trade-off is observed from this data. This study involves a random dot-motion experiment, where participants observe a field of moving dots and must decide the overall direction of motion (leftwards or rightwards). Some dots move coherently in the same direction while others move randomly, as seen in Figure 1. The participant's task was to determine the direction of motion as quickly and accurately as possible. The subjects would choose leftward or rightward dot-motion by pressing "C" or "N" with their thumbs (Desender, Vermeylen, & Verguts, 2022). There were two conditions where participants were instructed to either focus on speed or focus on accuracy when responding to the stimuli. After giving their response, they used a six-point confidence scale (ranging from "certainly wrong" to "certainly correct") to assess their decisions. During the training phase, participants began with 24 practice trials using a coherence level of 50%, and received feedback on their binary choices (left or right); this block was repeated until they achieved at least 85% correct responses (Desender et al., 2022). Subjects then proceeded to 24 practice trials using a coherence of 20% with binary choices and feedback; this was repeated until they achieved at least 60% correct responses (Desender

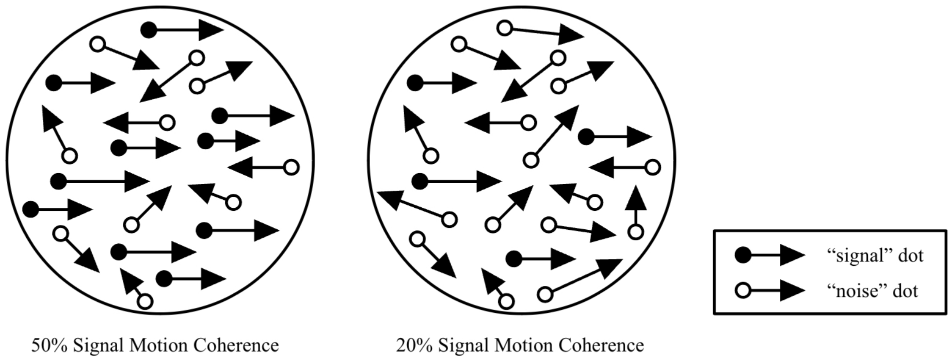

Figure 1: Random dot-motion pic caption: Display of the principle of the random dot cinematograms. Arrows represent the motion of the dots. Black dots move together (to the left or right of the screen). Clear dots move randomly. The proportion of dots moving in the same direction is the coherence. Having a higher coherence level means that detecting the direction of motion will be easier.

et al., 2022). Finally, participants completed 24 practice trials with a coherence level of 20%, this time including confidence ratings but without feedback; this block was repeated until they achieved at least 60% correct responses (Desender et al., 2022). This coherence level of 20% made the task challenging and required participants to rely on subtle motion cues. After completing the training phase, participants engaged in the main task consisting of 10 blocks of 60 trials each; they made their decision about the direction of dot-motion (with a coherence level of 20%), then rated their confidence in this decision (Desender et al., 2022). No feedback was provided during the actual task to prevent any learning effects that could bias the results.

The manipulation of instructions makes the data suitable to be analyzed under a hierarchical EZ diffusion model, which describes decision-making processes for multiple conditions where noisy evidence accumulates over time until it reaches one of two decision thresholds. This model uses three parameters on both the individual and group level: drift rate (δ), boundary separation (α), and non-decision time (τ). This α parameter is directly related to the speed-accuracy trade-off. Lower α values are typically associated with faster but less accurate decisions, while higher α values are typically associated with slower but more accurate decisions. By examining changes in α, researchers can infer how participants adjust their decision-making strategies under different task demands or instructions. Using a hierarchical model will help account for individual differences within each group while allowing for sampling from and comparison of the data on a group level.

Data

The data in this study was taken from experiment 1 in Desender et al. (2022). The data was found in the Confidence database on OSF in the format of a .csv file (Desender, Vermeylen, & Verguts, n.d.). The .csv file was loaded into a Jupyter Notebook using Python's "pandas" package. The original .csv variables included the subject ID, the type of stimulus shown, the participant's response, the participant's confidence level, the response time in seconds to the dot display, the response time in seconds to the confidence rating, the dots' coherence level in the trial, the type of instructions the subject was given, and whether the trial was a practice trial or not. It should be noted that the data were collected online during COVID-19. For this two-choice response time task, the observed variables are the response speed and response accuracy.

To prepare the data for interpretation under a hierarchical EZ diffusion model, the columns for confidence rating and the response times for the confidence level were dropped from the dataframe. Along with removing blank and duplicated rows, training trials and trials that had a coherence of 50% were eliminated (leaving trials with a 20% coherence level). This left the subject ID, the stimulus level, the participant response, the subject's reaction time to the stimulus, and the group that the subject followed instructions from. The data was then split into two separate data frames based on the condition, or set of instructions the subject was told to focus on for the trial (either speed or accuracy). There were 21 subjects in the speed group, and 22 subjects in the accuracy group. The subject ID was used to condense both data frames and group all of a subject's trials into one row. This helped organize the stimulus values, response values, and response times. The stimulus and response values were used to calculate the number of trials a subject completed and the number of trials the subject got correct. The response time column was used to determine the mean and variance response times of each individual for correct trials only (when the stimulus value aligned with the subject's response). These four measures along with the subject IDs were placed in new data frames for the speed and accuracy conditions. They were then exported as two separate .csv files into JASP. The data were analyzed using JAGS to compute parameters on both the individual and group level.

Results

A hierarchical EZ diffusion model was appropriate for analyzing this dataset because it can be used to explain the decision-making processes in two-choice tasks, such as determining the direction of motion in random dot-motion experiments. A key feature of the hierarchical EZ diffusion model is that it accounts for individual differences in decision-making parameters by estimating three parameters at both the group and individual levels. This is useful in understanding how different participants might employ varying strategies or exhibit different cognitive processes when performing the same task. The drift rate (δ) indicates the speed and direction of evidence accumulation. The boundary separation (α) reflects the amount of evidence needed to make a decision. The non-decision time (τ) accounts for perceptual and motor processes not related to making the decision.

The hierarchical aspect allows for individual differences in these parameters while estimating group-level effects. This is crucial in tasks where participants' sensitivity and speed-accuracy trade-offs vary. For example, the drift rate represents how quickly a participant discerns motion direction, boundary separation indicates the subject's caution when making a decision, and non-decision time accounts for other cognitive and physiological processes. Parameters on the participant level were important for calculating individual differences under the model. Without them, the EZ diffusion model would have shown different numbers for δ, α, and τ; these would have been based upon problematic psychological assumptions of no individual difference. JASP reported individual δ_i, α_i, and τ_i values along with group means μ_δ, μ_α, and μ_τ. These were compared with additional measures that were calculated for both speed and accuracy conditions in Python using overall group accuracy and the mean response time of the whole group. Individual parameters will not be examined because the study focuses on the group behaviors for speed and accuracy.

Table 1: The group-level parameters (including mean and standard deviation) and 95% credible intervals for δ, α, and τ of both speed and accuracy conditions.

Parameter	Speed			Accuracy		
	Mean	95% Credible Interval		Mean	95% Credible Interval	
		Lower	Upper		Lower	Upper
μ_δ	.64	.40	.89	.70	.52	.88
μ_α	1.70	1.57	1.82	1.53	1.32	1.73
σ_α	.28	.20	.39	.46	.33	.66
μ_τ	.11	.00	.26	.20	.04	.29

In Table 1 the speed group's μ_δ value of .64 is similar to the accuracy group's μ_δ of .70. Furthermore, the credible intervals of both groups' μ_δ values overlap, indicating that there is no difference between each group's drift rate. These findings are anticipated under the speed-accuracy tradeoff phenomenon. This is because the drift rate is a property of the stimulus, and δ corresponds to how easy/difficult the stimulus is. The coherence level was kept at 20% during the experiment and did not change between the task instructions, so μ_δ should not change between conditions.

The speed group's μ_α value is 1.70 and the accuracy group's mean μ_α value is 1.53. This is consistent with the group level findings. Calculations from Python show that the proportion of correct trials in the speed condition is .72 and the mean response time for all speed trials is 913ms, while the proportion of correct trials in the accuracy condition is .73 and the mean response time for all accuracy trials is 825ms. These findings do not follow the traditional expectations of the speed-accuracy trade-off. The boundary separation (α) is partly a property of the participant (and how cautious they are) and partly a property of the instructions they were given (speed or accuracy). Typically in an EZ diffusion model, as α increases, reaction times should increase (because subjects consider the evidence longer), but error rates should decrease; as α decreases, reaction times should decrease, but error rates should increase. The speed-accuracy tradeoff aspect of this model implies that participants can be fast or accurate, but not both. Although it appears that the μ_α value is higher for speed than accuracy, the credible intervals for these parameters overlap. This means that there is uncertainty as to where the true mean values lie; it is not clear whether the speed condition truly had a larger boundary separation than the accuracy group.

It is important to note that on average, the instructions seemed to have no impact on boundary separation; however, they did increase the variability for the range of individual differences, so that μ_σ increased in the accuracy condition. There is a bigger difference in the range of participants who are least cautious to most cautious in the accuracy group than speed.

Finally, the speed group had a μ_τ value of .11 and the accuracy group had a μ_τ value of .20. Additionally the credible intervals of both groups' μ_τ mostly overlap, suggesting that there is no difference between the speed and accuracy groups' mean non-decision time. These observations support the speed-accuracy tradeoff phenomenon. Non-decision time is a property of the subject for how quick their perceptual and motor processes are; it is not a property of the subject's caution.

Discussion

This study aimed to find a speed-accuracy tradeoff between participants who were given instructions to either focus on being quick or being accurate. Since there is no significant difference between the observed μ_α values for the speed and accuracy conditions, there is no clear evidence of a speed-accuracy tradeoff in this study. However, the σ_α values of both groups suggested there was a potential impact on decision-making processes at the individual level. In the accuracy group, there could have been some individuals who had large boundary separations, and got very cautious when told to be "accurate." It is possible that the participants in the speed condition were naturally cautious people, so they were already behaving like participants in the accuracy condition. Using a larger sample size in the study could have accounted for variability in individual differences.

A notable follow-up experiment would be to repeat this procedure using a within-subjects design. This would require the same participant to do both conditions, allowing for the comparison of their speed and accuracy performances. If someone had a lack of caution in the accuracy condition, but their caution decreased more in the speed condition, the speed-accuracy tradeoff would have applied to them. Studying the change in boundary separation between conditions would inform researchers on the effect given instructions have on decision making. Furthermore, it would provide insight into the amount of evidence an individual requires to make a decision.

References

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