Ratcliff Diffusion Model Assignment

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This assignment is due **Wednesday, March 18, 2020**. Submit your response via moodle as one HTML or PDF file.

Medical Decision Making Data Set

File `medical_dm.csv` contains part of the data presented in Trueblood et al. (2017), also discussed in the lecture, investigating medical decision making among medical professionals (pathologists) and novices (i.e., undergraduate students). The task of participants was to judge whether pictures of blood cells show cancerous cells (i.e., blast cells) or non-cancerous cells (i.e., non-blast cells). The current data set contains 200 such decision per participant. At the beginning of the experiment, both novices and medical experts completed a training to familiarize themselves with blast cells. After that, each participant performed the main task in which they judged whether or not presented images were blast cells or non-blast cells. Among them, some of the cells were judged as easy and some as difficult trials by an additional group of experts. Figure 1 contains examples of blast cells and non-blast cells. Here, we only consider the data from the "accuracy" condition (i.e., Trueblood et al. considered additional conditions that are not part of the current data set).

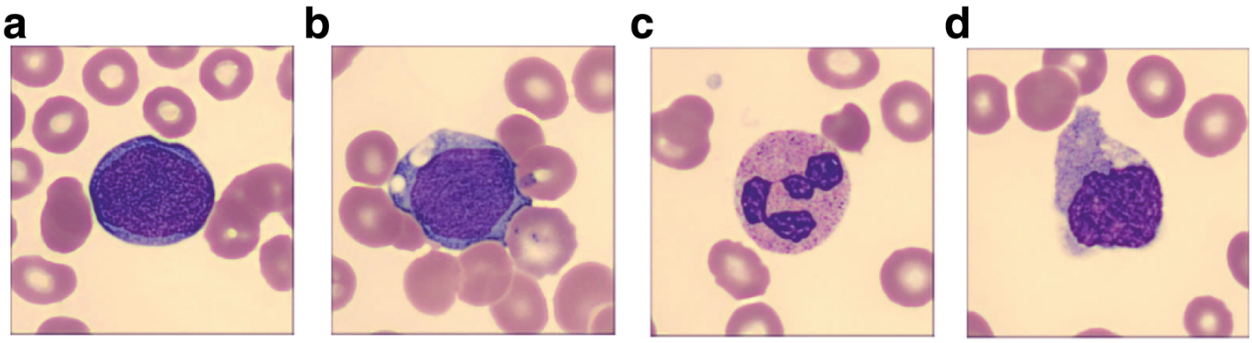

Figure 1: Sample images of blast and non-blast cells that were classified as easy and difficult. Panel a is an easy blast image, panel b is a hard blast image, panel c is an easy non-blast image, and panel d is a hard non-blast image.

```
med <- read_csv("medical_dm.csv")
glimpse(med)
```

```
## Observations: 11,000
## Variables: 9
## $ id             <chr> "002", "002", "002", "002", "002", "002", "002", "00...
## $ group          <chr> "experienced", "experienced", "experienced", "experi...
## $ block          <dbl> 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3, 3...
## $ trial          <dbl> 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 1...
## $ classification <chr> "blast", "non-blast", "non-blast", "non-blast", "bla...
## $ difficulty     <chr> "easy", "easy", "hard", "hard", "easy", "easy", "har...
```

```
## $ response       <chr> "blast", "non-blast", "blast", "non-blast", "blast",...
## $ rt             <dbl> 0.853, 0.575, 1.136, 0.875, 0.748, 0.706, 0.686, 0.8...
## $ stimulus       <chr> "blastEasy/BL_10166384.jpg", "nonBlastEasy/162580011...
```

The data contains 9 variables:

- `id`: participant identifier (note, participant identifier is not unique across groups).
- `group`: Group identifier with three levels: `"experienced"`, `"inexperienced"`, and `"novice"`. The first two levels refer to different type of medical professional that we will consider together (i.e., in your answer, please do not distinguish between `experienced` and `inexperienced` doctors).
- `block`: The block in which the trial was shown.
- `trial`: trial number.
- `classification`: true status of each image, either `"blast"` or `"non-blast"`.
- `difficulty`: difficulty of trial, either `"easy"` or `"hard"`.
- `response`: response of participant, either `"blast"` or `"non-blast"`.
- `rt`: response time in seconds.
- `stimulus`: stimulus shown.

Task Description

Your task is to analyse the data with a diffusion model using a no-pooling approach (i.e., fit the diffusion model to the data of each individual participant separately), `rtdists`, and trial-wise maximum likelihood estimation. Then, use ANOVA to compare the individual-level parameter estimates between the two groups (i.e., `experts` versus `novices`). There are two research questions here: Is the diffusion model able to describe real-life medical decision making for both experts (i.e., medical professionals) and novices? And if so, do the cognitive process captured by the diffusion model differ between experts and novices? Or said differently, how do cognitive processes underlying medical decision making differ between experts and non-experts?

As in PS 923, your answer to the research question and this assignment should have two separate sections. In the first section, write out your answer using complete sentences, as you might in a paper. This section should start with a description of the design and research question, the diffusion model used here (e.g., which and how many free parameters), and relevant aspects of the data (e.g., how many trials per participant on average, how many trials were excluded). Next, your answer should say something about the model fit or adequacy. Next, present the results comparing the parameter estimates across the two groups (`experts` versus `novices`). Remember to describe ANOVAs sufficiently. The final part should contain some sort of summary with respect to the research questions. Feel free to use headings to separate the parts in the first section in a reasonable manner. Include descriptive statistics in the text, or in tables or figures as appropriate. Tables and figures should be of publication quality (i.e., fully labelled, etc.). Integrate inferential statistics into your description of the results. **Given the correctness/appropriatness of the model and statistical analysis, the first section will play the main role for your mark. If an analysis is performed in the second section, but not reported in the first, it will usually not be considered. Do not forget to consider the research question in your answer.** The first part may be up to 2000 words long (but can of course be shorter). Please note that too many figures or tables in this part can also reduce your mark.

The second section should include the complete `R` code that you used and its output. Add potentially comments (after a `#`) to explain what the code does. The code should show all of the commands that you used, enough for me to replicate exactly what you did (I will be copying and pasting code to run it, so make sure that works). You can include figures here that you used to explore the data that you do not wish to include in the first section. I will use the second section to help identify the source of any mistakes. For practical reports and papers you would only submit the first section, and thus the first section should stand alone without the second section.

Model Specification

For your diffusion model, please estimate the same five model parameters as above: `a`, `v`, `t0`, `z`, `sv`, and `st0` (i.e., fix `sz` to 0). However, note that in contrast to all analysis performed in the worksheet, we now have two stimulus classes, `blast` or `non-blast` images. Consequently, both stimulus classes need to have independent drift rates. All other parameters should be shared across both stimulus classes. In total, the simplest possible diffusion model has 7 parameters per individual data set.

Instead of the simplest model, you can also fit and report a more complicated model. This model should have separate drift rates for easy and difficult trials, separately for each stimulus class. Such a model would have 10 parameters per individual data set.

Note that in either case, due to having two drift rates, you will have to write a new function for generating start values. In addition, you will need to modify the likelihood function, or write a new function that is a wrapper for the likelihood function that makes sure that for each data point the correct drift rate is used. For example, the function could split the data into two data sets for `blast` or `non-blast` stimuli and make sure that for each of those subsets the correct drift rate is used (note again, all other parameters should be shared across the two stimulus classes so you cannot separate the data into both stimulus classes before the fitting).

Fitting the model to all participants can be time consuming. On my laptop fitting the simple model with 7 parameters to all participants takes roughly 20 minutes with 5 fitting runs each. Fitting the more complicated model with 10 parameters takes around 40 minutes. Given this, it might not make sense to re-fit the data each time you want to work on this. To avoid this, note that you can save arbitrary `R` objects via `save()` and load them with `load()`. For example, if you have saved your fits in `res_med`, the following code can be used for saving and loading, respectively:

Additional Considerations

Please note that before fitting the data, you should exclude too fast and too slow trials. For example, exclude all trials that are faster than 250 ms and slower than 2.5 seconds. Such a cut-off is not uncommon when applying the diffusion model to data. If you use a cut-off (which probably makes sense), make sure to describe this in your text and how many trials were excluded that way (ideally using relative frequencies and not absolute values). If you use other tricks to ensure the validity and quality of your results (such as multiple fitting runs with different random starting values to avoid local optima or checks for parameter identifiability) make sure to describe this as well.

As described above, your answer should ideally also include some sentences on the adequacy of the model. How well does it describe the data? A common way to evaluate this across participants is by plotting observed and predicted response proportions in a scatter plot and report the correlation. If the model fits the data well, the correlation should be quite high (around .8 or .9) and the points near the main diagonal. One could do the same also for the observed and predicted RT quantiles (e.g., the median). As an example, take a look Trueblood et al. (2018), Figure 4 (p. 9).

If you see additional reasonable ways how to extend this analysis and you have not yet reached 2000 words for your section 1, feel free to add such additional analyses. However, make sure they address the research question at hand.

References

- Trueblood, J. S., Holmes, W. R., Seegmiller, A. C., Douds, J., Compton, M., Szentirmai, E., . Eichbaum, Q. (2018). The impact of speed and bias on the cognitive processes of experts and novices in medical image decision-making. Cognitive Research: Principles and Implications, 3(1), 28. https://doi.org/10.1186/s41235-018-0119-2