Differential effects of alcohol intoxication on decision making

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1 Abstract

This paper will assess the differential effects of alcohol intoxication and hangover on a perceptual-decision making task, using the Python drift decision model library (PyDDM) in order to estimate the parameters of the cognitive processes behind a dot-motion task conducted by 12 subjects. Following the statistical analysis of the task performance and model fitting, a minimal difference in reaction time yet high variability in the rate of evidence accumulation were observed. A slight difference in noise and side bias were also observed across the conditions, while the non-decision time remains virtually identical.

2 Introduction

Acute alcohol intoxication has its upsides and downsides, on one side it makes you feel relaxed and confident while on the other it may contribute towards decisions which you would regret the next morning. The more punishing aftermath, the hangover, also takes its toll on cognitive processes and psychomotor skills.(Gunn C et al, 2018)

This paper will present the investigation of the dataset and its fitted parameters within the DDM framework and discuss the interpretation of their effects on a perceptual-decision making task. PyDDM was used in order to model the dot-motion task and hopefully illustrate whether the outcomes are due to altered sensory evidence accumulation (drift rate), a side bias or response cautiousness (threshold).

The Drift Diffusion Model (DDM) is a sequential sampling model employing the accumulation of noisy stimulus within a decision-making task until it reaches a lower or upper boundary, then selecting the choice corresponding to that boundary. Within the problem that is modelled, the parameters which are of greatest interest are the ones which reflect sensory encoding, due to the visual and perceptual nature of the task, as well as the cognitive process corresponding to direction-selection and processing.

The literature and research into the effects of acute intoxication and subsequent hangover are rather conflicting, some suppositions being that the time and alcohol levels may vary from study to study, due to a rather vague definition of the 'hangover' state. Besides the differences in experimental parameters, individual resistances, metabolism, age and mass are all potential factors which may contribute to skewed results.

One of the researched problems is that of whether or not automatization and motor control are impaired by recreational drinking and/or abuse. Ethanol and its toxic by-product, acetaldehyde have an opposite influence on the GABAergic and dopaminergic systems in such a way that short-term inhibition of neuronal activity, which is felt as relaxation, is exchanged for restlessness and cognitive fog (Fumihiko Ueno et al., 2022) after ethanol metabolization. This, in theory, could lead to lapses in attention, increased reaction times and decreased evidence accumulation (Stock et al, 2017). However, notable executive function deficits like response selection have not been found in acute intoxication experiments, rather such deficits were observed in cases of high dosage habitual drinking and alcohol abuse (Catharine Montgomery et al, 2012) .

Due to the limited nature of the dataset and lack of additional information, as well as volatility of similar study outcomes, the purpose of this paper is exploration of a potential hypothesis derived from the initial analysis of the dataset. Thus, I initially assumed that drift rate, in accordance with the cognitive effects of ethanol and acetaldehyde, would have the highest chance of effect on the cognitive process.

2.1 Methods

In order to assess the potential effects of alcohol intoxication and hangover states on decision making an perception, a within-subjects design dot-motion task was executed among 12 subjects. For the first session, in the evening the subjects were administered alcohol as to reach a blood alcohol level (BAC) of 80mg/dL. For the second session, in the morning, the subjects performed the same task.

Each trial consisted of the presentation of a noisy visual stimulus represented by a field of dots moving randomly, with a small proportion moving in one consistent direction. The perceived direction of the dots was to be indicated by the press of the left or right mouse buttons.

The outcome is recorded within correct/incorrect choices and reaction times, which would represent the time between the beginning of the visual stimulus and the press of the button.

The DDM was then fitted with the dataset so that the estimated parameters could be compared across conditions.

An object-based DDM was modelled with all the generally used parameters that fit, except for the threshold, the reasons for which will be expanded upon more in the results rubric.

Firstly, the raw dataset was plotted into a histogram, illustrating the distribution of reaction times. For the sake of accessibility, another column for the correct responses was added.

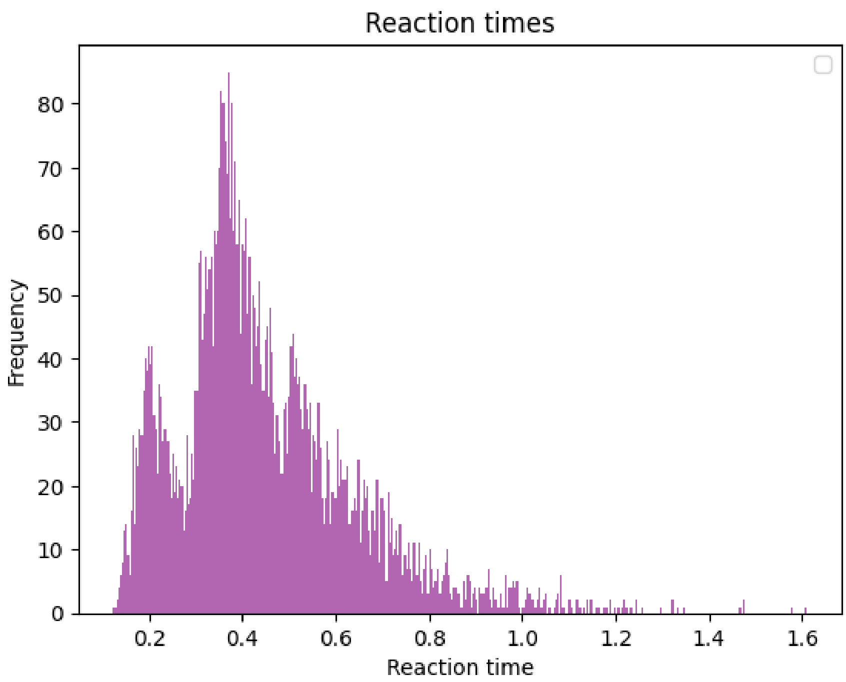

Figure 1: Raw RT

```
import pyddm.plot
dataset = pd.read_csv("dataset-10.csv")
dataset['correct'] = (dataset['S'] == dataset['R']).astype(int)
dataset.to_csv("dataset2-10.csv", index=False)
df = pd.read_csv("dataset2-10.csv")
```

```
plt.hist(df['rt'], bins = 400, alpha = 0.6, color = 'purple')
plt.xlabel('Reaction␣time')
plt.ylabel('Frequency')
plt.title('Reaction␣times')
plt.legend()
plt.show()
```

Using the '.describe()' function, I inspected the attributes of the dataframe, in order to better quantify the minimum and maximum values.

count	5520.000000
mean	0.446452
std	0.191449
min	0.123461
25%	0.325758
50%	0.406012
75%	0.541119
max	1.609944

Given that some of the reaction times are unusual: either faster than the average human reaction time or too slow to keep the model general or reliable upon fitting, the interquartile range was used to remove the outliers.

A boxplot was also computed for additional visual support.

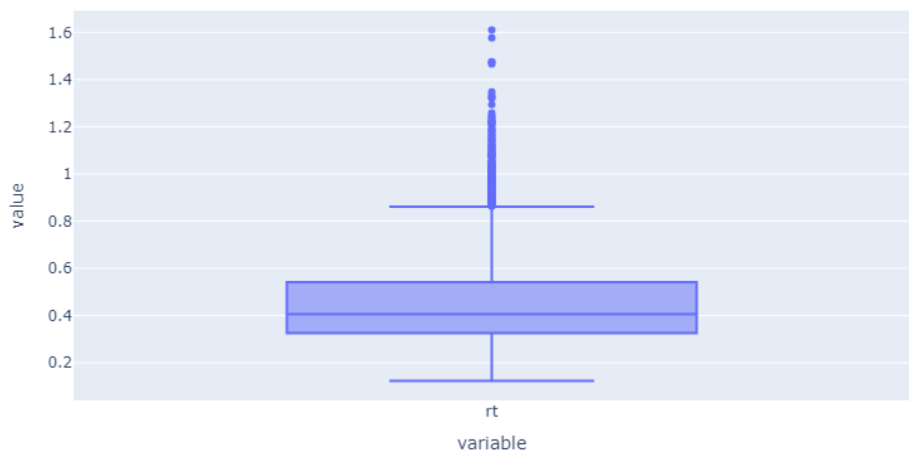

Figure 2: Boxplot of RT values

After cleaning the dataset, the correct and incorrect responses and reaction times per condition were plotted for a more detailed overview. Upon visual inspection, it

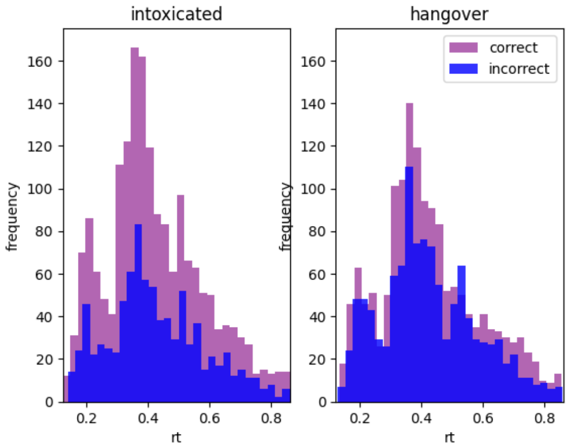

Figure 3: Reaction times per condition

is quite interesting to see that in the hangover condition, the proportion of erroneous choices was higher than in the intoxication condition. This could be due to the fact that during hangover, fatigue, reduced attention and perceptual distorsion may be playing a role. Further analysis of the individual parameters of the DDM may provide some answers.

2.2 Results

When separating the reaction times by subject, condition and correct answers, we can see the individual trends.

```
#median rt per ID, per condition
median_rt = df_clean.groupby(['subjects', 'condition'], sort = False)['rt'].median().reset_index()
median_rt.rename(columns={'rt':'median␣rt'}, inplace=True)
median_rt.head()
```

	subjects	condition	median rt
0	1	hangover	0.259185
1	1	intoxicated	0.267086
2	2	intoxicated	0.432433
3	2	hangover	0.448870
4	3	hangover	0.567029
5	3	intoxicated	0.557406
6	4	intoxicated	0.713094
7	4	hangover	0.703067

8	5	hangover	0.227796
9	5	intoxicated	0.232749
10	6	hangover	0.364731
11	6	intoxicated	0.365532
12	7	hangover	0.226520
13	7	intoxicated	0.215410
14	8	intoxicated	0.438051
15	8	hangover	0.434961
16	9	hangover	0.418530
17	9	intoxicated	0.412354
18	10	hangover	0.392786
19	10	intoxicated	0.384426
20	11	hangover	0.393438
21	11	intoxicated	0.386656
22	12	hangover	0.452526
23	12	intoxicated	0.45617

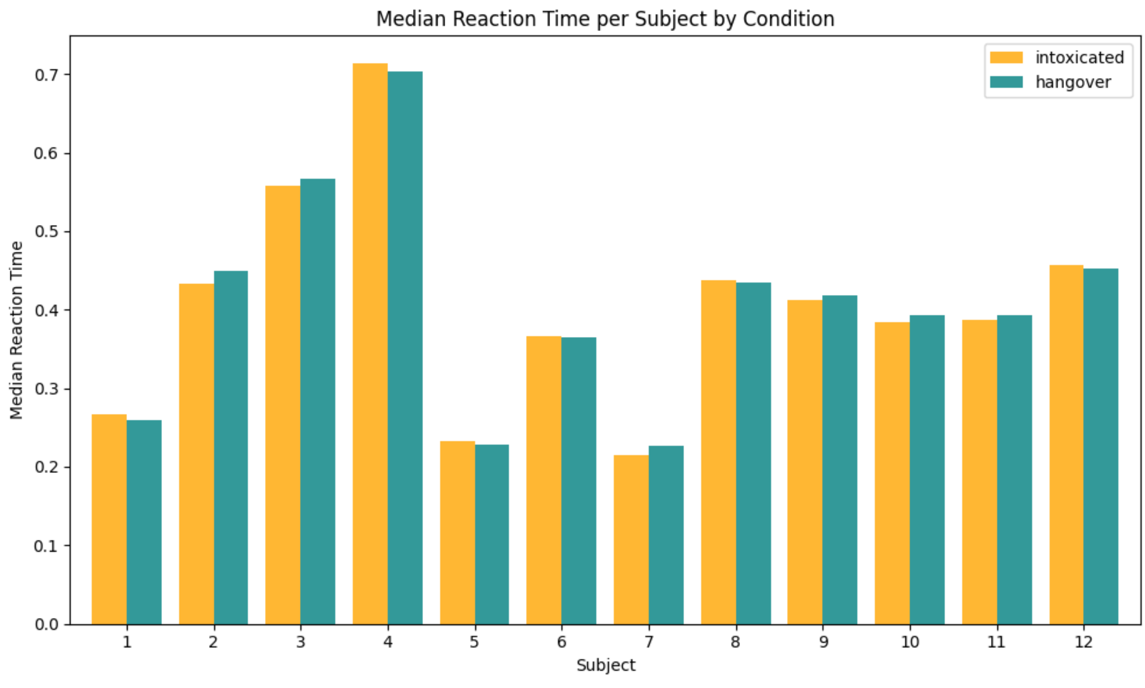

Figure 4: Median RT per Subject per Condition

While for some individuals, alcohol intoxication provided shorter reaction times, maybe due to decreased inhibition and increased recklessness, others were slower. In order to have a more general image, the median reaction times per condition were computed for the whole dataset.

```
#median rt per condition
median_rt_cond = df_clean.groupby(['condition'], sort = False)['rt'].median().reset_index()
median_rt_cond.rename(columns={'rt':'median␣rt'}, inplace=True)
median_rt_cond.head()
```

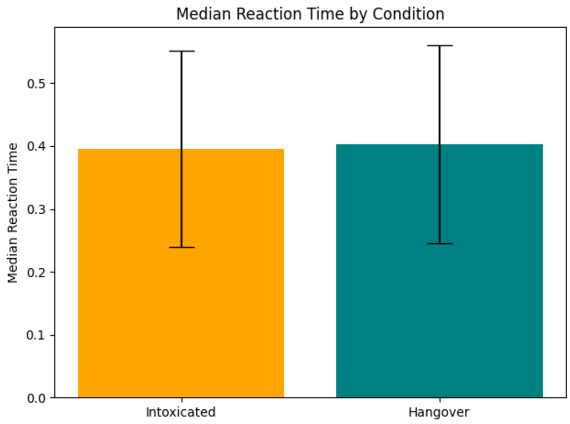

Figure 5: Median RT per Condition

The values for the two conditions in terms of reaction time are very close, potentially disproving heavy cognitive impairment as a likely effect. The high standard deviation variability I would interpret is due to individual differences, seeing how in the per-subject plot there are notable differences between each of them.

After getting some insight into the statistical analysis of the reaction times, the PyDDM model was computed. Beside the most often used parameters, side bias was added as a fittable parameter. This is done in order to assess whether the prior assumption that visual perception and/or encoding may be altered by the conditions.

```
#model

class ICPointSideBias(pyddm.InitialCondition):
    name = "A␣starting␣point␣with␣a␣left␣or␣right␣bias."
    required_parameters = ["x0"]
    required_conditions = ["R"]
    def get_IC(self, x, dx, conditions):
        start = np.round(self.x0/dx)
        # Positive bias for choices to side 1, negative for side 2
        if conditions['R'] == 2:
            start = -start
        shift_i = int(start + (len(x)-1)/2)
        assert shift_i >= 0 and shift_i < len(x), "Invalid␣initial␣conditions"
        pdf = np.zeros(len(x))
        pdf[shift_i] = 1. # Initial condition at x=self.x0.
        return pdf
```

```
m = pyddm.Model(drift=pyddm.DriftConstant(drift=pyddm.Fittable(minval=-5, maxval=5)),
         noise=pyddm.NoiseConstant(noise=pyddm.Fittable(minval=.1, maxval=3)),
         IC=ICPointSideBias(x0=pyddm.Fittable(minval=-.8, maxval=.8)),
         overlay=pyddm.OverlayNonDecision(nondectime=pyddm.Fittable(minval=0, maxval=.5)),
         bound=pyddm.BoundCollapsingExponential(B=1, tau=pyddm.Fittable(minval=.01, maxval=3)))

pyddm.plot.model_gui_jupyter(model=m, sample=sample)
```

The model was then fitted on a by-subject and by-condition basis, and the resulting parameters were retrieved. Due to issues with the library, I was unable to get a usable dataframe since it wasn't formatted in a usual way. Therefore, the parameters were introduced manually into a by-condition csv.

Parameters for intoxicated condition:

	subject	drift	noise	bound	IC	overlay
0	1	5.00	2.87	1	−0.030	0.170
1	2	2.24	2.80	1	−0.030	0.330
2	3	4.45	3.00	1	−0.003	0.480
3	4	3.15	1.83	1	−0.240	0.490
4	5	2.88	3.00	1	0.008	0.150
5	6	3.31	3.00	1	−0.006	0.280
6	7	1.70	2.80	1	0.060	0.100
7	8	2.19	2.71	1	0.020	0.320
8	9	1.99	2.51	1	0.040	0.299
9	10	2.97	2.87	1	0.070	0.290
10	11	2.10	2.50	1	0.100	0.280
11	12	2.80	2.40	1	−0.110	0.330

Parameters for hangover condition:

	subject	drift	noise	bound	IC	overlay
0	1	−0.79	2.83	1	0.080	0.16
1	2	0.28	2.70	1	−0.030	0.33
2	3	−0.79	2.99	1	0.220	0.48
3	4	1.61	1.94	1	−0.100	0.49
4	5	0.66	3.00	1	0.030	0.15
5	6	1.58	3.00	1	0.100	0.20
6	7	1.38	2.73	1	0.001	0.12
7	8	2.35	2.67	1	−0.006	0.32
8	9	1.82	2.45	1	0.070	0.29
9	10	0.16	2.81	1	0.030	0.29
10	11	0.79	2.62	1	0.029	0.28
11	12	1.81	2.68	1	0.010	0.34

Looking at the drift rates and noise, they are slightly higher than usual, with drift being arbitrarily set between 0.1 and 3 for binary choice tasks, and noise is typically between 0 and 1. For this particular dataset and model, the values for the drift rate vary between -0.79 and 5 for select individuals, and noise is often approaching or hitting the boundary of 3. These unusual values could be due to poor model fit, inappropriate handling of the dataset, the fact that the task is significantly easy and the task conditions promote impulsivity, or a combination. When introducing a variable threshold to verify whether recklessness may align with a collapsing bounds/variable threshold model, the drift and noise would become even more erratic, or harder to retrieve. For these reasons, the bounds are set to 1, the other parameters being communicative enough in their correlations despite the unusual values. Therefore, the following slope plots were computed, with dots marking the by-subject drift values, and the line connecting the median drifts corresponding to each condition.

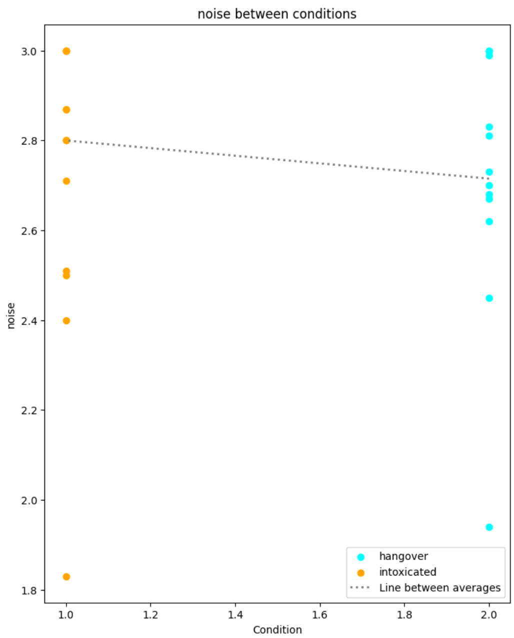

Figure 6: Noise between conditions

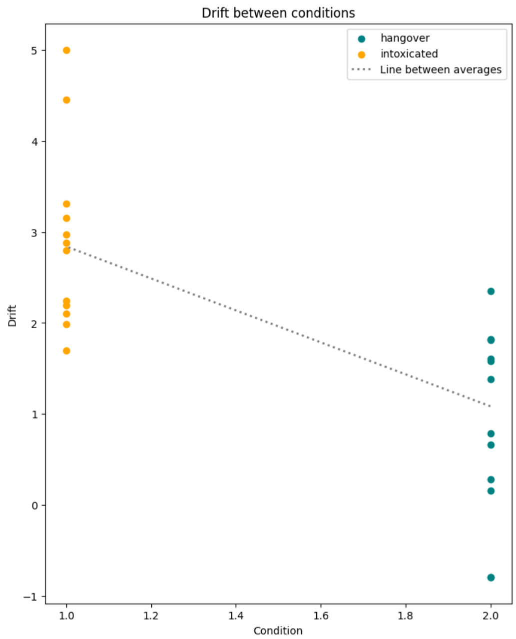

Figure 7: Drift between conditions

Firstly, the drift rate is quite higher in the intoxicated condition, which could be due to increased confidence and impulsivity, even though the answers may be wrong. Secondly, the noise is also higher in the intoxicated condition, although it does not prove as significant as the drift rate. Reasons may be consistent with impaired visual processing, although it could also account for a loss of attention, given that the hangover state has similar values. Third, the non-decision time proves inconclusive, with almost identical values across the conditions, and high variability due to the

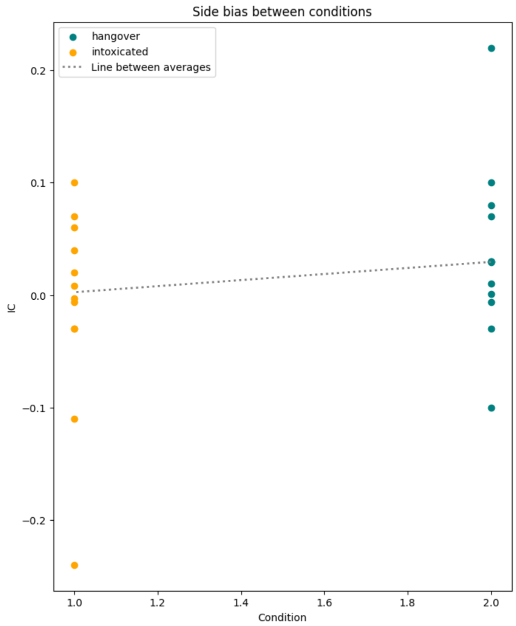

Figure 8: Side Bias between conditions

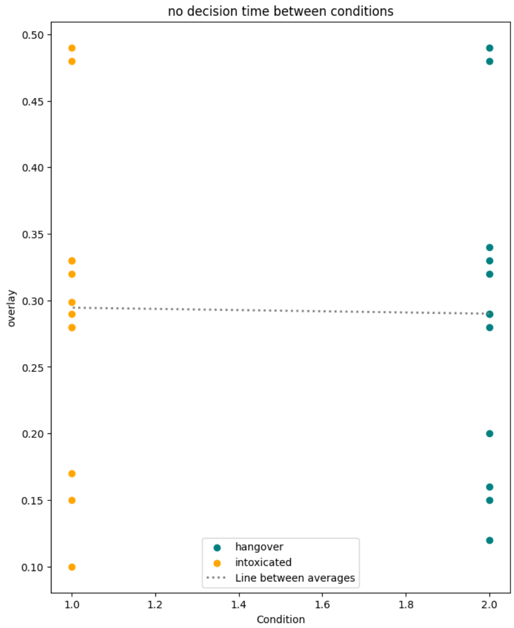

Figure 9: Non-decision time between conditions

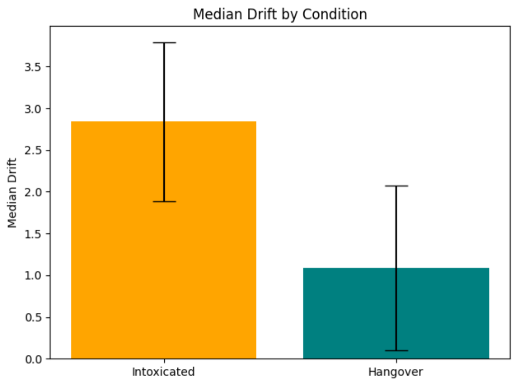

Figure 10: Median drift

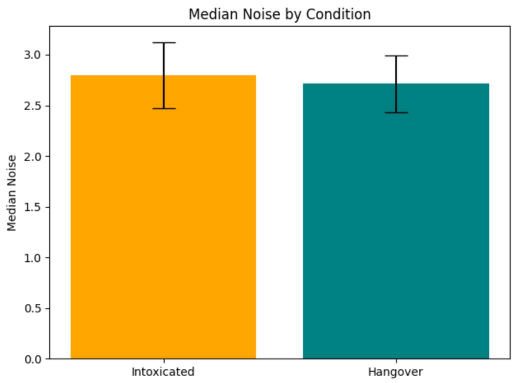

Figure 11: Median Noise

difference in subject ability. Lastly, the side bias is almost inconclusive, since it is pretty much non-existent, yet there is slightly more bias in the hangover condition.

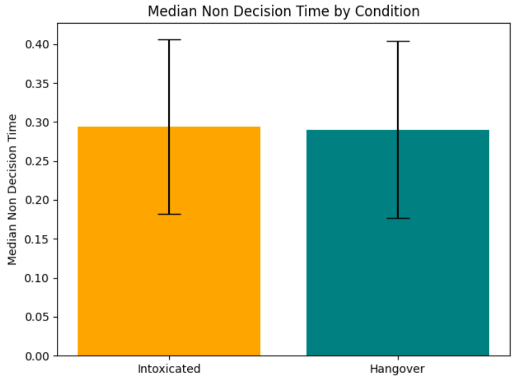

Figure 12: Median Non Dec Time

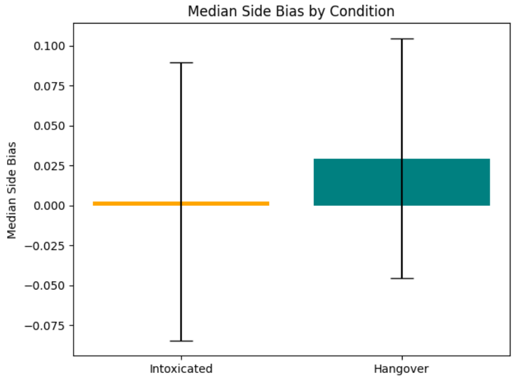

Figure 13: Median Side Bias

2.3 Discussion

The drift diffusion model was used to provide additional insight into the distribution of reaction times and accuracy of the subjects within a perceptual decision making task, with regard to sensory evidence accumulation, response cautiousness and response bias. For this paper two conditions were analyzed for their effects on cognition and performance. The estimated DDM parameters provided additional insight into the potential variations in cognitive computation under the influence of alcohol. The parameter of most interest was the evidence accumulation, or drift rate. Despite the initial hypothesis being that drift rate is the primary cause for differential effects across the conditions, the results themselves are quite unexpected, and set a need for further research. The other parameters still demonstrate that there is no lasting damage inflicted on executive function in the case of acute intoxication, as long as it is not prolonged exposure. Initially, the expected outcome, as well as what is present in some of the literature is the fact that drift rate is lower in intoxication trials (Stock et al, 2017). The similar reaction times were also expected, though this seems to differ quite a lot from study to study, given that some are conducted with varying amounts of BAC, different drinking habits among subjects and different aims.

Additionally, as stated in the Methods, upon inspection of the dataset, there was a higher proportion of erroneous choices in the hangover trials, compared to the intoxication trials. Coupled with the high drift rates in the intoxication trials, it is surprising how these results are not reversed.

For a future research, baseline trials would prove useful in assessing the differential effects of the two conditions. Therefore, more variation in the parameters may arise in comparison to non-intoxicated trials, and specific areas which may change only slightly between the intoxicated and hangover states could become significant. Another limitation is the small population sample, which cannot make for a well distributed dataset due to the high individual variation.

An area of improvement would be a better model setting, which would account for changes in threshold as well, while maintaining stability within the other parameters.

2.4 Conclusion

A dot motion task was used to explore the differential effects of alcohol intoxication and hangover on decision making. The PyDDM library was used to model a drift diffusion model in order to estimate the parameters governing the cognitive processes underlying the decisions. The results are partly aligned with the hypothesis, yet they are not demonstrating a particular physiological or cognitive impairment. The most significant parameter was drift rate, with small significance for noise and side bias. Non decision time is not significant. The reaction times do not reflect lasting impairments, yet the proportion of correct versus incorrect choices in the experimental conditions may have some root in cognitive fog, overall exhaustion and negative acetaldehyde reactions.

2.5 Generative AI

Generative AI was not used for writing the report, nor for the code.

2.6 References

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