Grenoble INP – ENSIMAG

Engineer assistant internship report

Okayama University - Human behavior understanding laboratory

Reciprocity in encounter between individual pedestrians and dyads

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1 Introduction

For this internship, my main objective was to discover the working world, particularly the field of research. I have always been interested in research because I find its approach to be very noble. Aiming for discoveries using scientific rigor is intellectually appealing, but unfortunately, it is not well valued in today's society. That's why I absolutely wanted an experience in the research domain to envision my future career.

Moreover, doing this in Japan adds a highly attractive cultural dimension to this activity. It is very interesting to combine science with English and to work with international professors and colleagues. You discover new words to describe ideas/concepts, as well as different working methods. This makes the experience more enriching and allows for personal growth in addition to professional development.

I have also lot of personal interest in this country because of its culture mostly. I always wanted to come one time in my life for that reason. That is why I was really happy to be able to come for 3 months because that means I could use my time outside my workdays in order to visit the country.

The field of human behavior suits me perfectly; it provides a great playground to apply my knowledge in data science and learn new things. Working in this domain gives a sense of dealing with something tangible, which is more enjoyable. Overall, the framework and content of the internship offer an excellent first immersion into the working environment.

2 Context

The internship takes place at Okayama University, located in Japan, in the Human Behavior Understanding Laboratory under the supervision of Professor Zeynep Yucel , who is also my internship supervisor. The laboratory consists of two doctoral students (one French and one Thai), four interns (three French and one Thai), and around eight Japanese students pursuing their Master's degree in Computer Science. The Japanese students are expected to work on research projects in parallel with their Master's studies at the university. Working in this lab allowed me to do the experiments of other students who needed data for their research.

The Human Behavior Understanding Laboratory focuses on investigating various aspects of human behavior, employing scientific methodologies to understand and analyze human actions, reactions, and decision-making processes. As an intern, my mission was to actively participate in ongoing research projects and contribute to the team's efforts in exploring new avenues in the field of human behavior studies.

Throughout the internship, I had regular meetings with Professor Yucel Zeynep, my internship supervisor, as well as another researcher in the domain, Francesco Zanlungo.

These meetings occurred several times a week and served as opportunities to discuss the progress of my work, analyze the results I obtained, and collaboratively strategize on the future direction of the research. These interactions not only helped me gain valuable feedback and guidance but also allowed me to be actively involved in the decision-making process, giving me a sense of ownership and responsibility for the project's outcomes.

I worked from Monday to Friday, generally from 9:00 AM to 12:00 PM and from 1:30 PM to 5:45 PM. In reality, the hours were quite flexible, and my main priority was to make progress in my research for my meetings, which sometimes occurred on a daily basis.

3 Internship topic

3.1 Problem to solve

My internship project focuses on studying the trajectories of pedestrians based on their social aspects. Specifically, I needed to investigate the deviation of pedestrians and pedestrian groups in various situations, such as encounters or undisturbed. This is a specific case study within a broader research domain centered on human behavior, which serves as the guiding theme of the laboratory.

Using public databases, which I will describe in more detail later, I had to identify biases or patterns in the behavior of pedestrians on a straight street to simplify the task. Specifically, the focus was on groups of 2 pedestrians, which are the most common group in the street. The question was how a group of 2 pedestrians behaves when walking alone (undisturbed case) and when encountering other pedestrians and having to avoid them (encounter case).

3.2 Existing work

This topic had already been studied by Prof. Zeynep Yucel , who has published research papers on it [5] . This allowed me to quickly immerse myself in the subject and understand its challenges and issues. Additionally, my work environment was in Python, and some progress had already been made by Adrien Gregorj, one of the doctoral students in the laboratory. He had previously worked on this subject and had already made progress on organizing data related to databases. Additionally, he was able to share some of the results he had obtained. In summary, he efficiently trained me in the domain, which was facilitated by the fact that he was French, and he provided me with the Python files he had created.

3.3 Goal to reach

My objective was to adopt a rigorous methodology to measure human behavior. For this purpose, several metrics were proposed to me, which I will detail in the following paragraph.

My goal was to explore the avenues of these metrics with the aim of publishing a research paper on the subject. My results had to be comprehensible, scientifically accurate, and rigorous. The comprehensible aspect led me to create graphs that I could present and explain, and each of these graphs had to be supported by statistical validation.

3.4 Technical aspect

3.4.1 DataBase

The databases used in this project is DIAMOR (public databases [6] [10] [3] [9] [4]), which contain the successive positions of numerous pedestrians in delimited rural spaces with a sampling time of 0.1 sec. In this database, pedestrian groups have been classified based on their level of social interaction with each other (from 0 to 3) 0 represents no interaction in the group, 1 a weak interaction, 2 a mid interaction and 3 represents a big interaction. My role was to find a way to measure the deviation of these pedestrians based on their level of social interaction, in other words, to find a metric capable of providing consistent results to measure their deviation.

3.4.2 "Baseline" deviation

To calculate the deviation of pedestrians, my main approach was to utilize the concept of "baseline" deviation, which I will now explain. In this method, the primary objective is to create a line that represents the initial trajectory the pedestrian appears to follow in their initial steps, and then measure how much they deviate from this trajectory. To achieve this, I implemented the following process :

- For Undisturbed trajectories, I divided the pedestrian trajectories into sets of 5 consecutive points and then used the first two velocity vectors of each sub-trajectory to determine a "baseline".
- For encounter situation, I just compute the baseline for both of encounter using the two velocity vectors.

This baseline essentially forms a straight line that represents the path the pedestrian would have taken had they continued along their initial course. Subsequently, I identified the point that deviated the farthest from this baseline. When referring to the distance between the point and the baseline, I actually calculated the length of the segment perpendicular to the baseline passing through the trajectory point as shown in Figure 1, the baseline for an encounter situation between one group and one alone pedestrians (7 trajectory points)

The explanation I provided constitutes the final solution I refined over the course of my internship. For instance, the idea of using trajectories of 5 points was discovered through empirical observations and the aim of it is to be able to compare undisturbed case to encounter case. In reality, in order to compare the deviation of two trajectories, these trajectories must have approximately the same length. Encounter situations are detected using a vicinity threshold, and since the pedestrians' speed is lower in these situations, that's why, for an equal distance in an encounter situation and an undisturbed situation, we have more trajectory points in the encounter situations. Considering that the actual solution is more intricate, I have omitted several other assumptions in my explanation to enhance clarity.

3.4.3 Other metrics : Curvature, sinuosity, tortuosity

I will briefly explain the other measures that were attempted to measure pedestrians' deviation :

- Curvature is a measure of the amount of bending or curvature in a trajectory at a specific point. It represents the rate at which the direction of the path changes. Higher curvature values suggest more significant deviations from a smooth, straight path.

- Sinuosity : This measure was introduced in [2] as a way to quantify the randomness of an animal's path (especially in the case of foraging patterns, for instance when studying how ants locate and collect food). It is formally defined as $S_i = 1.18\frac{\sigma_q}{\sqrt{q}}$ where q is the step size of the trajectory, i.e. the distance between two consecutive positions and σ_q is the standard deviation of the turning angles Θ.

- Tortuosity [1] Tortuosity is defined as the ratio of the net displacement to the gross displacement : $\tau = \frac{D}{L}$ It is clear that τ takes values between 0 and 1. In particular, for an infinitely tortuous trajectory, τ assumes the value of 0, whereas for a perfectly straight trajectory (i.e. D = L), it leads to the value of 1.

Unfortunately, these last three measures did not yield good results, so I will not present them in the results section. Only the "baseline" deviation provided convincing results from both a statistical perspective and in terms of graphical interpretation. In reality, these measures are not bad or difficult to calculate, but the issue is that they do not correspond to our specific situation. While they provide different information about our trajectory, ultimately, they do not contribute significantly to the understanding of the pedestrian's movement.

3.5 Statistical relevance

3.5.1 Anova test

To demonstrate the coherence of my results, I need to focus on the statistical aspect of the data I am handling. First let me describe what ANOVA is and then explain why it is relevant in my case. ANOVA (Analysis of Variance) is a statistical test used to compare means of three or more groups to determine if there are significant differences among them. It assesses the variability within and between groups, allowing researchers to identify whether the observed differences in means are due to random chance or meaningful factors.

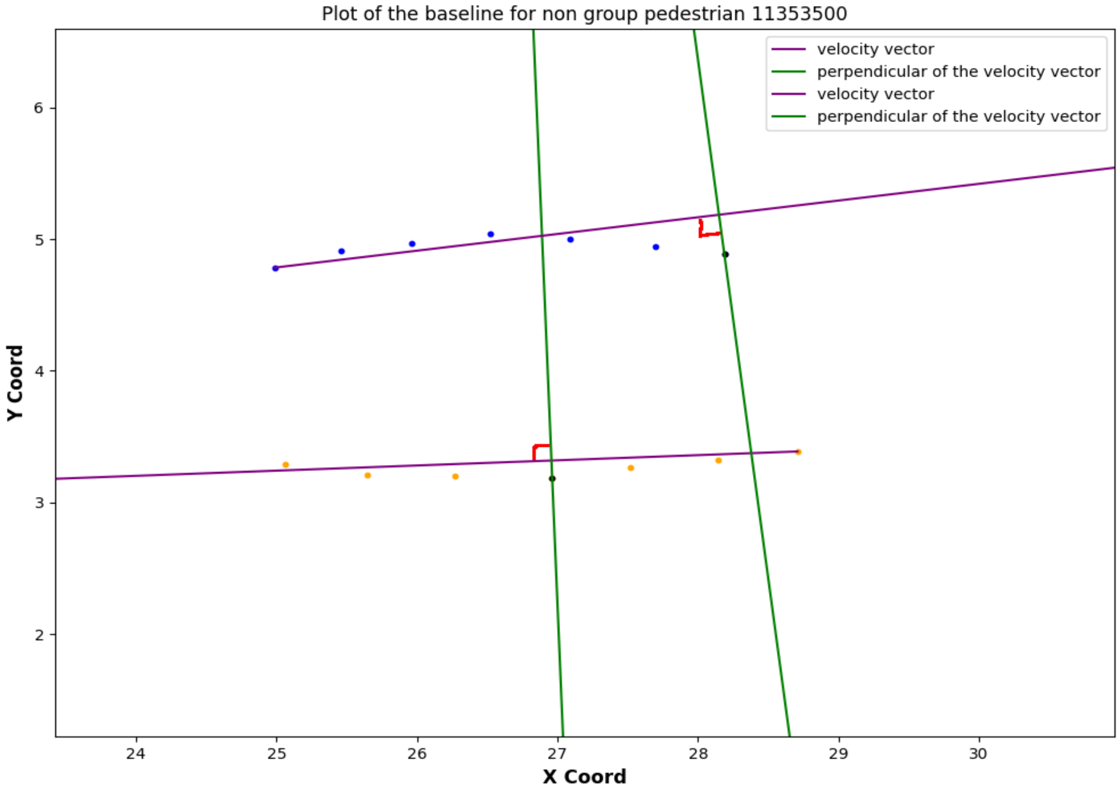

Figure 1: Baseline for an encounter situation of one group and one alone pedestrian (non group)

ANOVA is relevant in my case because I am analyzing the deviation of pedestrians in different social interaction scenarios. By using ANOVA, I can compare the mean deviations of pedestrians in various situations, such as encountering other pedestrians or walking alone. This statistical test will help me to determine if there are significant differences in deviations between the different social interaction levels, providing insights into how social factors may influence pedestrian behavior on the street.

3.5.2 Effect Size test

As I analyze the data and interpret the results of my study, it is crucial to consider the effect size test and Cohen's coefficient [7] [8] (p.599). These statistical measures are essential in my case to assess the practical significance and strength of the observed differences between groups.

Effect size provides a standardized measure of the magnitude of the effect or relationship under investigation. In my research on pedestrians' deviation, it allows me to quantify how much the social interaction levels impact their behavior. By calculating Cohen's coefficient, I can express the size of the effect in standard deviation units, making it easier to compare and interpret the results across different studies.

Cohen's coefficient d is calculated as the difference between the means of two groups divided by the pooled standard deviation $d = \frac{\bar{x}_1 - \bar{x}_2}{s}$. The pooled standard deviation is defined as follow $s = \sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}}$ where the variance for one of the groups is defined as $s_1^2 = \frac{1}{n_1-1}\sum_{i=1}^{n_1}(x_{1,i} - \bar{x}_1)^2$. It can be interpreted as the number of standard deviations that separates the means of the two groups. A small effect size corresponds to a d value around 0.2, indicating a relatively small difference between the groups. A moderate effect size ranges from 0.5 to 0.8, while a large effect size is typically considered to be above 0.8, indicating a substantial difference between the groups.

By including Cohen's coefficient in my analysis, I can go beyond simply determining if there is a statistically significant difference between groups and gain insights into the practical significance of the observed differences. This information is invaluable in understanding the real-world implications of my research findings and their relevance in the context of pedestrian behavior.

Using these statistical tools is relevant in my case because they complement the traditional significance tests like ANOVA. While ANOVA helps determine if there are significant differences among groups, effect size (Cohen's coefficient) gives a clearer picture of the practical significance of those differences. By incorporating effect size measures, I can better understand the real-world implications of social interactions on pedestrians' deviation and provide more meaningful insights in my research.

In brief, the essence and challenge of this project lie in the fact that we do not know what results we are supposed to find (which is often the case in research). Therefore, it is crucial to maintain rigor and precision in all the assumptions made about the data to be able to interpret the obtained results from our own perspective. Unlike a typical classification project, where metrics like F1-score or accuracy can provide immediate "measured" feedback on progress and direction, in my internship project, such tools do not exist. Of course ANOVA can tell you if your result is statistically relevant but not tell you if it means something. Instead, we must rely on our intuition and the rigor of our approach to navigate through the uncertainties and complexities inherent in the research domain.

4 My work

4.1 Architecture of my solution

4.1.1 Working tools, existing architecture

I implemented everything using Python, which was well-suited for the task due to its various libraries like Matplotlib, Pickle, NumPy, and SciPy. Python's object-oriented programming was crucial for organizing the data. The data preprocessing to convert the DIAMOR database into Python dictionaries was already done and has been write mostly in object oriented code. To detect encounter situations, I used a vicinity window during a pedestrian's trajectory and checked for other pedestrians with opposite velocity vectors at each time step. For undisturbed trajectories, I considered all the data, excluding encounter situations.

To provide some more detail about my architecture, there was an object structure implemented by Adrien GREGORJ that simplify the organisation of data. Here is a list of most usefull object that exist :

- Pedestrians (containing information like their trajectories)
- Groups which include the number of pedestrian in the group, the social binding and other information

By utilizing iterative loops, it is possible to perform almost any desired operation on the data. This ranges from simple filtering, for instance, to find all groups of three people considered as friends, to calculating deviation using each trajectory point from all pedestrians in the dataset.

Given that the dataset is quite substantial, operations that involve extensive calculations (e.g., filtering trajectories to identify encounter situations) or computing metrics based on various assumptions could easily take several hours without proper code optimization.

Hence, it became essential to devise a method of data storage to minimize computation time. This is where the use of Python's Pickle library proved highly beneficial. It allows the storage of dictionaries, enabling, for example, the differentiation of undisturbed trajectories from encounter situations using specific thresholds for vicinity and sampling time. These trajectories are then saved in a dictionary via Pickle, and subsequently, the desired algorithm is applied to each of the saved trajectories.

4.1.2 What I added

Since data preprocessing was already done, I focused on implementing algorithms to calculate metrics from the trajectories. I created an evaluation grid for hyperparameters such as vicinity window, sampling time for trajectories, and the minimum number of points required per trajectory to find the best values. For each hyperparameter I wanted to test, I used iterative loops to test the desired hyperparameter values. Then, for each hyperparameter, I plotted the associated graphs and performed the desired statistical tests. These results were saved in folders, allowing me to study and analyze the results whenever I wanted. The most frequently used graphs in my case were boxplots and scatter plots generated using the matplotlib library. The statistical tests were also automated to be performed at each iteration.

4.2 Methodology

Throughout the internship, I regularly engaged in discussions with my professor (internship supervisor), the researcher, and the doctoral student to interpret the results I obtained and exchange ideas to progress in resolving the problem.

In summary, the final solution I achieved in this project was the result of a long and iterative process. The calculation of pedestrian deviation involved making numerous assumptions, and the previous paragraph only provided a partial list. To arrive at the selected hypotheses, I went through multiple phases of research and reflection.

In hindsight, the approach I used resembles a scrum-like method. My work was organized as follows:

- The professor provided me with a metric to explore for calculating pedestrian deviation. It could also be, "I want you to compute that ... in that case ..." (for instance if the speed have an influence in deviation)
- I conducted a research phase, where I contemplated how to implement these measurements to resolve the problem.
- I implemented my solution with specific assumptions and hyperparameters.
- I performed tests to identify the best hypotheses and hyperparameters, discussed the results with the professor and researcher, and then returned to the previous steps as needed.

Communication played a vital role in my work. With almost weekly feedback from experts in the field, I was able to progress efficiently and propose a robust solution that addressed the problem effectively. The continuous feedback loop and open discussions were instrumental in refining the approach and achieving a solid solution.

Overall, the project was an intensive and collaborative effort, involving critical thinking, experimentation, and adjustments. Through this process, I gained valuable experience in research methodologies and problem-solving, further enhancing my understanding of pedestrian behavior and its intricate dynamics in different social scenarios.

4.3 Test

4.3.1 Algorithm test

Testing my code was a crucial and integral part of my work, as data manipulation could sometimes be challenging. For instance, I had to develop graphical methods to visually inspect the trajectories I was filtering. Having a graphical representation of the data under analysis also helped me in making informed decisions during the hyperparameter tuning process. Additionally, a significant portion of my work involved implementing mathematical formulas, such as those related to curvature calculations. Therefore, I had to rigorously test my algorithms on small datasets to ensure they produced the desired results before applying them to the larger dataset.

By testing my code on smaller subsets of data, I could verify if the algorithms yielded accurate and reliable outcomes. It also allowed me to gain confidence in the correctness of my implementation. Whenever necessary, I made adjustments and improvements to enhance the code's performance and accuracy.

Having a visual understanding of the data and observing the algorithm's behavior with smaller datasets were instrumental in refining and perfecting my implementation. As a result, I could ensure that my code was robust and capable of handling the larger dataset, leading to meaningful and trustworthy results in my analysis.

Overall, the testing process played a vital role in guaranteeing the quality and accuracy of my work, enabling me to confidently draw conclusions from the data and achieve reliable results in my research.

4.3.2 Statistical test

The organization of ANOVA tests was conducted on various data arrangements, and here are a few examples. As a reminder, the social binding of the pedestrian groups is represented as 0, 1, 2, 3, where 0 indicates the weakest bond and 3 the strongest. "Alone" corresponds to individual pedestrians. I performed ANOVA tests for both encounter cases and undisturbed cases. ANOVA test has been realized between the following categories :

- 0 / 1 / 2 / 3 / alone
- Group (which is all 0 to 3 social binding together) / Alone
- 0 / 1 / 2 / 3
- 0 and 1 / 2 and 3

Next, in order to verify if there was a significant difference in various situations, I realised ANOVA test in the following situation :

- 0 in encounter case / 0 in undisturbed case
- 1 in encounter case / 1 in undisturbed case
- 2 in encounter case / 2 in undisturbed case
- 3 in encounter case / 3 in undisturbed case
- Alone in encounter case / Alone in undisturbed case

Of course, the verification of effect size was also conducted in each of these situations, and the results were presented in tabular form. By calculating Cohen's coefficient for each comparison, I was able to quantitatively assess the magnitude of the observed differences between the various groups. This approach allowed me to determine the practical significance of the effects and understand the strength of the relationships between social binding levels and pedestrians' deviation behavior. By presenting the effect sizes in tabular format, I could easily compare the results across different situations and identify patterns or trends in the data. This enabled me to draw more robust conclusions about the influence of social binding levels on pedestrians' deviation behavior in various encounter scenarios and undisturbed situations.

5 Obtained results

In both boxplot graphs Figures 2 and 3, the first box represents deviation for social binding 0, followed by 1, 2, 3, and finally, the last box represents individuals pedestrians. So in the y axis we can see the deviation and in the x axis the social binding. Also next to the social binding, the number of data used for the boxplot is written. The x and y-axis scales are the same for both graphs. In the boxes, the black line represents the median, and the two points represent the mean. Quartiles, minimum, and maximum values for each situation can also be read. The left graph corresponds to an undisturbed situation, while the right graph corresponds to an encounter situation.

Firstly, it can be observed that for each social category, the deviation values are higher in an encounter situation than in an undisturbed situation. This is because during an encounter situation, the group needs to avoid the approaching people and deviate from their original trajectory. Secondly, it can be noticed that regardless of the situation, groups with a strong bond tend to deviate less than others. This is because stronger interaction within the group leads to less attention being paid to the surroundings, resulting in less deviation from the baseline trajectory to avoid obstacles. However, this deviation becomes almost similar between groups with social binding 0 and individuals walking alone. The latter are the most likely to alter their trajectory to avoid confrontation.

These two graphs are supported by increased statistical significance as the p-value associated with the ANOVA test is well below 0.05. Although the deviation difference between the groups is more pronounced in the encounter situation, the ANOVA test produces a less favorable result. This is simply due to having significantly fewer data points for the encounter situation in our database. However, the quantity of data remains sufficient to obtain a meaningful result, as shown by the p-value.

Here are also presented the tables listing the data related to the size effect 1 2, including the Cohen's d values for each data pair. The first row of the table represents the social binding of the group (including "alone") along with the corresponding number of deviation values. This number of data points is different from the number of pedestrians for the "undisturbed" case because the pedestrians' trajectories have been subdivided into trajectories of 5 consecutive points. As a result, there is actually a deviation value for each sub-trajectory of the pedestrian. Therefore, for each given pedestrian, there can be

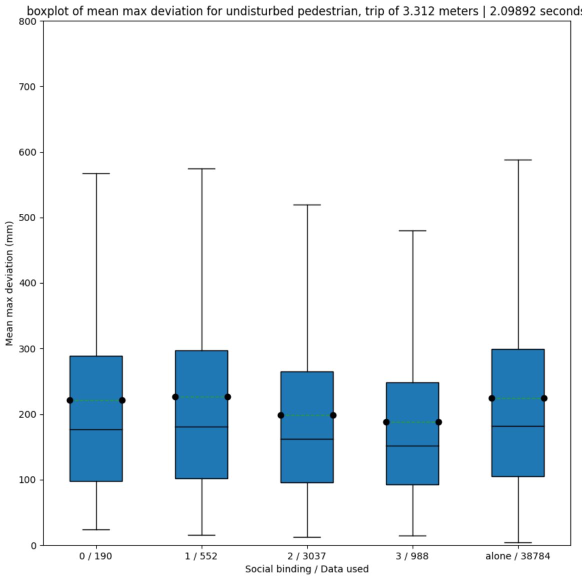

Figure 2: 0/1/2/3/Alone
Undisturbed case
ANOVA p-value $\approx 10^{-24}$

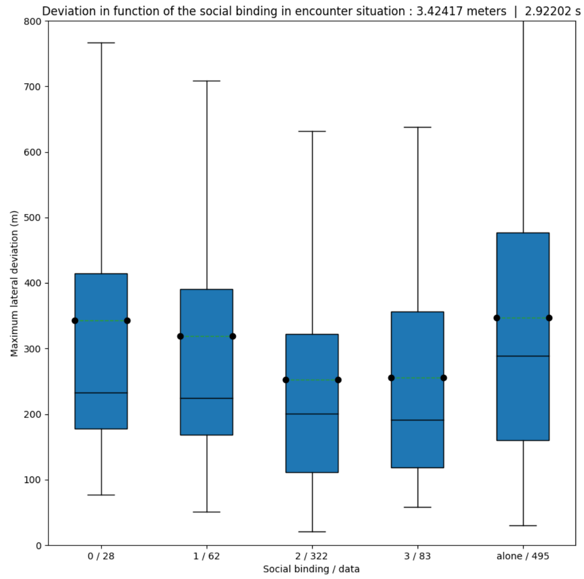

Figure 3: 0/1/2/3/Alone
Encounter case
ANOVA p-value $\approx 10^{-8}$

multiple deviation values. The number in the table corresponds to the number of deviations calculated from the pedestrian sub-trajectories.

I would like to remind you that this division into sub-trajectories was done to have trajectories with comparable distances to those in the encounter case, allowing for deviation calculation under similar experimental conditions. In the case of encounter situations, there is only one data point per studied group (no sub-trajectories in this case).

The table below 3 contains descriptors for magnitudes of d = 0.01 to 2.0, as initially suggested by Cohen and expanded by Sawilowsky [7] . For the undisturbed case we mostly have Cohen's d coefficient between 0.01 and 0.2. That suggests that there is a small difference between the two compared groups, but this difference is weak and not practically significant. In other words, the effect is present, but it is minimal and cannot be considered clinically or practically relevant.

In the other end, the ANOVA test shows a very low p-value, indicating that there is a statistically significant difference among the groups. However, it's important to interpret this result in conjunction with the small effect size observed with Cohen's d. A low p-value only indicates that the observed difference is unlikely to be due to random chance, but it doesn't provide information about the magnitude or practical significance of the effect.

Given the small effect size and the low p-value from the ANOVA test, it suggests that

Table 1: Cohen's d in undisturbed case for baseline deviation

Social Binding / Data points	0 / 190	1 / 552	2 / 3037	3 /988	alone / 38784
0 / 190	0.0	/	/	/	/
1 / 552	0.02932	0.0	/	/	/
2 / 3037	0.15599	0.18449	0.0	/	/
3 / 988	0.24443	0.25570	0.07484	0.0	/
alone / 38784	0.02254	0.00750	0.15964	0.22274	0.0

Table 2: Cohen's d in encounter case for baseline deviation

Social Binding / Data points	0 / 28	1 / 62	2 / 332	3 / 83	alone / 495
0 / 28	0.0	/	/	/	/
1 / 62	0.09494	0.0	/	/	/
2 / 332	0.46850	0.34023	0.0	/	/
3 / 83	0.41261	0.29613	0.01972	0.0	/
alone / 495	0.01747	0.11950	0.43774	0.39911	0.0

Table 3: Descriptor of magnitude for Cohen's d

Effect size	d
Very small	0.01
Small	0.20
Medium	0.50
Large	0.80
Very large	1.20
Huge	2.0

while there might be a statistically significant difference between the groups, this difference may not have substantial real-world implications. The effect size of Cohen's d between 0.01 and 0.2 implies that the practical significance of the observed differences may be negligible, and any practical implications or applications based solely on statistical significance should be considered with caution.

The same reasoning can be applied to the encounter situation, even though the results may appear higher overall, they are not significantly higher.

6 Conclusion

It may sound strange, but the most challenging aspect for me was maintaining impeccable code rigor. When writing 200 lines of code to generate a graph that needs to be interpreted, ensuring the precision and reliability of the code becomes crucial. Without rigorous code, the results obtained lack fundamental value. However, this challenge is also an essential part of the charm of research and the scientific process in general. I had not encountered this level of rigor in my previous projects, especially those completed at the university.

Another significant aspect that this internship provided was the daily communication in English for work purposes. It required a whole different vocabulary and necessitated preparation when presenting my results regularly. Having an external perspective on my work regularly acted as a catalyst for my efficiency.

In conclusion, my internship was a highly enriching cultural experience. It allowed me to explore the profession of a researcher in the university setting. Working here with my team for three months was an enjoyable and enlightening experience. While I have always been curious about this profession, I had never seriously considered pursuing it as a career. As a student, the experience was rewarding and pleasant, given that most of us in the laboratory were of similar age. However, my professor was the only one at her age, making it a bit harder for me to envision myself in that role. I still think of pursuing a career in the corporate world for my future.

Of course, the geographical context of the internship allowed me to become familiar with the local culture, and I was able to enjoy the country during my weekends, which made the experience even more enjoyable.

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