

How do different modes of transport affect data from the Xovis PC2R outdoor sensor at bicycle parking facilities

Research on distinguishing modes of transport when reading sensor data

Lars Dijkstra



Delft

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by

Lars Dijkstra

Student Name	Student Number
Lars Dijkstra	4490150

Instructor: A. Gavriilidou
Second Instructor: Y. Yuan
Project Duration: September 2022 - October 2022
Faculty: Faculty of Civil Engineering, Delft

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Preface

This thesis has been made as a bachelor thesis in the area of transport and planning at the faculty of Civil Engineering at the TU Delft. My thanks go out to Alexandra Gavrilidou and Yufei Yuan for advising and giving feedback on my progress. Also my fellow student have given me great advice on my thesis and I thank them for that. Lastly thanks to Winnie Daamen for providing the information on and the data of the sensor used in this thesis.

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Summary

Bicycle parking facilities are widely used across the Netherlands. However a lot of times these parking facilities have trouble tracking how many bicycles are in the facility. Sensors have been implemented to have real-time information on the occupancy of a parking facility, but these sensors are not perfect and that results in miscounts. In this thesis the focus is on determining the occupancy from the data provided by the Xovis PC2R outdoor sensor located at the underground parking facility at Industrial engineering at the TU Delft.

Chapter 2 describes how the sensor works and it gives trajectory data for each entity. As long as the entity is in range the sensor notes timestamps with an x and a y location. This chapter also describes that errors are any occurrence of either a non-bicycle entry being traced or an occurrence of a bicycle not being traced by the sensor for this specific thesis.

The following chapter described that data is gathered real-time by noting down entries and exits along with the mode of transport for every entity to try and find entries that result in an error. This was done for both manual data and the sensor data. Furthermore the sensor data is analysed by calculation the average x-position and average speed for every entity found in the data from the sensor. This helps in finding ways to distinguish between modes of transport. This chapter also introduces three hypotheses that are tested:

1. Pedestrians without bicycles result in error
2. Cyclist have higher average speed than other modes
3. Pedestrians with bicycles have a higher average x-position

These hypotheses are tested based on the proposed methods.

The results are that the sensor works as intended as it tracks every entity that comes into its range. The problem with that is that it tracks people entering without a bicycle and that results in faulty occupancy numbers. It was also found that there are differences between modes of transport that are found in the sensor data as people walking walk slightly closer to the side of the door as opposed to people with bicycles that walk more in the middle of the door. This can be derived from the data by looking at the average x-position of the entities. Also found was that people cycling have a slightly higher average speed than others.

To conclude it was noted that while the findings are useful to differentiate in general, they are not clear enough in this specific case to make use of them to accurately track the occupancy of the parking facility. There are too many outliers and there is a lot of variance in the data. Future research should be done at a different location to get a clearer idea of the differences and how to implement a way to use the data to track occupancy.

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1

Introduction

This chapter consists of three sections. First the inspiration for this thesis is explained. Next the goal of the research is outlined. Finally the structure of this report is given.

1.1. Problem Description

Bicycles are an integral part of Dutch society since they are the main mode of travel. When using the bicycles to travel, they need to be parked somewhere. This can become a problem when there is not enough space when the demand for bicycle parking gets larger. A lot of large bicycle parking facilities have issues with insufficient amounts of space for bicycles [2]. A solution to this is to track the occupancy of the parking facilities to see how many parking spaces are needed. Tracking the occupancy manually takes a lot of time, is not very efficient, it is prone to miscounts, and it does not track real-time occupancy. The occupancy can be tracked in a much better way using sensors. There are a lot of ways to use sensors to track parking occupancy. A commonly used way is to have signs signalling the number of free spaces left in a facility where the number of unoccupied spaces is tracked by optical sensors that determine if a space is free [3]. This way is good but it requires a lot of sensors that cost a lot of money. A different, cheaper way to track occupancy is to use the Xovis PC2R outdoor sensor [4] at the entrances of the facility. This sensor tracks the number of people coming in and leaving. That way, when combined with the initial occupancy of the facility, you can track the real-time occupancy of the parking area. By having real-time occupancy tracking, the facility management can better track if more bicycle parking spaces are needed. Sensors however come with other problems. First of all, sensors are not perfect and that will result in untrue occupancy numbers. Secondly, the Xovis sensor only gives trajectory data that has to be interpreted to gain an occupancy number. This interpretation is vital because some trajectories don't involve bicycles and would therefore not count towards the occupancy while they do show up on the trajectory data. These trajectories therefore need to be filtered out.

1.2. Research Method

This thesis focuses on finding differences in the data from the sensor when looking into different modes of transport. The occupancy of a facility is learned by counting all of the trajectories that enter or leave with a bicycle. Therefore all of the modes of transport that contain a bike need to be counted while all of the ones that don't, need to be filtered out. The research is done by gathering manual data that is then compared to the sensor data. The sensor data is also analysed. Both are done to find out whether certain modes lead to miscounting errors and to find out whether modes of transport can be distinguished by speed and position.

The research question for this thesis is: What is the impact of the mode of transport on the data from the Xovis PC2R Outdoor sensor at the parking facility by Industrial Engineering?

To answer the main research question a couple of things need to be known. First of all, when the sensor generates errors needs to be found. Errors will happen at some point and they will result in faulty occupancy numbers. Afterwards, the sensor data needs to be looked at to determine if the modes of transport resulting in an error can be found inside the data. The following subquestions have been devised to answer these questions.

1. What modes of transport result in error when interpreting the data from the Xovis PC2R outdoor sensor?
2. What is the correlation between average speed and average x-position?
3. What is the difference between different modes of transport when analysing average speed gathered from the Xovis PC2R outdoor sensor?
4. What is the difference between different modes of transport when analysing average x-position gathered from the Xovis PC2R outdoor sensor?

The first subquestion is needed to find out what modes of transport result in errors and therefore need to be filtered out. The second subquestion is used to find the correlation between speed and x-position to know if conclusions can be made separately on these parameters. The last two subquestions focus on finding out whether speed and x-position can be used to distinguish between modes of transport.

1.3. Research relevance

With the outcome of this research, different modes of transport can be distinguished from each other when interpreting the data. When combined with the knowledge of what modes of transport result in miscounts, the occupancy of a bicycle facility can be determined using the Xovis PC2R outdoor sensor. This would mean that only one sensor per entrance needs to be used for a parking facility to gain knowledge on real-time occupancy. This would make maintaining and regulating these facilities would be much easier.

1.4. Thesis Structure

This thesis has the following structure. First some background information is given. Next the methodology of this paper is formulated. Here the process of the thesis is explained. The following section is the section where the results are posted. These are the results from the data collection and the analysis compared to the data collected from the sensor. The results are discussed in the next section. Here the research questions are answered and conclusions are made. Lastly future work on this topic is discussed.

2

Background Information

In this section first background on different sensor types is given. Next the workings of the Xovis PC2R outdoor sensor is explained. Then the way the sensor records data is outlined. Then the section explains what errors are and what types are researched, as well as the ways in which they can occur. Then the way that errors are specifically defined for this thesis is explained. Finally, the different modes of transport that are examined in this research are outlined.

2.1. Sensor types

There are many different types of sensor that can be used to track occupancy [5][6]. These sensors include:

- Load sensors
Load sensors sense changes in pressure due to added weight on top of the sensor. When something moves over the sensor, it would notice the change in weight and track that.
- Photoelectric sensors
Photo-optic sensors are video based and they can detect objects via optical properties by transmitting light and receiving the reflected light.
- Vision sensors
Vision sensors work by applying image processing to captured images. These sensors can calculate certain characteristics from the images such as: area, length and position.
- Radar based sensors
Radar based sensors work via transmitting electromagnetic waves and receiving the reflected signal back. Using this the sensor can detect the distance of the object
- Proximity sensors
Proximity sensors can detect if an object is near the sensor. They do this by detecting changes in its electromagnetic field.

In this research the Xovis PC2R outdoor sensor is used. This is a video based sensor that used 3D stereo tracking to gain information on entities.

2.2. How does the Xovis PC2R outdoor sensor work?

The Xovis PC2R outdoor sensor uses 3D stereo tracking to locate objects. Stereo vision works by perceiving the depths of points on an object in 3D gathered from two views from two different cameras [7]. The Xovis PC2R has two cameras and it records images every 0.25 seconds. With this information trajectories of everything that passes through the sensor range can be determined. This can include anything from people on bikes to birds flying by. Because the sensor tracks everything, it is hard to distinguish when the facility is used by a person using a bicycle.

2.3. Sensor location

The Xovis PC2R outdoor sensor is located in the basement of the faculty of industrial engineering at the TU Delft. The entrance is at the north side of the building, where a ramp leads down to an entrance on the right as can be seen in Figure 2.1a. The entrance door requires a keycard to enter and the door is not big enough for two people to go through at once. The sensor is located on the inside of the building, right above the door slightly off the center. For the sensor the positive y is on the outside of the building and the positive x is to the north side of the building. This and the trajectory of the users can be seen in figure 2.1b.

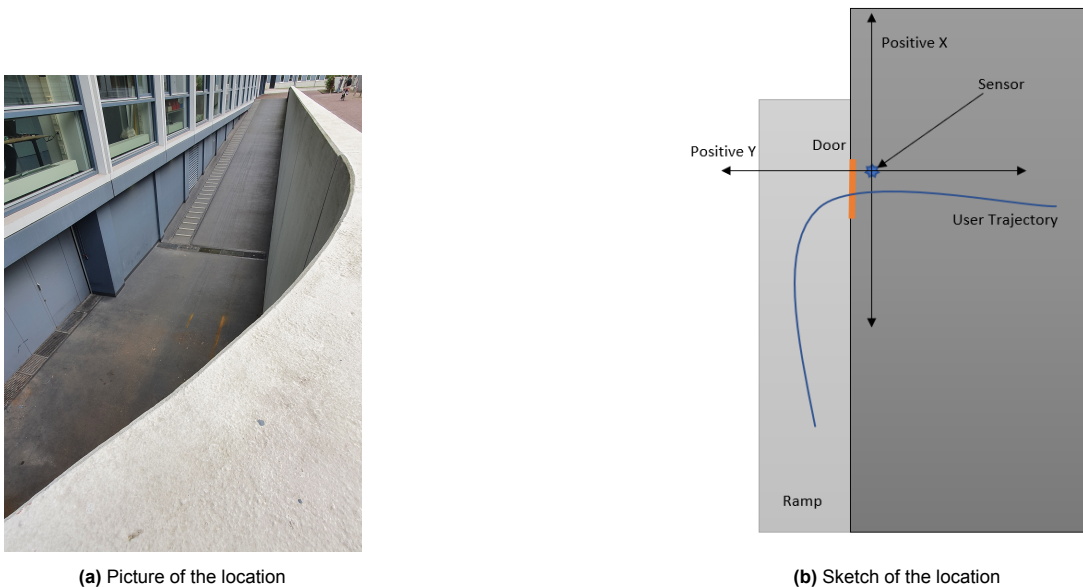


Figure 2.1: Sensor location

2.4. How is the sensor data structured?

The sensor data is given in a JSON file for every 30 seconds. In this file every 0.25 seconds, if an object is registered, the time, x- and y locations are given. The object is given an id and for every occurrence of this object the time, x- and y-locations are noted under this id. The time is given as an epoch timestamp. An example file can be seen in Appendix A. From this data the trajectory of the entities can be determined as well as the average speed of the trajectory.

2.5. What is an error?

From Merriam-Webster an error is defined as: 'an act involving an unintentional deviation from truth or accuracy'[8]. These deviations can occur in two different ways: random error and systematic error [9]. Random errors happen by chance and therefore are very hard to locate. Scientists get around random error by measuring multiple times and taking the average. Systematic errors are errors that are consistently made and occur in the same circumstances. This research will focus on systematic errors that occur due to limitations of the Xovis PC2R outdoor sensor.

2.6. How are errors defined for this thesis?

There are two main types of systematic errors that can occur. Firstly errors occur when the sensor tracks anything that is not a bicycle. This could be anything from pedestrians to someone on a skateboard. Any case in which the sensor registers a trajectory for something that is not a bicycle is an error. Secondly the opposite case would be that the sensor misses a bicycle passing through the sensor range. This could be the case when multiple bicycles come through at the same time.

2.7. Modes of transport

These are many different modes of transport that be used when entering a bicycle parking area. These include but are not limited to:

- On foot
- Bicycles
- Scooters
- E-bikes
- Mopeds
- Skateboards

In this specific research however, the number of different occurring modes of transport is limited due to the location and its users because the location is only used by faculty members with keycard access. Among the users there were no modes of transport besides walking and cycling. Therefore this research will focus only on the pedestrians and cyclists combined with people who walk with their bicycle. While the latter is not a mode of transport, it is interesting to research because it is a very common occurrence for this location.

3

Methodology

In this chapter the methodology for this paper will be outlined. Here is explained how the data collection is done and how the data gathered is analysed and compared to data from the sensor.

3.1. Objectives and Hypotheses

The objective of this research is to find out how the Xovis PC2R Outdoor sensor tracks the three different modes of transport: walking, cycling and walking with a bicycle. First the goal is to find out what modes of transport are traced and result in error. And the second goal is to find ways to distinguish between modes of transport using the sensor data. In this research what modes of transport are traced is done via comparing manual collected data to data from the sensor. To find ways of distinguishing between different modes of transport, analysis on the data is done by comparing different characteristics of different modes of transport. First the average speed of the different modes of transport are compared to each other and next the average x-position of the different modes of transport are compared. These methods are explained in more detail in the following sections.

There are three hypotheses that are made based on this approach.

1. Pedestrians without bicycles result in error
2. Cyclist have higher average speed than other modes
3. Pedestrians with bicycles have a higher average x-position

If the sensor works as intended, it should trace everyone that comes through the sensor range. Therefore the pedestrians that are traced result in errors as explained in section 2.6. On average cyclists have much higher speeds than the other two modes of transport. Even though they would have to stop to open the door with their keycard, their acceleration is also a lot higher than those who walk. Therefore the expectation is that the average speed for cyclists is higher than for the other two modes. Finally for the average x-position, it is assumed that the sensor tracks the person and not the bicycle. When someone walks next to their bike, their position would be slightly more towards the left for most people when going through the door to make room for the bicycle. These hypotheses are tested by using the methods explained in the following sections.

3.2. Manual data collection

The manual collected data is done to get a dataset to compare to the sensor data. The goal of the comparison is to learn what situations result in error when tracking the real-time occupancy. To compare the datasets the following characteristics for all situations are noted: Time of entry, incoming or outgoing and mode of transport. These were noted down on a piece of paper that can be seen in Appendix B. The data collecting is done in eight sessions of 15 minutes listed in Table 3.1. These sessions were done at periods of time when the facility was busiest to get as many entities as possible. The sessions are split up into sections of 15 minutes to have equal lengths for all sessions. The goal for total amount of entries was at least 100 because that is a large enough sample size to draw conclusions [10].

Table 3.1: Schedule for gathering data

Date	Time
04/10/2022	8:30-8:45
04/10/2022	8:45-9:00
04/10/2022	15:30-15:45
04/10/2022	17:30-17:45
07/10/2022	8:20-8:35
07/10/2022	8:35-8:50
07/10/2022	8:50-9:05
11/10/2022	8:40-8:55

For every entry a mark was place in the occurring minute row and corresponding column and the mode of transport was also noted down, except for the first two sessions when the methodology was originally different, here the modes of transport are listed as unknown. The unknown modes of transport do not include pedestrians as they were noted down correctly. When multiple entries occur in a single minute, the mode of transport is listed in occurring order. If a pedestrian entered without a bike, they were noted with a 0 because the occupancy would not change. That way errors can be found by comparing the total number of marks for a session. Finally, for every session the total number of counted bicycles is noted by adding the incoming and outgoing columns together. This is done to get a better visual representation when comparing total numbers as the expected result is that the manual data will have a smaller total number than the sensor data. An example can be seen in figure 3.1

7-10-2022	Incoming	Outgoing	Notes
08:35	1		walking bike
08:36			
08:37	1		cycling
08:38	1		cycling
08:39	2		walking bike, big bike
08:40	1		cycling
08:41	2		cycling, walking bike
08:42			
08:43	1		walking bike
08:44	1		walking bike
08:45	1		walking, walking bike
08:46			
08:47			
08:48	1		walking bike
08:49	1		walking bike
Total	13	0	

Figure 3.1: Manual data example

3.3. Sensor data collection

The sensor data is gathered in a very similar manner as the manual data. As explained in chapter 2, the sensor data consists of ids with timestamps, x-locations and y-locations. For the 15 minute sessions, there are about 30 files for each session to check. Sometimes there was one extra because of slight delays. Every file in the timeframe is checked and every id is noted down on the same sheet used for the manual data, this time without the mode of transport. An entry is considered incoming when the y-locations go from positive to negative and outgoing if the reverse is true. The timestamp is checked to determine the occurring minute.

3.4. Data comparison

The two datasets are compared to each other by comparing the total counts for all sessions in a bar-graph. Then every single entry is specifically looked at to determine if that entry is an error. Finally, the modes of transport that resulted in errors are listed in a graph with the percentage of errors for that mode of transport.

3.5. Data analysis

For all the trajectories in the sensor data, the average x-position and the average speed are calculated. The average x-position is calculated by adding all of the x-positions per trajectory and then divided by the number of x-positions seen in formula 3.1.

$$\frac{\sum x - positions}{\#x - positions} \quad (3.1)$$

Speed is calculated by taking the first and last y-position and dividing them by the number of timestamps times 0.25 because that is the time between timestamps. This number is then converted to kilometers per hour. The equation is seen in formula

$$\frac{|first - y - position| + |last - y - position|}{\#timestamps * 0.25} * \frac{3.6}{1000} \quad (3.2)$$

These two parameters are calculated to test the second and third hypotheses mentioned at the beginning of this chapter.

To make any conclusions about speed and x-position however, first it needs to be known if these are correlated in any way. If they are correlated the conclusion has to take that into account. If they are not correlated, then they are independent from each other and conclusions can be made separately from each other. Therefore a scatterplot is made by plotting the speed and x-position in the same plot to find the correlation between these two parameters. If the two parameters form any pattern in the plot, then they are correlated. If they don't, they they are not correlated.

After the correlation has been analysed, boxplots are made for the two attributes based on different situation types. These show clearly whether the different modes of transport have different values for x-position and speed.

4

Results

In this chapter the results of the research are posted. These include the number of occurring errors and the analyses of the two parameters.

4.1. Occurring errors

In Table 4.1 the incoming and outgoing bicycles for every session can be seen. The people walking without a bike are not counted or mentioned in this Table. In table 4.2 the counts from the sensor data are noted. These are all the traces found in the JSON files.

Table 4.1: Incoming and outgoing from manual data

Session data and time	Incoming	Outgoing	Walking
4/10/2022 8:30-8:45	15	0	1
4/10/2022 8:45-9:00	15	0	2
4/10/2022 17:15-17:30	0	15	1
4/10/2022 17:30-17:45	0	12	0
7/10/2022 8:20-8:35	5	0	1
7/10/2022 8:35-8:50	13	0	1
7/10/2022 8:50-9:05	7	0	1
11/10/2022 8:40-8:55	16	0	3

Table 4.2: Incoming and outgoing from sensor data

Session data and time	Incoming	Outgoing
4/10/2022 8:30-8:45	16	0
4/10/2022 8:45-9:00	17	0
4/10/2022 17:15-17:30	1	16
4/10/2022 17:30-17:45	0	12
7/10/2022 8:20-8:35	6	0
7/10/2022 8:35-8:50	14	0
7/10/2022 8:50-9:05	7	1
11/10/2022 8:40-8:55	17	1

In figure 4.1 the total counts for both the manually collected data and the sensor data can be seen. In the figure all of the sensor total are either equal or higher than the totals for the manual data.

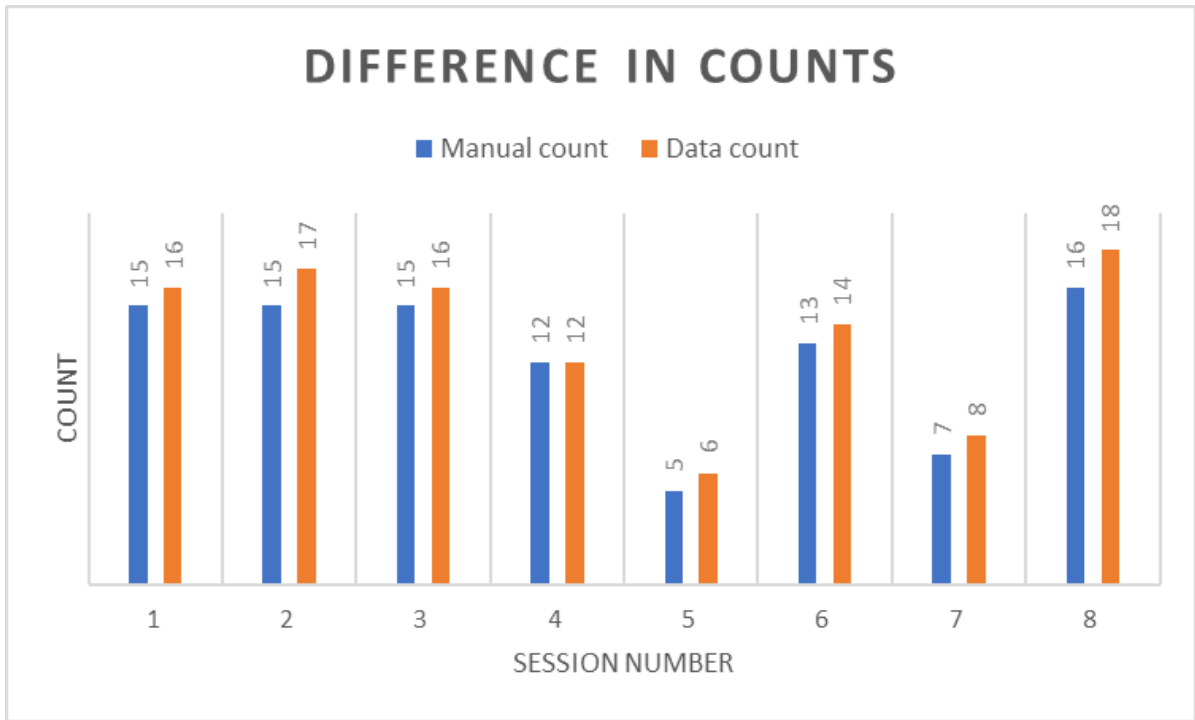


Figure 4.1: Counts

Looking into where the differences come from, all of the differences occur when someone walks in without a bike. In table 4.3 the number of occurring modes of transport are listed along with the number of errors and the percentage of errors

Table 4.3: Modes of transport with errors

Situation	Number of occurrences	Number of errors	Percentage of errors
Cycling	26	0	0%
Walking	9	9	100%
Walking with bike	50	0	0%
Unknown	22	0	0%

4.2. Data analysis

For the analysis of the data the unknown modes of transport are not used because they are unknown and therefore not useful in these analyses. Firstly, it is determined if the average x-position and average speed are correlated in any way. Next the two different parameters are analysed for different situation types. The full processed data file can be found in Appendix D.

4.2.1. Correlation

To find out whether speed and x-position are correlated, a scatterplot is made. This scatterplot can be seen in Figure 4.2. In this figure it can be seen that there is no correlation between average x-position and average speed. Because these two parameters are not correlated, conclusions can be made independently for each parameter.

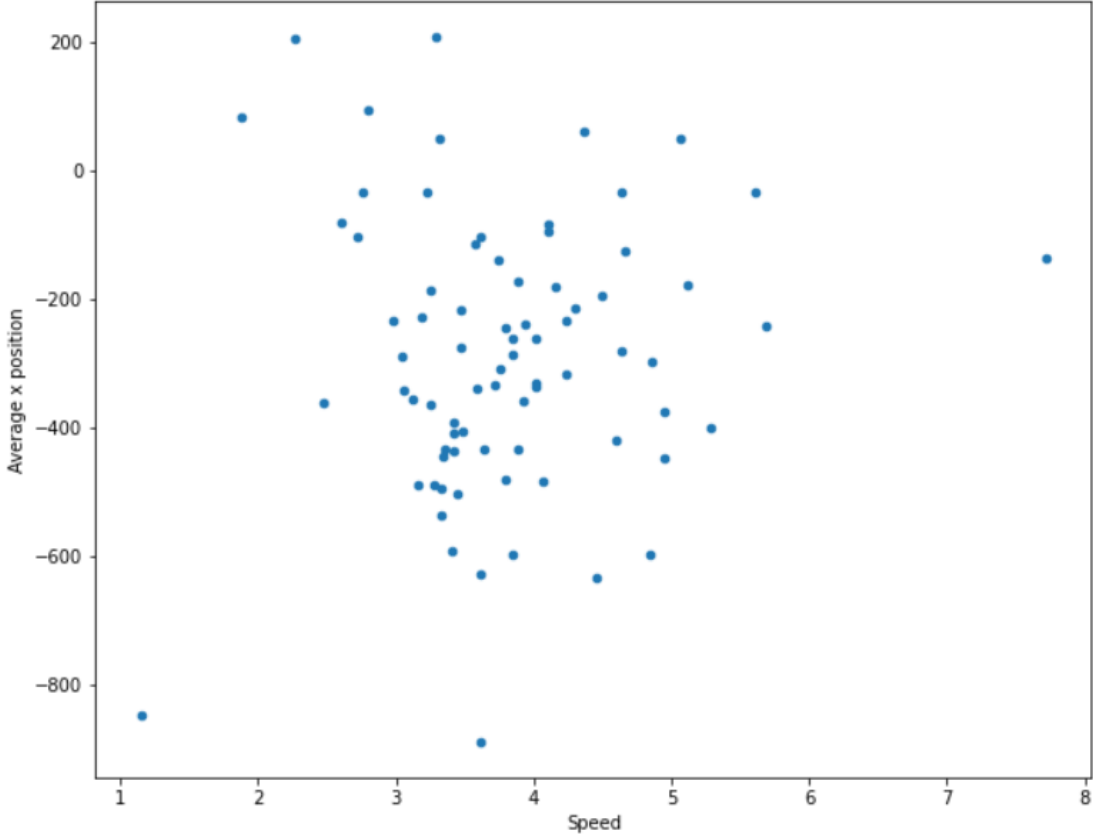


Figure 4.2: Scatterplot of x-position compared with speed

4.2.2. Average Speed

Analysing the average speed gives insight into whether certain modes of transport lead to different speeds of users. In Figure 4.3 the boxplot for the average speed is shown and in Table 4.4 the means and standard deviations are given. Speed is given in kilometers per hour. In these figures it can be seen that the average speed of cyclists is higher than the other two situation types. Most of the cyclist have a speed that is higher than 4 km/h while the other situation types have most or their occurrences below 4 km/h. 4 km/h would therefore be a good starting point to filter out certain traces when trying to determine occupancy. While this is not perfect as there are some outliers in all other types, most of the trajectories above 4 km/h would be cyclist that count towards the occupancy number.

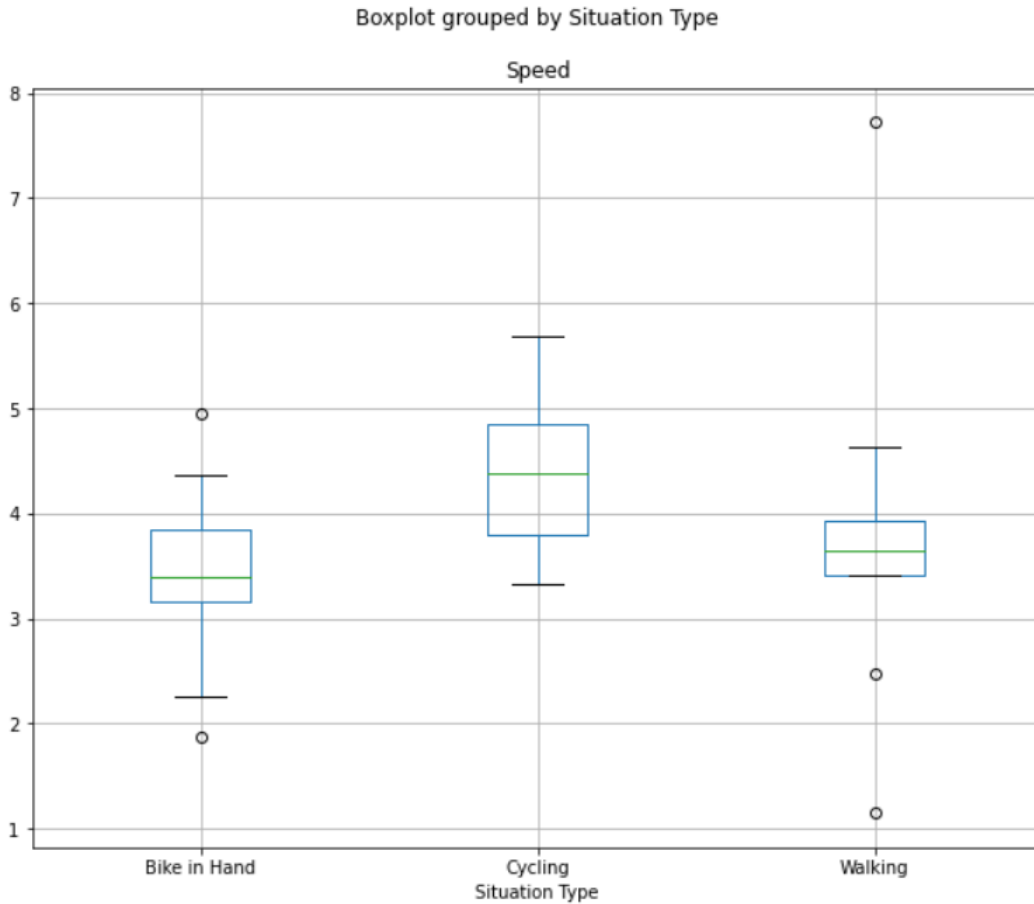


Figure 4.3: Boxplot of average speed

Table 4.4: Means and standard deviations for average speed

Situation type	Mean	Standard Deviation
Cycling	4.38	0.68
Walking	3.82	1.77
Walking with bike	3.43	0.57

4.2.3. Average x-position

In Figure 4.4 a boxplot for the three different modes of transport is shown and in table 4.5 the means and standard deviations are noted. In these it can be seen that the means for cycling and walking with a bicycle have a very similar mean while walking results in a different average x-position, more towards the south of the building where the hinges of the door are. People walking have a mean x-position of -487 which is about 200 of the other 2 modes of transport. The standard deviation however is large which means that there is a lot of variance in the data for people walking. This makes drawing conclusions more difficult.

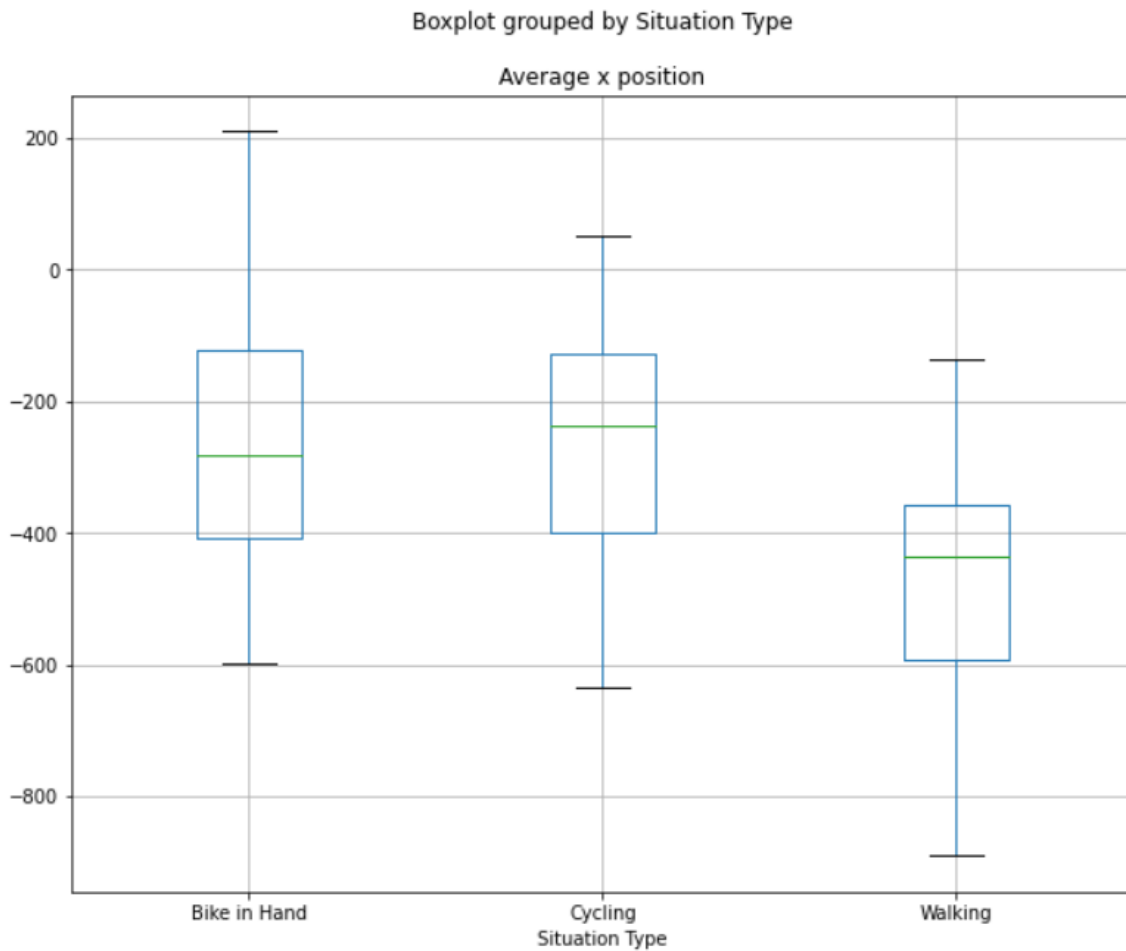


Figure 4.4: Boxplot of average x-position

Table 4.5: Means and standard deviations of average x-position

Situation type	Mean	Standard Deviation
Cycling	-274	188
Walking	-487	250
Walking with bike	-254	204

5

Conclusion

In this section the conclusion of the thesis is made, all of the subquestions are answered and the main research question is answered.

For this research three hypotheses were made based on the subquestions formulated in the introduction. These were:

1. Pedestrians without bicycles result in error
2. Cyclist have higher average speed than other modes
3. Pedestrians with bicycles have a higher average x-position

The first hypotheses is correct. All of the people walking through were registered by the sensor and therefore result in error. No other modes of transport yielded any errors. It can be concluded that the sensor works very well as all of the noted users found during the manual data collection, were identified by the sensor.

The second hypotheses is also correct. The average speed of cyclist is about 4.4 while the other modes of transport have average speeds at 3.8 for walking and 3.4 for walking with a bike. Even though the entrance requires a keycard to be scanned, and therefore the cyclist must stop, their speed is still higher due to their higher acceleration. It is noted that there was one outlier for walking that was way higher than the average at around 7.5. Therefore it can be concluded that the average speeds for walking and walking with a bicycle are similar while cyclists have higher average speed. Cyclists can therefore be separated by average speed.

The final hypotheses is incorrect. The assumption was that the sensor would register the person with the bike and not the bike itself. This is not the case as can be seen in the results in section 4.2.3. However the pedestrians do have a different average x-position than the other modes of transport. The pedestrians walk more towards the side of the hinges. One explanation would be that most of the pedestrians were entering the facility and people tend to walk towards the right. The pedestrians would go toward the right sooner than the other modes due to them not having a bike. It has to be noted however that the variance for all three modes of transport is very high and more research needs to be done.

A test was done to find out whether the found means could be used to filter out the pedestrians. The results of this however were not good enough to get an occupancy number that is closer to the true number. The test resulted in 18 pedestrians filtered out. There were originally 9 pedestrians so the occupancy would go from +9 to -9 from the true number. More research needs to be done to gain more insight on numbers to use for filtering.

The main research question was: What is the impact of the mode of transport on the data from the Xovis PC2R Outdoor sensor at the parking facility by Industrial Engineering?

The impact of different modes of transport on the data can be seen through the different speeds and x-positions when reading the data. These can be used to differentiate the modes of transport. It was also found that pedestrians are the mode of transport that needs to be filtered out to find the occupancy. It was concluded that the sensor is very good because it registered every single person that entered. Finally the results of the average speed and x-position were distinguishable but they were not different enough to properly use to filter out the pedestrians.

6

Future Research

In this section, future research for this topic is discussed.

For this research topic there is a lot of further research that can be done. First of all, the current research could be expanded with a lot more data points to gain further knowledge into how to filter the data to remove trajectories that lead to errors. In the current research the number of people walking was very limited which lead to an unsatisfactory conclusion. with more data points, the conclusion made could have been expanded upon to find clearer differences between modes of transport.

Furthermore, the number of unique circumstances in this thesis was limited due to the placement of the sensor and the entrance of the parking facility. another way to improve upon this research, is to find a location with the same sensor where more situations can occur. The parking facility at IO has a door that is impossible to enter with two people at the same time. Therefore any location that allows for two or more people on bikes to enter at the same time will vastly expand the number of situations that can occur. The current location also is not very busy, so the sensor is not stress tested on a lot of entities at the same time. The location is also limiting in the way of the entrants needing to provide a keycard. This limits the speed of the entries. If the speed is higher, modes of transport are easier to distinguish.

Both busier times and multiple entries would lead to more interesting and difficult situations for the sensor to track and would therefore lead to more interesting conclusions. A busier location would also result in more trajectories that would lead to more accurate readings on speed and positioning.

Finally, the main goal on this topic would be to use the gained knowledge in a practical situation. For that research needs to be done on how to implement the gained knowledge on gathered data and to write a code or script to process the data in a way to eliminate as many errors as possible so that occupancy can be tracked real-time. This could also include having a second sensor of another type to distinguish between circumstances.

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Appendix A: JSON data example

```
{
  "TUD_SPX14": {
    "1665471329": {
      "traces": {
        "797": {
          "timestamp": [
            1665471284,
            1665471284,
            1665471284,
            1665471285,
            1665471285,
            1665471285,
            1665471285,
            1665471285,
            1665471286,
            1665471286
          ],
          "x": [
            -109.48174594073043,
            -92.68484551149022,
            -126.35615325239814,
            -193.86808111378213,
            -278.5634667485319,
            -312.6397862531255,
            -329.84811949462096,
            -398.1233274353538,
            -517.9933638044324
          ],
          "y": [
            1172.6043653653978,
            870.4306076592749,
            551.1942059633416,
            264.88163803476215,
            -73.19164903499899,
            -344.5187125952062,
            -650.4484849363822,
            -940.5692141522981,
            -1335.0177280704988
          ],
          "id": 797
        }
      }
    }
  }
}
```

Figure 1: JSON data sample file

Appendix B: Manual data gathering sheet

Minute Start Time: End Time	Incoming	Outgoing	Notes
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
13			
14			
15			

Figure 2: Data gathering sheet

Appendix C: Data from trajectory counts

4-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
08:30					
08:31					
08:32	1		1		
08:33	3		4		one incoming walking, last big bike
08:34	1		1		
08:35	1		1		
08:36					
08:37					
08:38	2		2		
08:39	2		2		
08:40	1		1		walking bike
08:41	1		1		cycling
08:42	1		1		weird bike
08:43					
08:44	2		2		1st walking bike
Total	15	0	16	0	
		Count	Data count	Difference	
		15	16	-1	

Figure 3: session 1

4-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
08:45	3		1		
08:46	2		4		
08:47	2		2		
08:48					
08:49	2		2		
08:50	1		3		2 walking before and after
08:51	1		1		
08:52					
08:53	2		2		second walking bike
08:54					
08:55					
08:56	1		1		walking bike
08:57					
00:00	1		1		walking bike
08:59					
Total	15	0	17	0	
Count	Data count	Difference			
15	17	-2			

Figure 4: session 2

4-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
17:15					
17:16		2			2 both walking bike
17:17		1			1 cycling
17:18		2			2 1st walking bike, cycling
17:19		1			1 cycling
17:20		1			1 big bike
17:21	0	1	1		1 incoming walking, cycling
17:22		2			3 walking, door struggle
17:23		1			1 walking bike
17:24		1			1 cycling
17:25					
17:26		1			1 big bike
17:27		1			1 cycling
17:28					
17:29		1			1 cycling
Total	0	15	1	16	
Count	Data count	Difference			
-15	-15	0			

Figure 5: session 3

4-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
17:30		4		4	cycling, cycling, walking bike, cycling
17:31					
17:32		1		1	cycling
17:33					
17:34					
17:35					
17:36		3		2	walking bike, door struggle, cycling
17:37				1	
17:38					
17:39		1		1	walking bike
17:40		1		1	walking bike
17:41					
17:42					
17:43		2		2	both walking bike
17:44					
Total	0	12	0	12	
Count	Data count	Difference			
-12	-12	0			

Figure 6: session 4

7-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
08:20					
08:21					
08:22	1		1		walking bike
08:23					
08:24					
08:25	1		1		cycling
08:26					
08:27					
08:28	1		1		walking bike
08:29	1		1		cycling
08:30	1		1		walking bike
08:31					
08:32					
08:33	0				walking
08:34			1		
Total	5	0	6	0	
Count	Data count	Difference			
5	6	-1			

Figure 7: session 5

7-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
08:35	1		1		big bike
08:36					
08:37	1		1		cycling
08:38	1		1		cycling
08:39	2		2		walking bike, big bike
08:40	1		1		cycling
08:41	2		2		cycling, walking bike
08:42					
08:43	1		1		walking bike
08:44	1		1		walking bike
08:45	1		2		walking, walking bike
08:46					
08:47					
08:48	1		1		walking bike
08:49	1		1		walking bike
Total	13	0	14	0	
Count	Data count	Difference			
13	14	-1			

Figure 8: session 6

7-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
08:50	1	0	1	1	walking, walking bike
08:51					
08:52					
08:53	2		2		cycling x2
08:54					
08:55					
08:56					
08:57					
08:58					
08:59	1		1		walking bike
09:00	1				cycling
09:01			1		
09:02	2		2		walking bike, cycling
09:03					
09:04					
Total	7	0	7	1	
Count	Data count	Difference			
7	6	1			

Figure 9: session 7

11-10-2022	Incoming	Outgoing	Data Incoming	Data outgoing	Notes
08:40	2		2		walking bike, cycling
08:41	1		1		walking bike
08:42					
08:43	2		2		walking bike x2
08:44	1		1		walking bike
08:45	1		1		walking bike
08:46	1		1		walking bike
08:47	2		2		walking bike, cycling
08:48					
08:49	1		1		walking bike
08:50	2		3	1	3 people walking, walking bike, cycling
08:51	1		1		walking bike
08:52	1		1		walking bike
08:53					
08:54	1		1		walking bike
Total	16	0	17	1	
Count	Data count	Difference			
16	16	0			

Figure 10: session 8

Appendix D: Excel data file

Situation number	Date	Time	Session Number	In or out	Situation Type	Situation Number	Error	Sensor id	number of timestamp	Average x position	Starting y	Ending y	Speed (km/h)
1	4-10-2022	08:32	1	In	Unknown	0	No	3668	8	-118	1086	-1043	3.83
2	4-10-2022	08:33	1	In	Unknown	0	No	3669	6	-562	214	-1354	3.76
3	4-10-2022	08:33	1	In	Unknown	0	No	3670	8	-212	954	-1332	4.11
4	4-10-2022	08:33	1	In	Walking	3	Yes	3671	10	-359	1268	-1459	3.93
5	4-10-2022	08:33	1	In	Large bike	4	No	3672	8	-77	1134	-1315	4.41
6	4-10-2022	08:34	1	In	Unknown	0	No	3673	10	-401	1223	-1407	3.79
7	4-10-2022	08:35	1	In	Unknown	0	No	3674	12	-249	1305	-1487	3.35
8	4-10-2022	08:38	1	In	Unknown	0	No	3675	10	-301	1206	-1352	3.68
9	4-10-2022	08:38	1	In	Unknown	0	No	3676	10	-325	1188	-1489	3.85
10	4-10-2022	08:39	1	In	Unknown	0	No	3677	9	-431	1022	-1353	3.8
11	4-10-2022	08:39	1	In	Unknown	0	No	3678	15	-229	1341	-1657	2.88
12	4-10-2022	08:40	1	In	Bike in Hand	2	No	3679	11	-289	1054	-1267	3.04
13	4-10-2022	08:41	1	In	Cycling	1	No	3680	8	-95	1154	-1127	4.11
14	4-10-2022	08:42	1	In	Large bike	4	No	3681	5	-489	-5	-1199	3.47
15	4-10-2022	08:44	1	In	Bike in Hand	2	No	3682	9	-484	1172	-1370	4.07
16	4-10-2022	08:44	1	In	Cycling	1	No	3683	6	-126	885	-1058	4.66
17	4-10-2022	08:45	2	In	Unknown	0	No	3684	10	-578	1022	-1495	3.62
18	4-10-2022	08:45	2	In	Unknown	0	No	3685	10	-172	1171	-1555	3.93
19	4-10-2022	08:45	2	In	Unknown	0	No	3686	8	-318	1123	-1249	4.27
20	4-10-2022	08:46	2	In	Unknown	0	No	3687	12	-433	1255	-1440	3.23
21	4-10-2022	08:46	2	In	Unknown	0	No	3688	10	-565	1307	-1391	3.89
22	4-10-2022	08:47	2	In	Unknown	0	No	3689	20	-166	937	1142	1.5
23	4-10-2022	08:47	2	In	Unknown	0	No	3690	11	-402	1089	-1404	3.26
24	4-10-2022	08:49	2	In	Unknown	0	No	3691	8	-222	1019	-1146	3.9
25	4-10-2022	08:49	2	In	Unknown	0	No	3692	11	8	1234	-1620	3.74
26	4-10-2022	08:50	2	In	Walking	3	Yes	3693	10	-435	1204	-1325	3.64
27	4-10-2022	08:50	2	In	Unknown	0	No	3694	6	-160	785	-973	4.22
28	4-10-2022	08:50	2	In	Walking	3	Yes	3695	8	-281	1204	-1369	4.63
29	4-10-2022	08:51	2	In	Unknown	0	No	3696	10	-280	1205	-1265	3.56
30	4-10-2022	08:53	2	In	Cycling	1	No	3697	10	-392	972	-1404	3.42
31	4-10-2022	08:53	2	In	Bike in Hand	1	No	3698	9	-263	1005	-1400	3.85
32	4-10-2022	08:56	2	In	Bike in Hand	2	No	3699	12	-275	1324	-1570	3.47
33	4-10-2022	08:58	2	In	Bike in Hand	2	No	3700	9	-288	1156	-1250	3.85
34	4-10-2022	17:16	3	Out	Bike in Hand	2	No	3922	15	-104	-1380	1450	2.72
35	4-10-2022	17:16	3	Out	Bike in Hand	2	No	3923	10	49	-1143	1166	3.32
36	4-10-2022	17:17	3	Out	Cycling	1	No	3924	7	-34	-939	1316	4.64
37	4-10-2022	17:18	3	Out	Bike in Hand	2	No	3925	12	209	-1359	1383	3.29
38	4-10-2022	17:18	3	Out	Cycling	1	No	3926	6	-242	-1078	1287	5.68
39	4-10-2022	17:19	3	Out	Unknown	0	No	3927	6	-48	-904	985	4.53

Figure 11: excel file part 1

40	4-10-2022	17:20	3 Out	Large bike	4 No	3928	7	-209	-1197	1336	5.21
41	4-10-2022	17:21	3 In	Walking	3 Yes	3929	4	-136	-975	1169	7.72
42	4-10-2022	17:21	3 Out	Unknown	0 No	3930	7	-636	248	-1492	3.58
43	4-10-2022	17:22	3 Out	Bike in Hand	2 No	3931	13	-34	-1313	1598	3.22
44	4-10-2022	17:22	3 Out	Struggle with doo	5 No	3933	9	-42	-1040	1337	3.8
45	4-10-2022	17:23	3 Out	Bike in Hand	2 No	3934	13	-33	-1226	1268	2.76
46	4-10-2022	17:24	3 Out	Cycling	1 No	3935	8	-235	-1129	1220	4.23
47	4-10-2022	17:26	3 Out	Large bike	4 No	3936	8	42	-1124	1035	3.89
48	4-10-2022	17:27	3 Out	Cycling	1 No	3937	7	-35	-1177	1552	5.61
49	4-10-2022	17:29	3 Out	Cycling	1 No	3938	8	-299	-1130	1570	4.86
50	4-10-2022	17:30	4 Out	Cycling	1 No	3939	8	-83	-1159	1118	4.1
51	4-10-2022	17:30	4 Out	Cycling	1 No	3940	6	50	-1137	970	5.06
52	4-10-2022	17:30	4 Out	Bike in Hand	2 No	3941	9	61	-1279	1449	4.36
53	4-10-2022	17:30	4 Out	Cycling	1 No	3942	6	-401	-996	1203	5.28
54	4-10-2022	17:32	4 Out	Cycling	1 No	3943	10	-140	-1179	1419	3.74
55	4-10-2022	17:36	4 Out	Bike in Hand	2 No	3944	22	83	-1372	1500	1.88
56	4-10-2022	17:36	4 Out	Struggle with doo	5 No	3945	31	229	-1078	1136	1.03
57	4-10-2022	17:36	4 Out	Cycling	1 No	3946	8	-172	-839	1317	3.88
58	4-10-2022	17:39	4 Out	Bike in Hand	2 No	3947	15	-80	-1245	1467	2.6
59	4-10-2022	17:40	4 Out	Bike in Hand	2 No	3948	18	205	-1307	1514	2.26
60	4-10-2022	17:43	4 Out	Bike in Hand	2 No	3949	13	93	-1206	1318	2.8
61	4-10-2022	17:43	4 Out	Bike in Hand	2 No	3950	12	-234	-1217	1267	2.98
62	7-10-2022	08:22	5 In	Bike in Hand	2 No	284	11	-538	1155	-1390	3.33
63	7-10-2022	08:25	5 In	Cycling	1 No	285	9	-629	1071	-1186	3.61
64	7-10-2022	08:28	5 In	Bike in Hand	2 No	286	12	-365	1257	-1454	3.25
65	7-10-2022	08:29	5 In	Cycling	1 No	287	9	-115	935	-1297	3.57
66	7-10-2022	08:30	5 In	Bike in Hand	2 No	288	11	-503	1139	-1494	3.45
67	7-10-2022	08:33	5 In	Walking	3 Yes	289	6	-890	215	-1291	3.61
68	7-10-2022	08:35	6 In	Large bike	4 No	290	4	-650	-618	-1440	7.41
69	7-10-2022	08:37	6 In	Cycling	1 No	291	9	-634	1221	-1567	4.46
70	7-10-2022	08:38	6 In	Cycling	1 No	292	8	-215	986	-1402	4.3
71	7-10-2022	08:39	6 In	Bike in Hand	2 No	293	9	-182	1235	-1368	4.16
72	7-10-2022	08:39	6 In	Large bike	4 No	294	11	-645	1139	-1514	3.47
73	7-10-2022	08:40	6 In	Cycling	1 No	295	7	-194	885	-1300	4.49
74	7-10-2022	08:41	6 In	Cycling	1 No	296	9	-316	1121	-1523	4.23
75	7-10-2022	08:41	6 In	Bike in Hand	2 No	297	10	-356	1022	-1146	3.12
76	7-10-2022	08:43	6 In	Bike in Hand	2 No	298	10	-599	1105	-1565	3.84
77	7-10-2022	08:44	6 In	Bike in Hand	2 No	299	11	-334	1288	-1556	3.72
78	7-10-2022	08:45	6 In	Walking	3 Yes	300	6	-480	315	-1268	3.8
79	7-10-2022	08:45	6 In	Bike in Hand	2 No	301	9	-331	1122	-1386	4.01

Figure 12: excel file part 2

80	7-10-2022	08:48	6 In	Bike in Hand	2 No	302	10	-102	1018	-1487	3.61
81	7-10-2022	08:49	6 In	Bike in Hand	2 No	303	12	-407	1324	-1576	3.48
82	7-10-2022	08:50	7 Out	Walking	3 Yes	304	14	-362	-1119	1287	2.47
83	7-10-2022	08:50	7 In	Bike in Hand	2 No	305	10	-187	500	-1756	3.25
84	7-10-2022	08:53	7 In	Cycling	1 No	306	7	-178	1201	-1283	5.11
85	7-10-2022	08:53	7 In	Cycling	1 No	307	8	-377	1102	-1646	4.95
86	7-10-2022	08:59	7 In	Bike in Hand	2 No	308	10	-409	1022	-1354	3.42
87	7-10-2022	09:00	7 In	Cycling	1 No	309	7	-598	703	-1651	4.84
88	7-10-2022	09:02	7 In	Bike in Hand	2 No	310	10	-491	973	-1303	3.28
89	7-10-2022	09:02	7 In	Cycling	1 No	311	11	-438	1004	-1611	3.42
90	11-10-2022	08:40	8 In	Bike in Hand	2 No	780	9	-449	1205	-1886	4.95
91	11-10-2022	08:40	8 In	Cycling	1 No	781	4	-419	96	-1181	4.6
92	11-10-2022	08:41	8 In	Bike in Hand	2 No	782	8	-338	1087	-1147	4.02
93	11-10-2022	08:43	8 In	Bike in Hand	2 No	783	9	-229	416	-1570	3.18
94	11-10-2022	08:43	8 In	Bike in Hand	2 No	784	7	-239	584	-1332	3.94
95	11-10-2022	08:44	8 In	Bike in Hand	2 No	785	12	-444	1290	-1490	3.34
96	11-10-2022	08:45	8 In	Bike in Hand	2 No	786	11	-340	1206	-1539	3.59
97	11-10-2022	08:46	8 In	Bike in Hand	2 No	787	12	-433	1239	-1560	3.36
98	11-10-2022	08:47	8 In	Bike in Hand	2 No	788	12	-341	1088	-1457	3.05
99	11-10-2022	08:47	8 In	Cycling	1 No	789	11	-496	1186	-1359	3.33
100	11-10-2022	08:49	8 In	Bike in Hand	2 No	790	9	-217	885	-1282	3.47
101	11-10-2022	08:50	8 In	Bike in Hand	2 No	791	10	-491	754	-1439	3.16
102	11-10-2022	08:50	8 In	Walking	3 Yes	792	31	-847	-1143	1338	1.15
103	11-10-2022	08:50	8 In	Cycling	1 No	793	8	-309	600	-1488	3.76
104	11-10-2022	08:50	8 Out	Walking	3 Yes	794	12	-593	1202	-1636	3.41
105	11-10-2022	08:51	8 In	Bike in Hand	2 No	795	9	-434	1105	-1322	3.88
106	11-10-2022	08:52	8 In	Bike in Hand	2 No	796	9	-246	1239	-1128	3.79
107	11-10-2022	08:54	8 In	Bike in Hand	2 No	797	9	-261	1172	-1335	4.01

Figure 13: excel file part 3