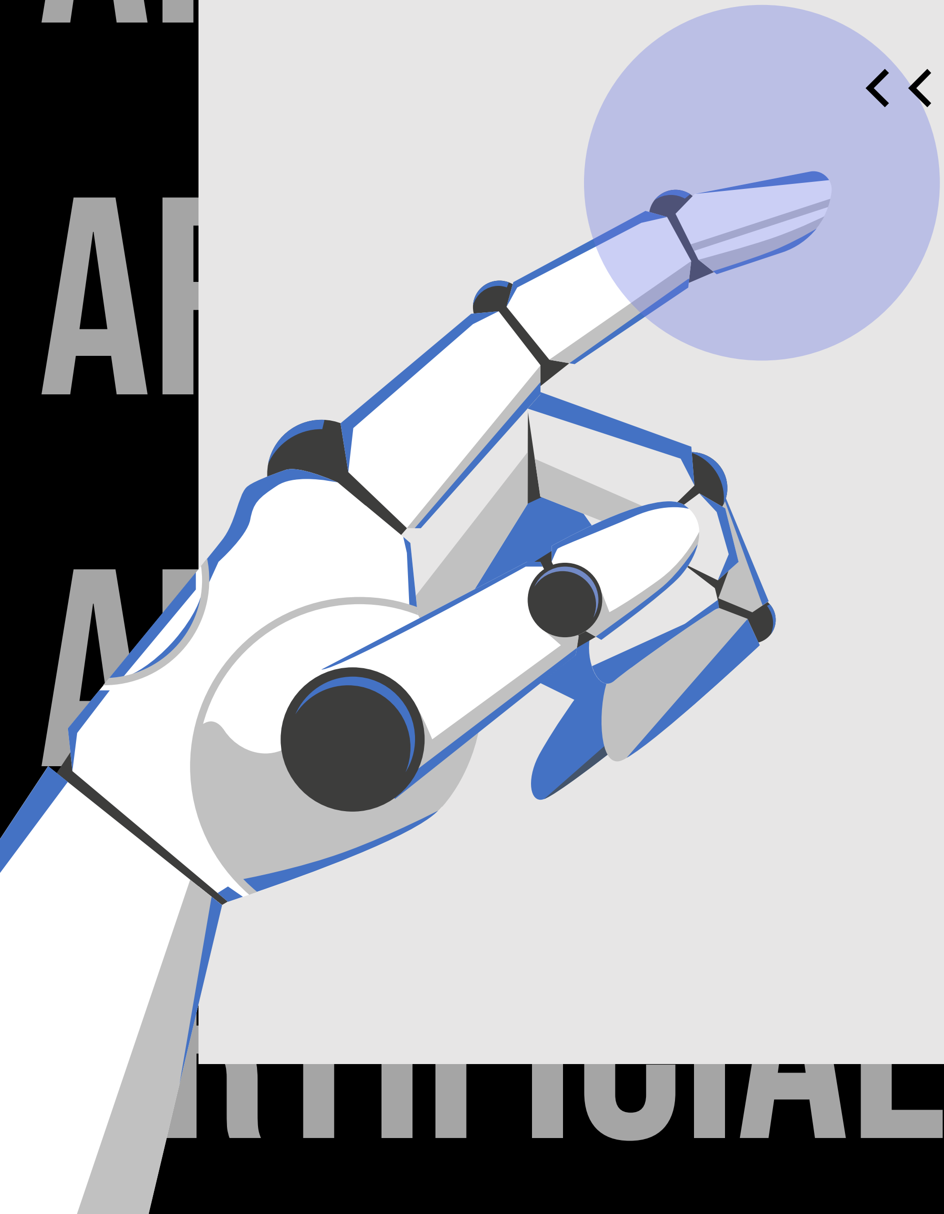
ARTIFICIAL INTELLIGENCE (AI)



A.I Project

Ventilation Group

Prof. Glauner

Objective

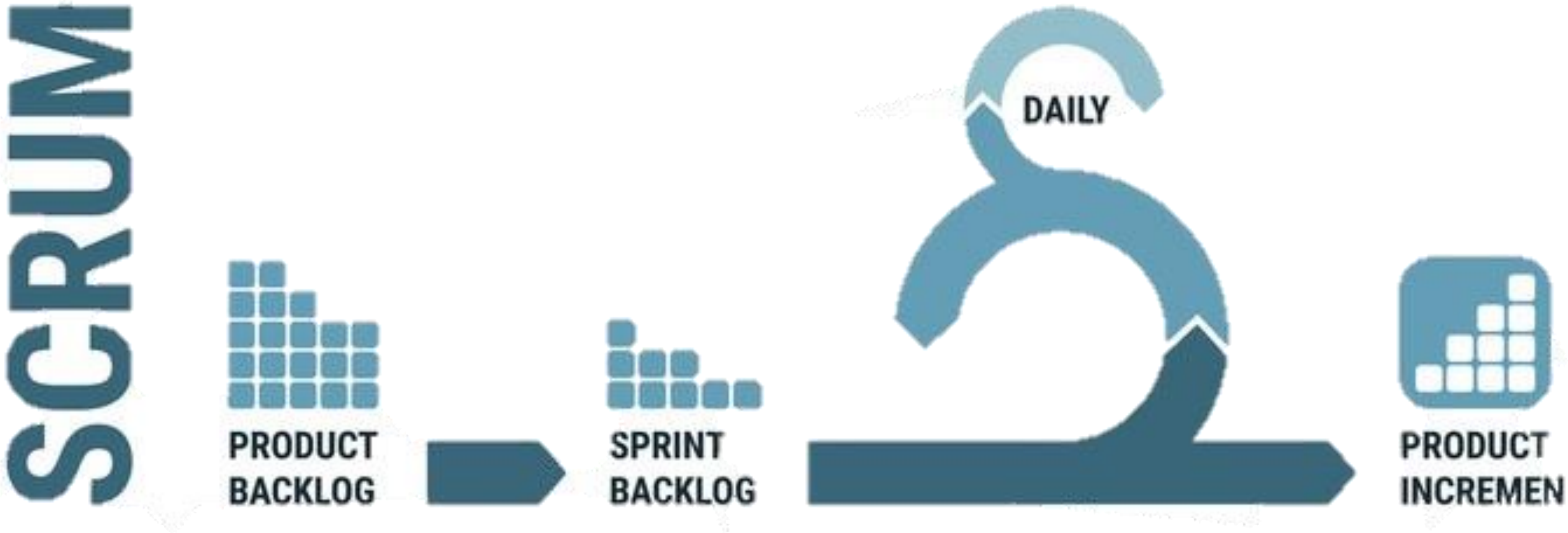
How can a longer life at home be made possible by means of technical-digital support systems?

Justification – Ventilation as a topic

The development of this work was temporarily located during the lifting of the restriction measures due to the COVID-19 epidemic. Which makes us reflect on the respiratory problems present in people and the importance of adequate ventilation at home.

Therefore, given the need to provide prevention measures against respiratory diseases in the framework of providing a better life quality to older adults it has been decided to chose the topic “ventilation and temperature

TOOLS USED


SCRUM
PRODUCT BACKLOG
SPRINT BACKLOG
DAILY
PRODUCT INCREMEN

Theoretical Framework

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this study proposes a novel DCV (demand-control ventilation) for the CAVMV (Mechanical Ventilation). Intermittent ventilation can generate dynamic thermal conditions for improved thermal comfort. Meanwhile, the intermittent ventilation can also reduce energy consumption by reducing the ventilated air volume.

Novel demand-controlled optimization of constant-air-volume mechanical ventilation for indoor air quality, durability and energy saving

There are strong associations between insufficient building ventilation and the transmission of infectious diseases such as COVID-19, influenza, measles, tuberculosis, chickenpox, smallpox, and SARS

The concentration of indoor airborne pollutants could be 2–5 times higher than outdoor airborne pollutants

Associations of bedroom temperature and ventilation with sleep quality

1. An indoor environmental quality monitoring station (SAMBA) was installed in each survey bedroom for continuous measurements of thermal and air quality parameters at 5-minute intervals for five consecutive days.

The study was conducted during summer in Sydney with a sample of 48 householders (male and female).

Subjects wore the wristband device. The calculated sleep statistics from Fitbit Charge 2 included the number of awakenings, total time asleep (min), time awake (min), time in bed (min), and total duration in each of the sleep stages; “light” , “deep”, and REM sleep.

2. Higher CO2 concentration during the night was associated with a drop in self-reported sleep quality the morning after.

3. As bedroom operative temperature increases by 1 K, the estimate of sleep efficiency and REM sleep percentage decrease

4. In this study, it was only analyzed the key thermal comfort parameters including Accepted Manuscript air temperature, radiant temperature, humidity, air velocity, along with the general ventilation index of carbon dioxide concentration.

5. Deep sleep percentage was negatively related to bedroom CO2 concentration with a 4.3% decrement for every 100 ppm increase in the overnight mean CO2 concentration.

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build a model that can be used to predict the actual ventilation effect under daily conditions by taking occupants' behaviour into consideration.

The outdoor weather data collection system refers to the obtaining of outdoor temperature, relative humidity, and wind strength data by the city meteorological department.

For real buildings, many studies have chosen indoor CO2 as an indicator of the ventilation/infiltration rate.

Neural network model using environmental parameters

IAQ sensors were installed in the bedrooms, and they measured the indoor CO2 concentration (Senseair S8, 400–10000 ppm), temperature and relative humidity every minute

The purpose of this study was to develop a model that can predict the probability of the ventilation rate being insufficient.

In this study, 24 apartments were monitored, collecting data on the nighttime indoor CO2 concentration, nighttime outdoor and indoor air temperature, nighttime outdoor relative humidity, and wind strength, together with some basic information about the apartments.

The main components of the system as used in the present study, which are the indoor air quality (IAQ) monitoring system and weather data collection system.

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Utilized five-minute interval data from a smart monitoring system that included indoor and outdoor temperature and humidity and solar radiation to predict indoor temperature using an artificial neural network approach.

One of the most important machine-learning enabled data applications for buildings is the forecasting of heating and cooling demand

Self-Learning Algorithm to Predict Indoor Temperature and Cooling Demand from Smart WiFi Thermostat in a Residential Building

What-if analysis is a data intensive simulation with the goal to inspect the behavior of a complex system under some given hypotheses called scenarios

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Modelling natural ventilation has been very complicated. It is consider a technical challenge.

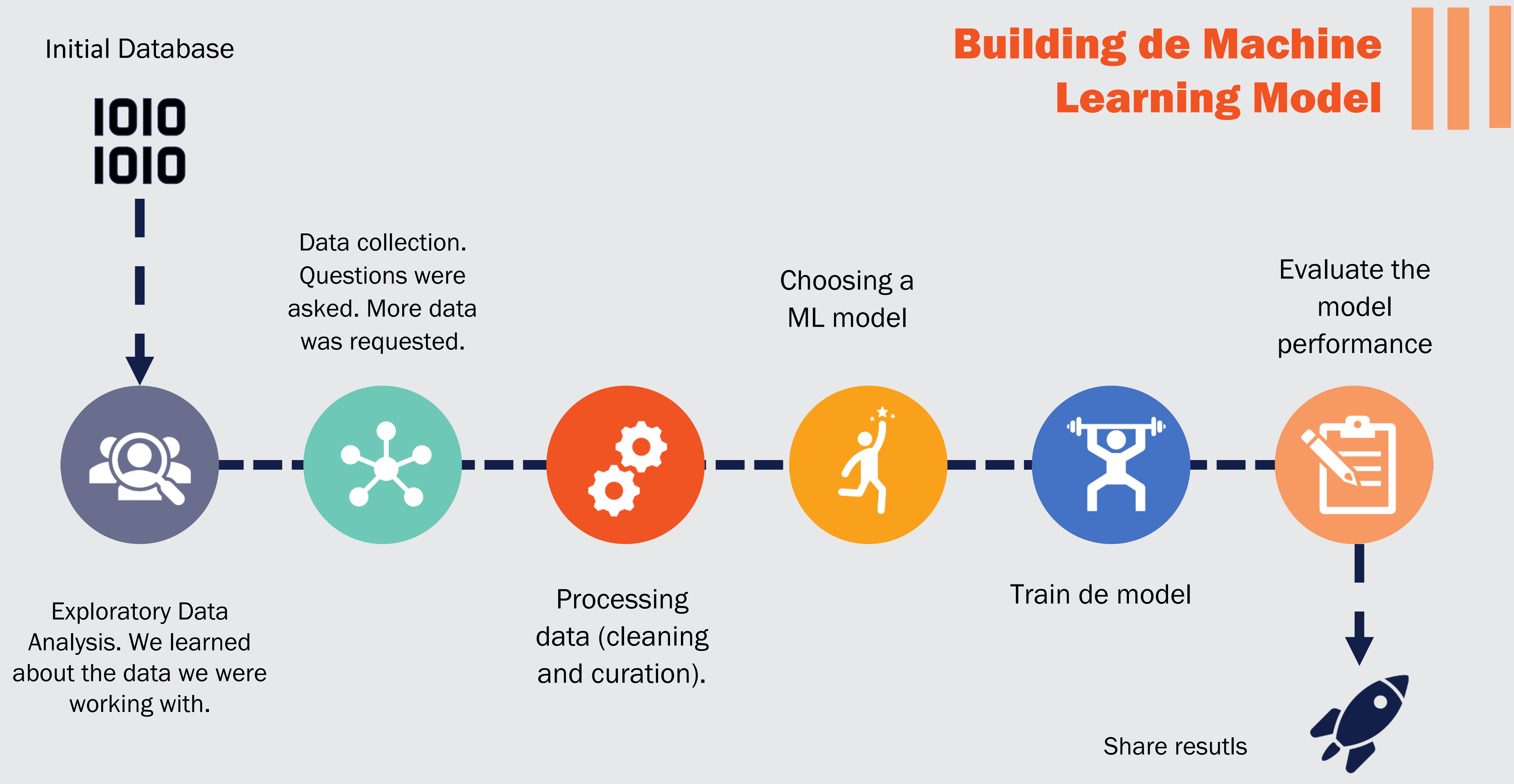
Since neural networks are purely data-driven models, the quality of data will largely determine the quality of the model. The data collected for model training should have significant size, diversity, and coverage.

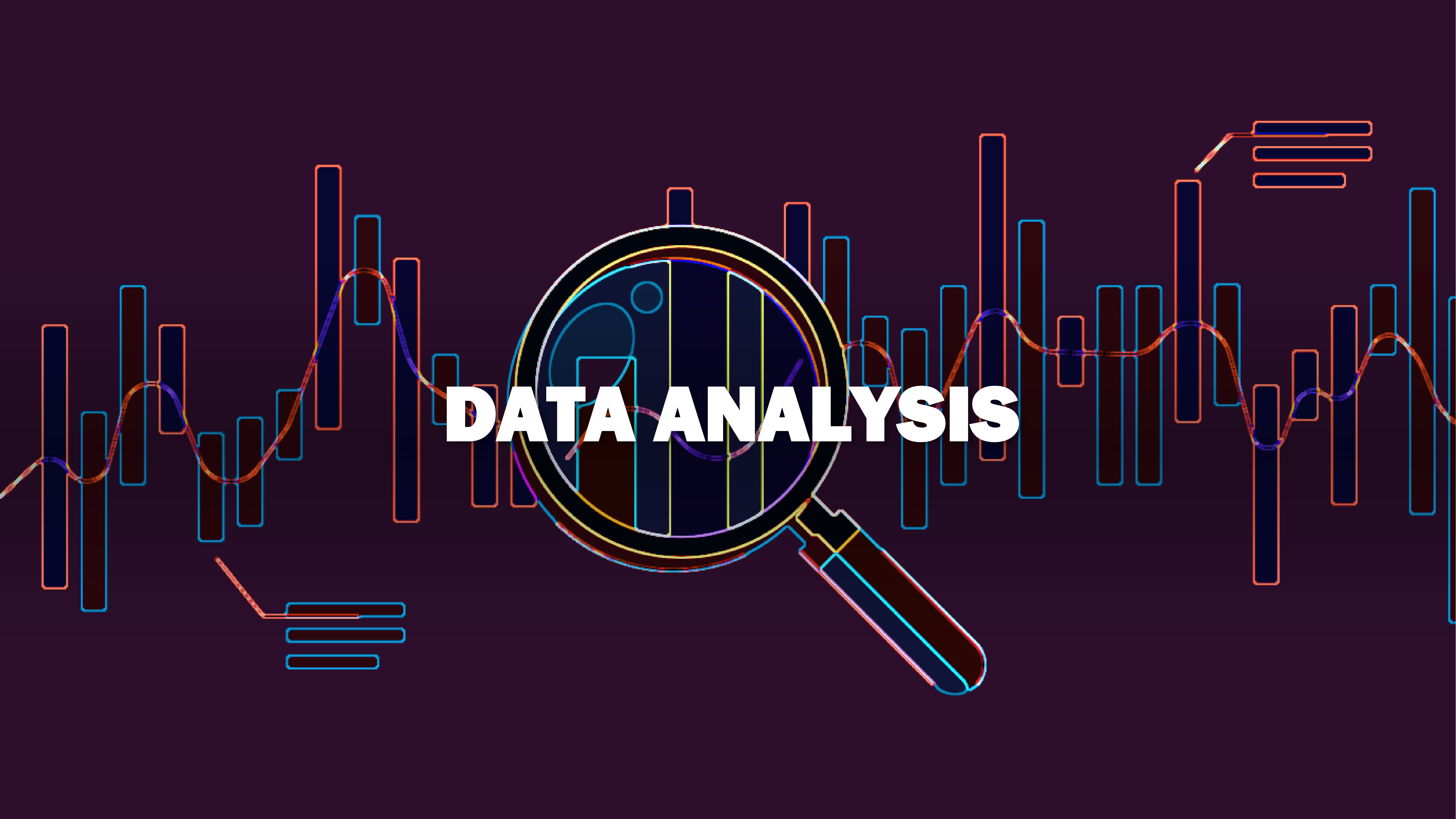
Neural network models may help in the modeling of natural ventilation

Predictive control of HVAC & Natural ventilation

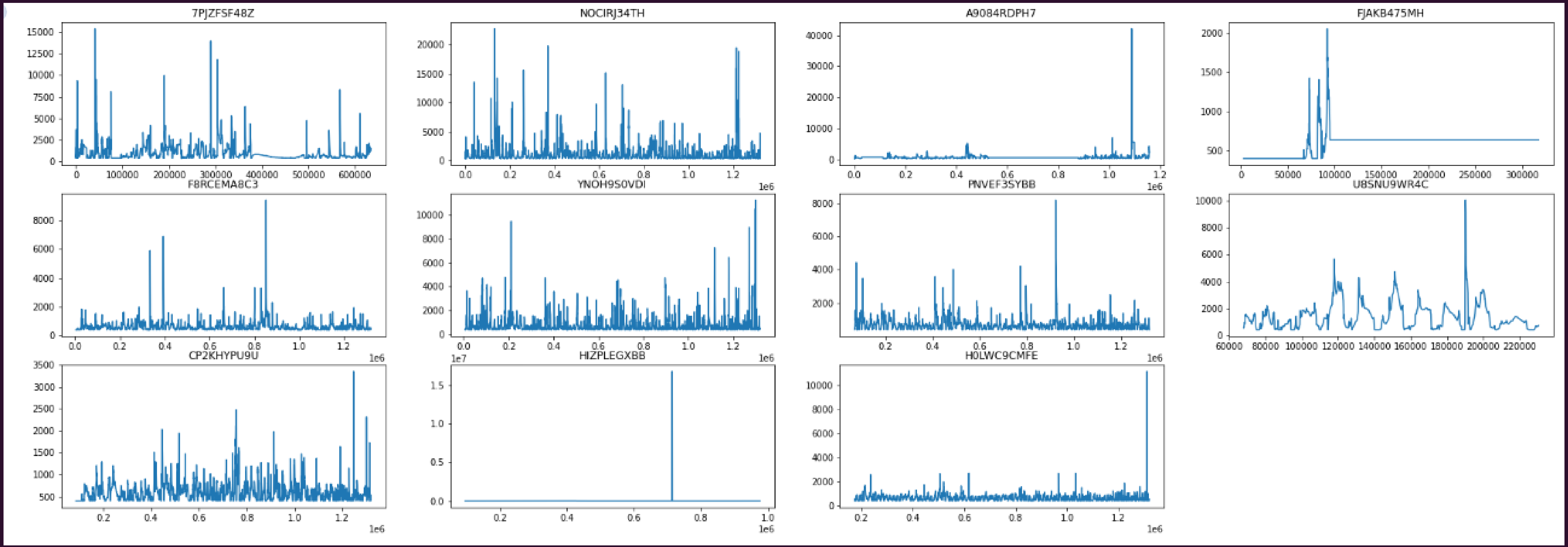
The room that was subject to the experiment is located in Beijing.

This project discusses how transfer learning can help with model creation in the context of smart-building control of HVAC and natural ventilation.

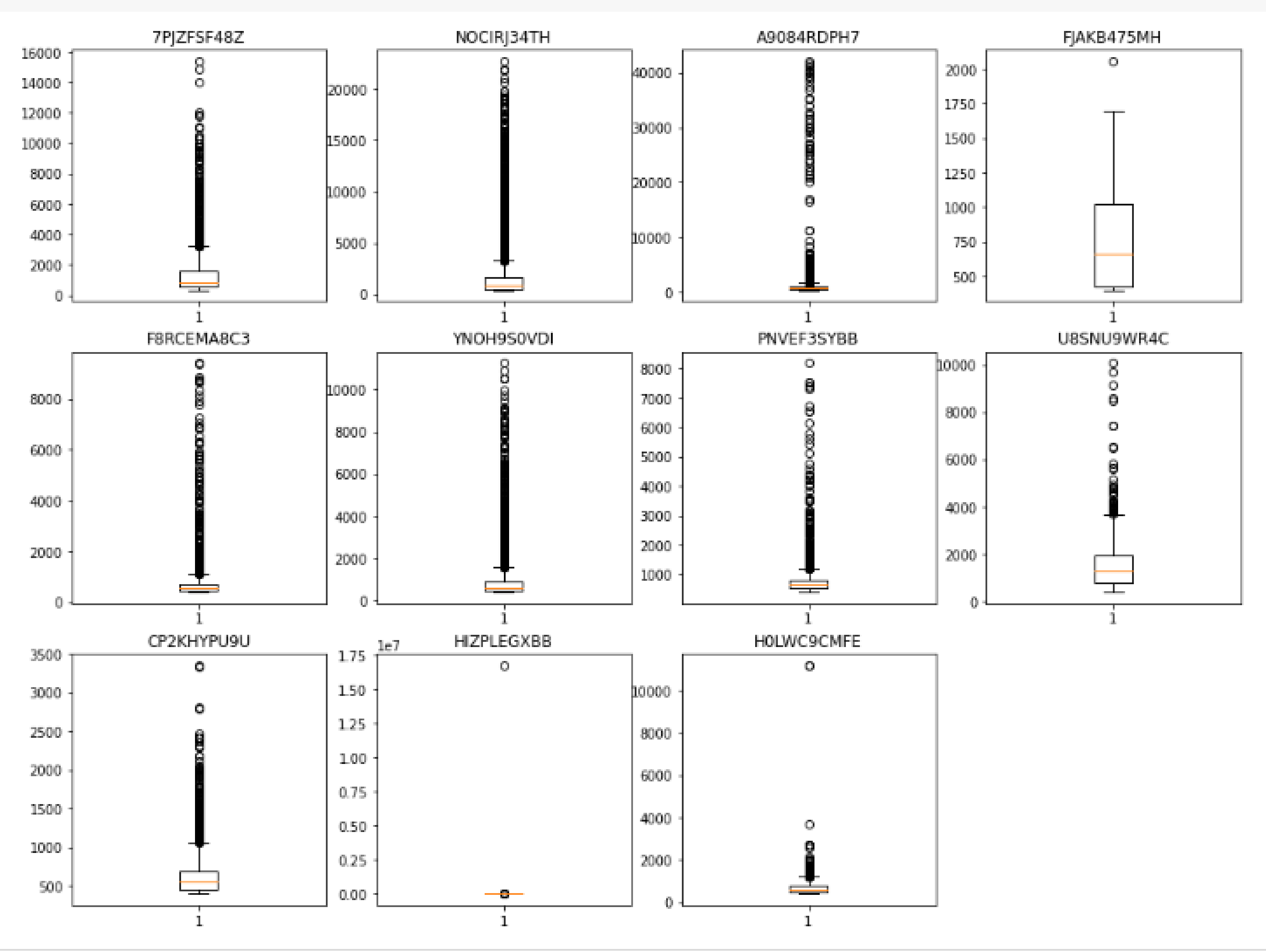

Building de Machine Learning Model
Initial Database
1010
1010
Exploratory Data Analysis. We learned about the data we were working with.
Data collection. Questions were asked. More data was requested.
Processing data (cleaning and curation).
Choosing a ML model
Train de model
Evaluate the model performance
Share resutls


DATA ANALYSIS

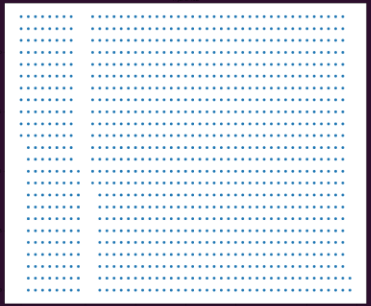
Carbon Dioxide CO2 level- timestamp vs value

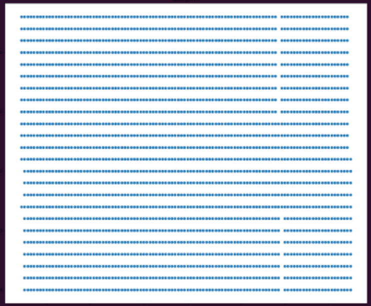


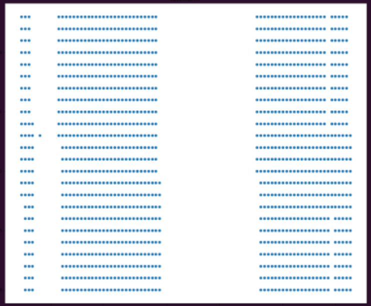
Carbon Dioxide CO2 level- boxplot

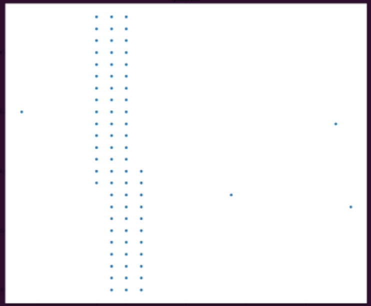


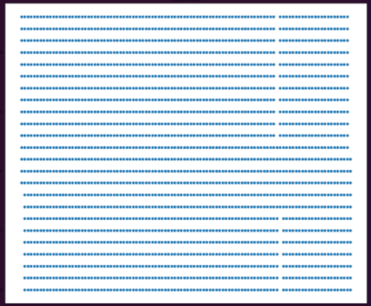
Carbon Dioxide CO2 level- hour vs timestamp

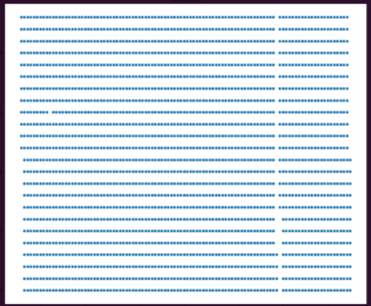


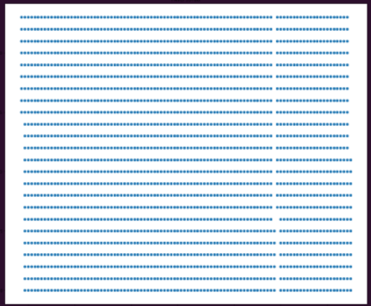


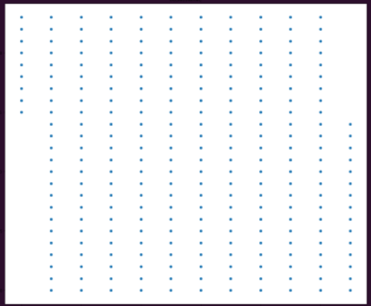


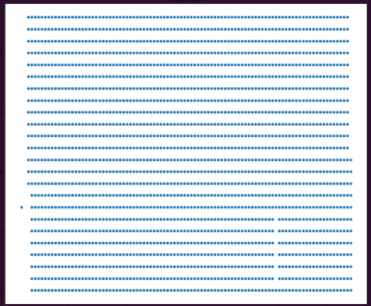


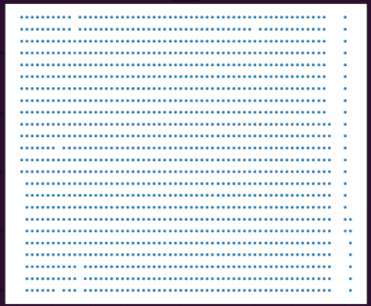


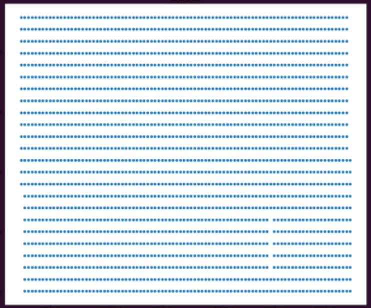




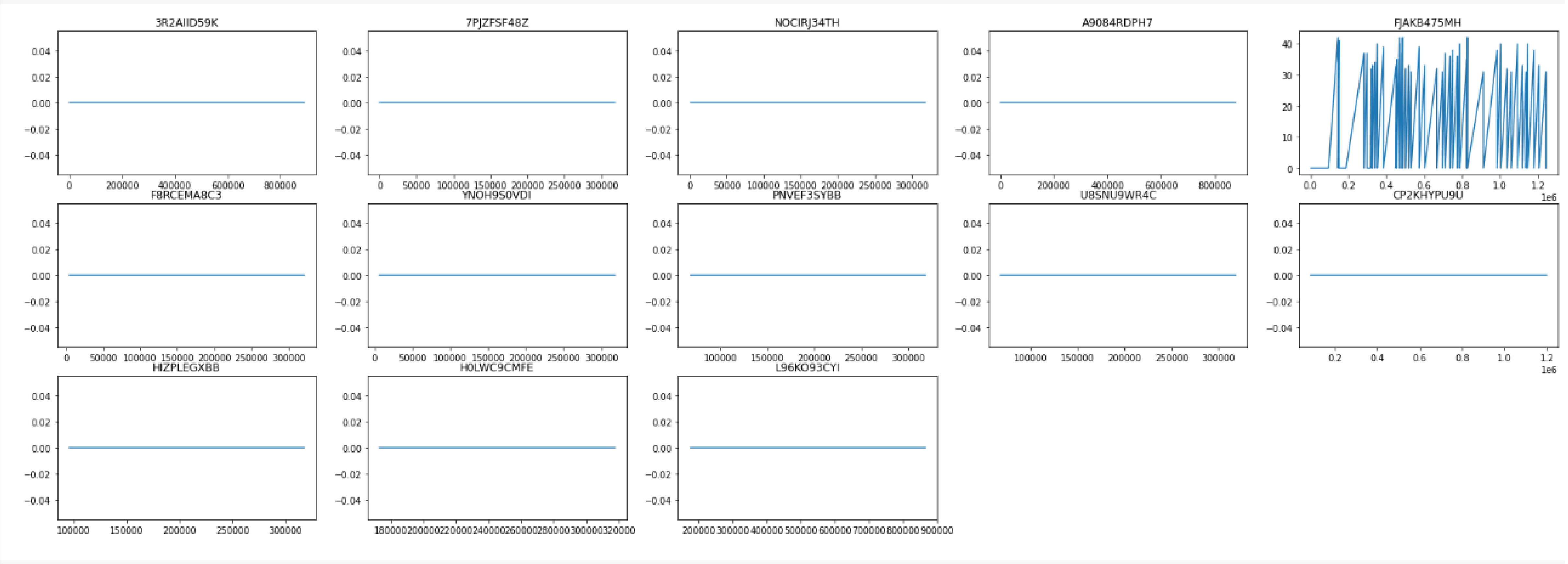




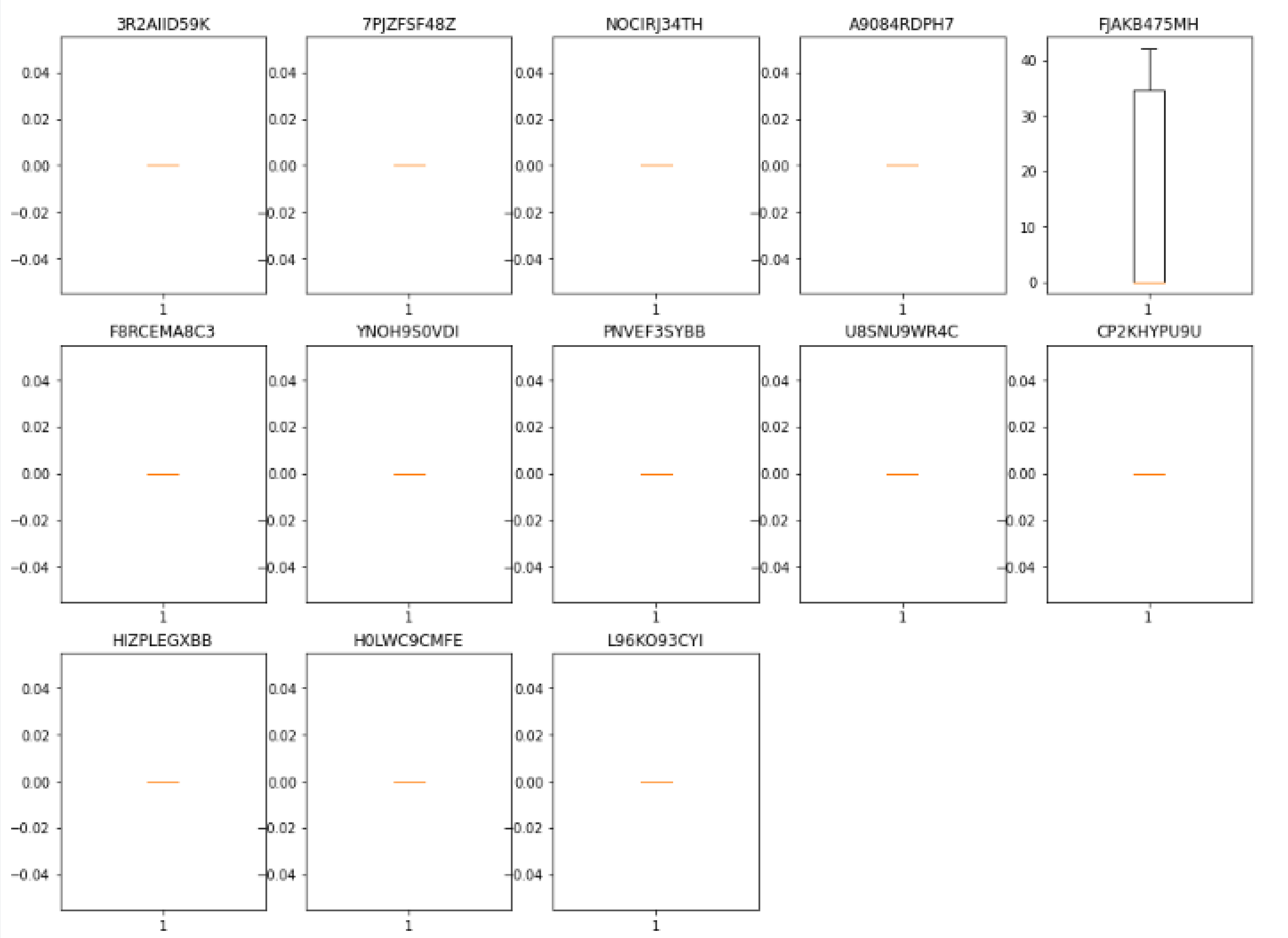




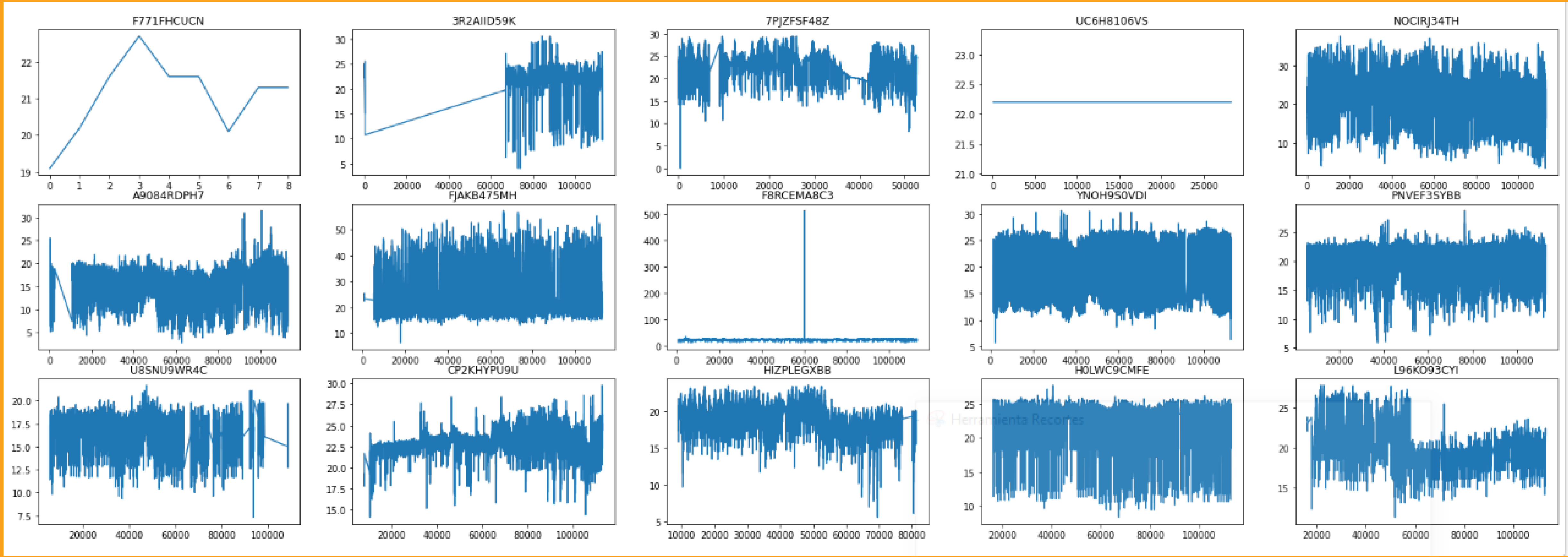
Carbon monoxide level- timestamp vs value



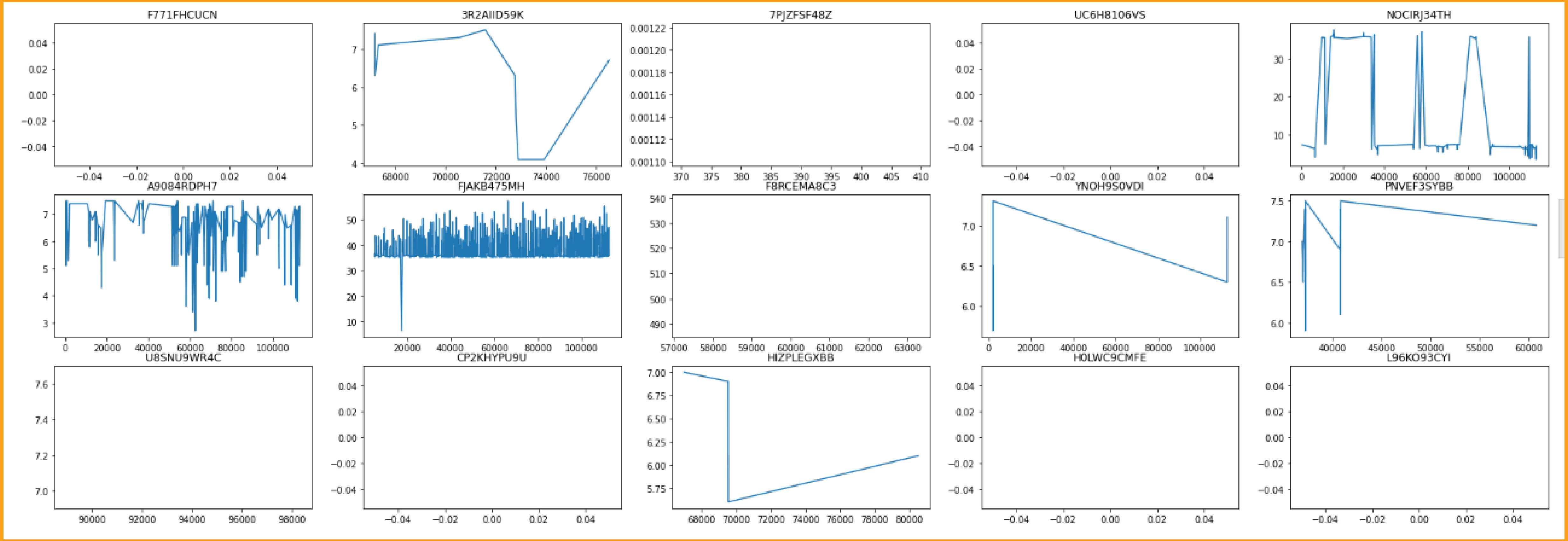
Carbon monoxide level- boxplot



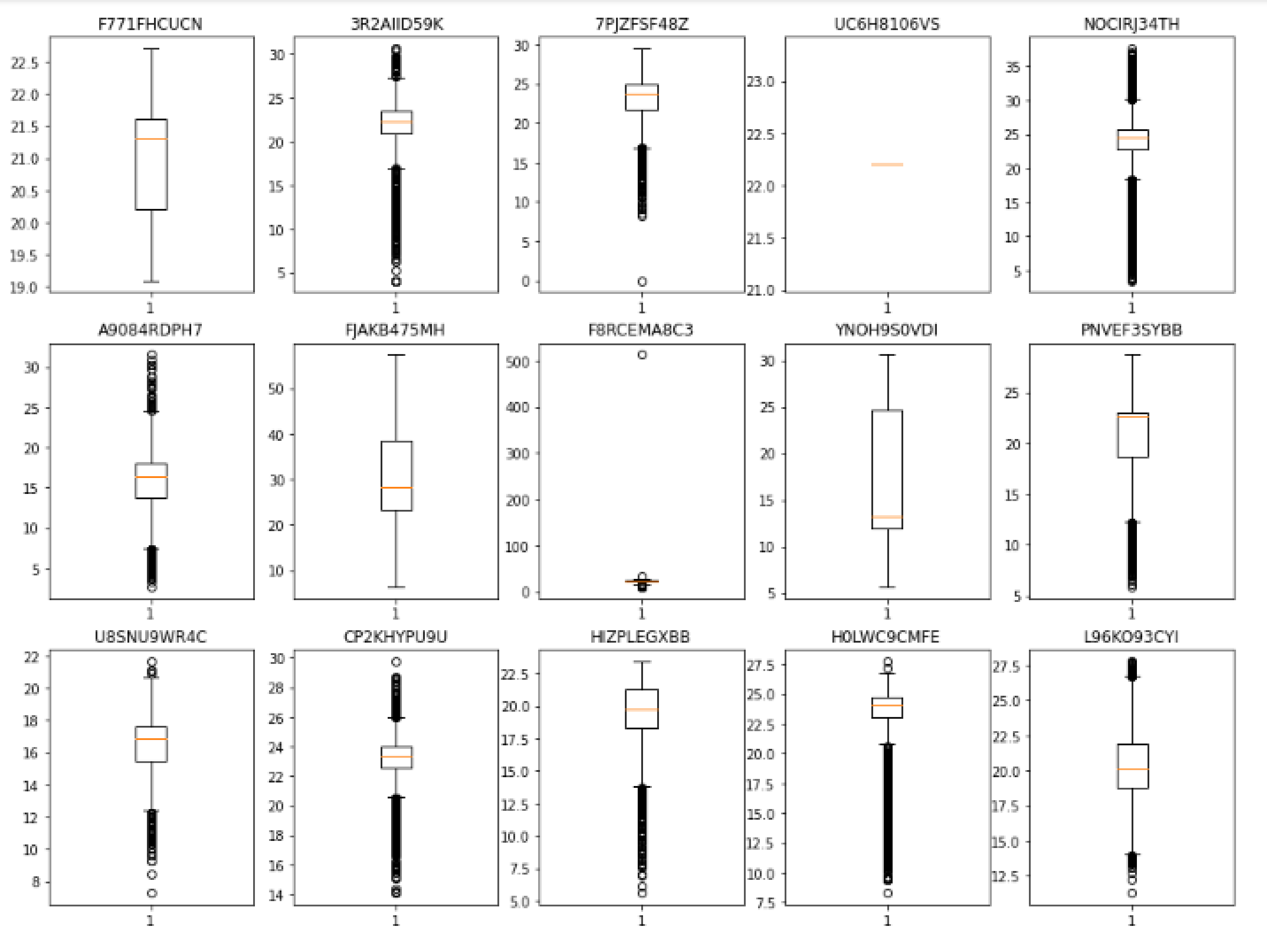
AIR TEMPERATURE – Timestamp vs Value per ID



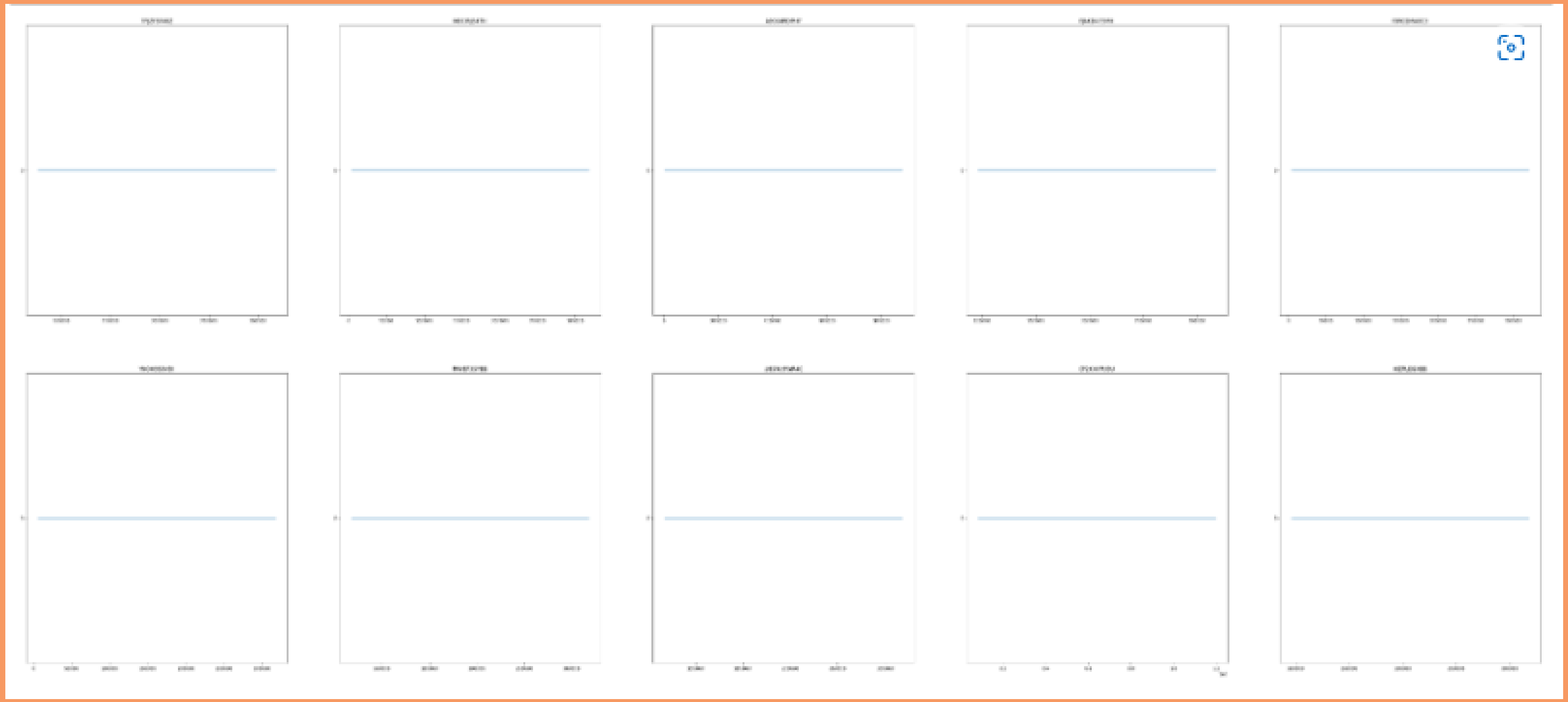
AIR TEMPERATURE -Visualization of the outliers



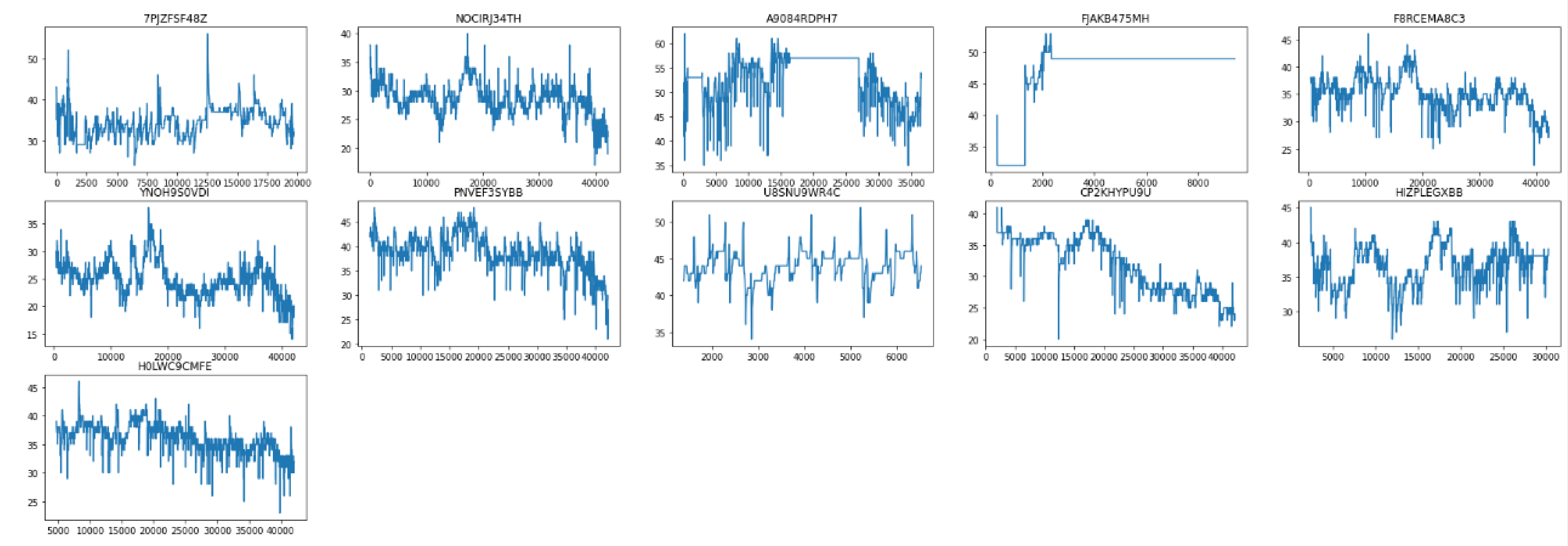
AIR TEMPERATURE -Boxplot



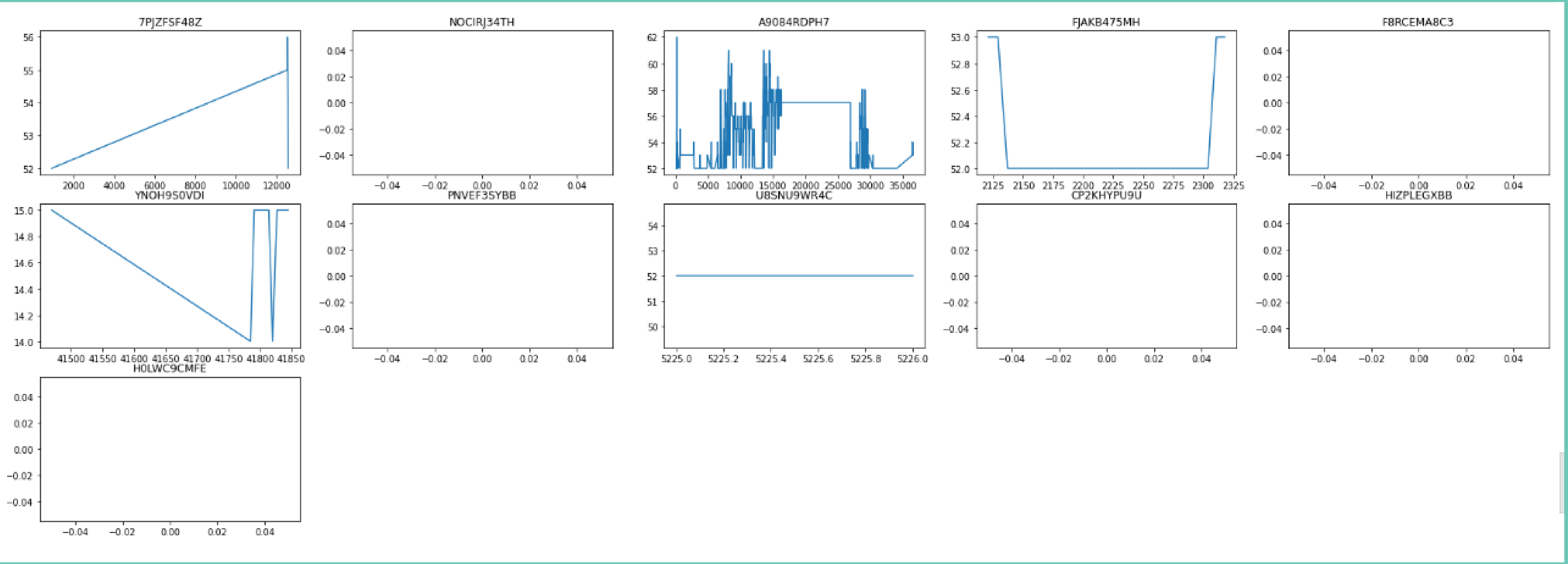
Heat Sensor status– Timestamp vs Value per ID



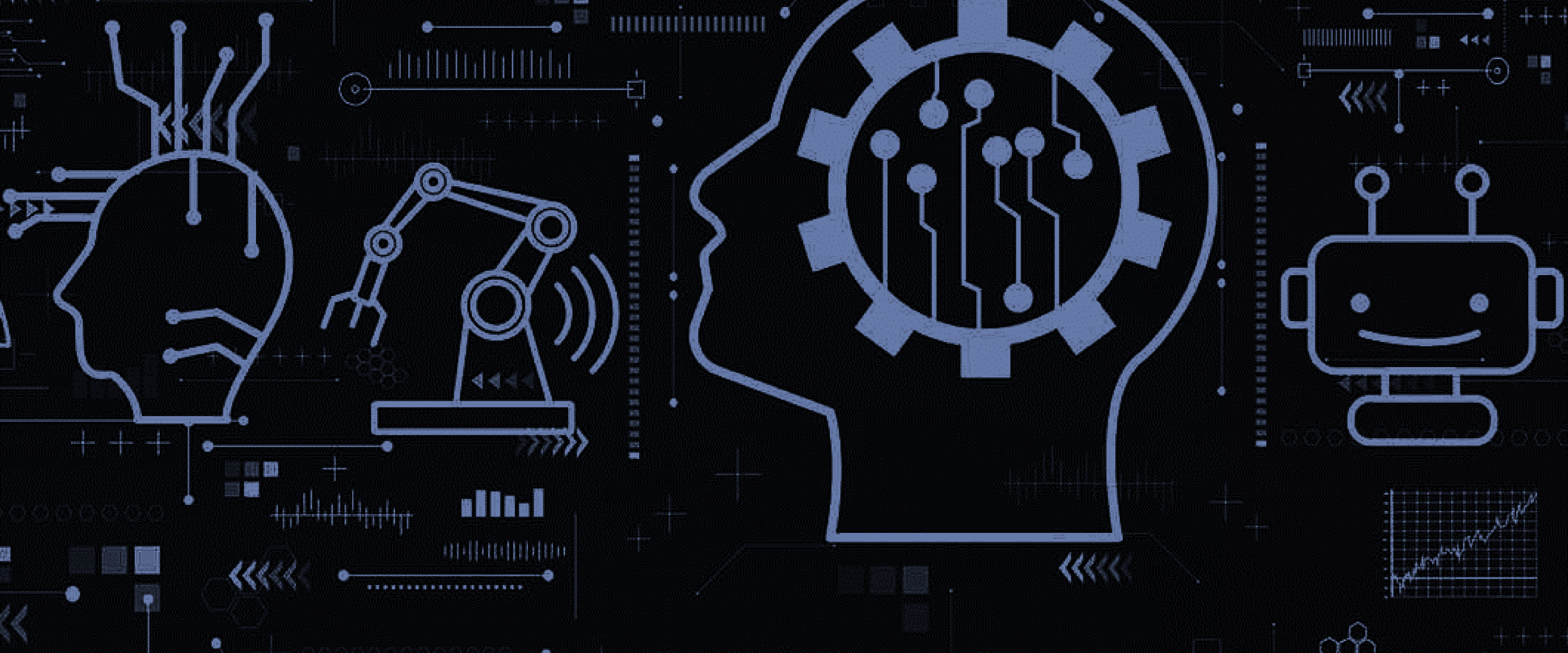
Humidity –Timestamp vs Value per ID

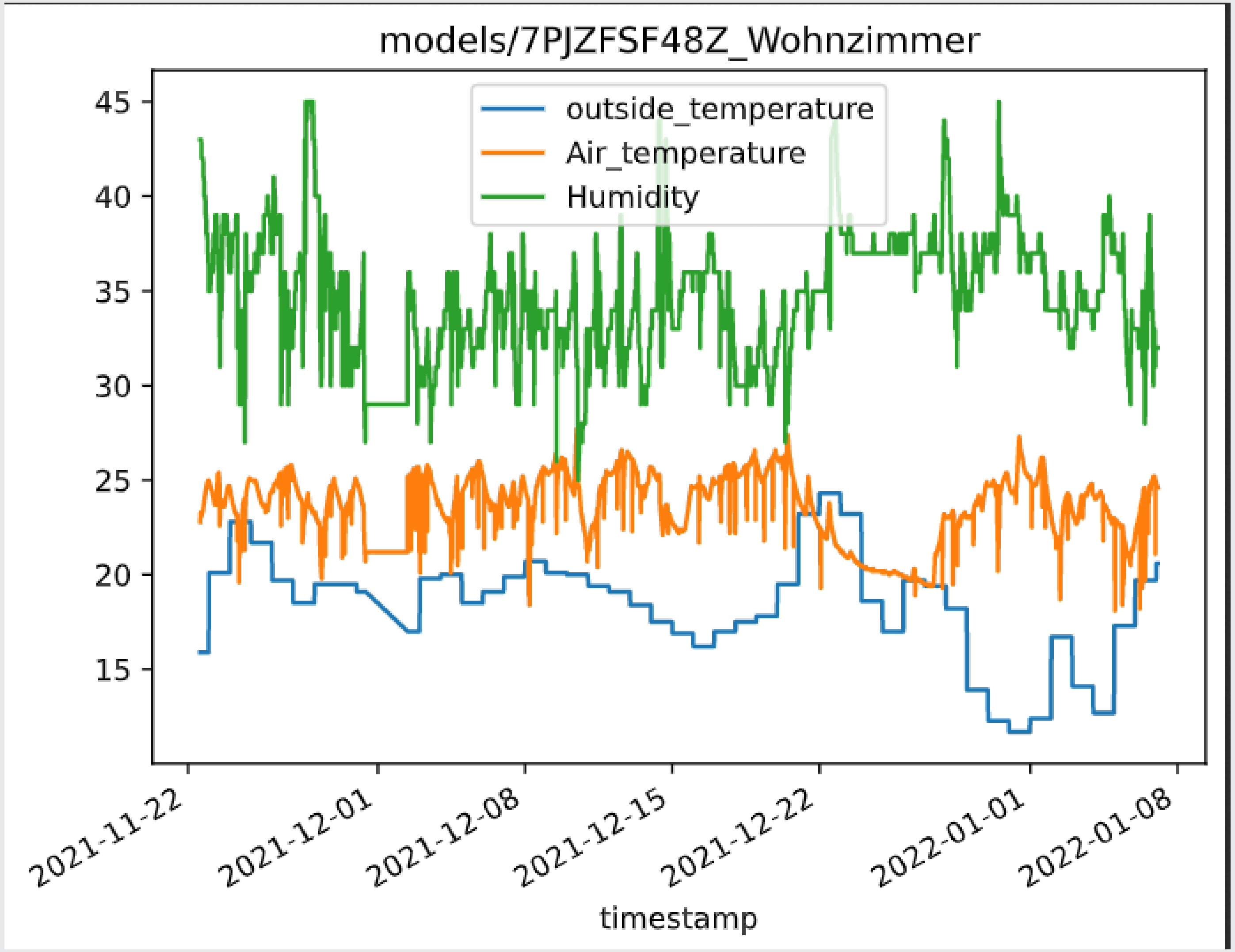


Humidity – Visualization of outliers



MACHINE LEARNING MODEL





models/7PJZFSF48Z_Wohnzimmer
outside_temperature
Air_temperature
Humidity
45
40
35
30
25
20
15
2021-11-22
2021-12-01
2021-12-08
2021-12-15
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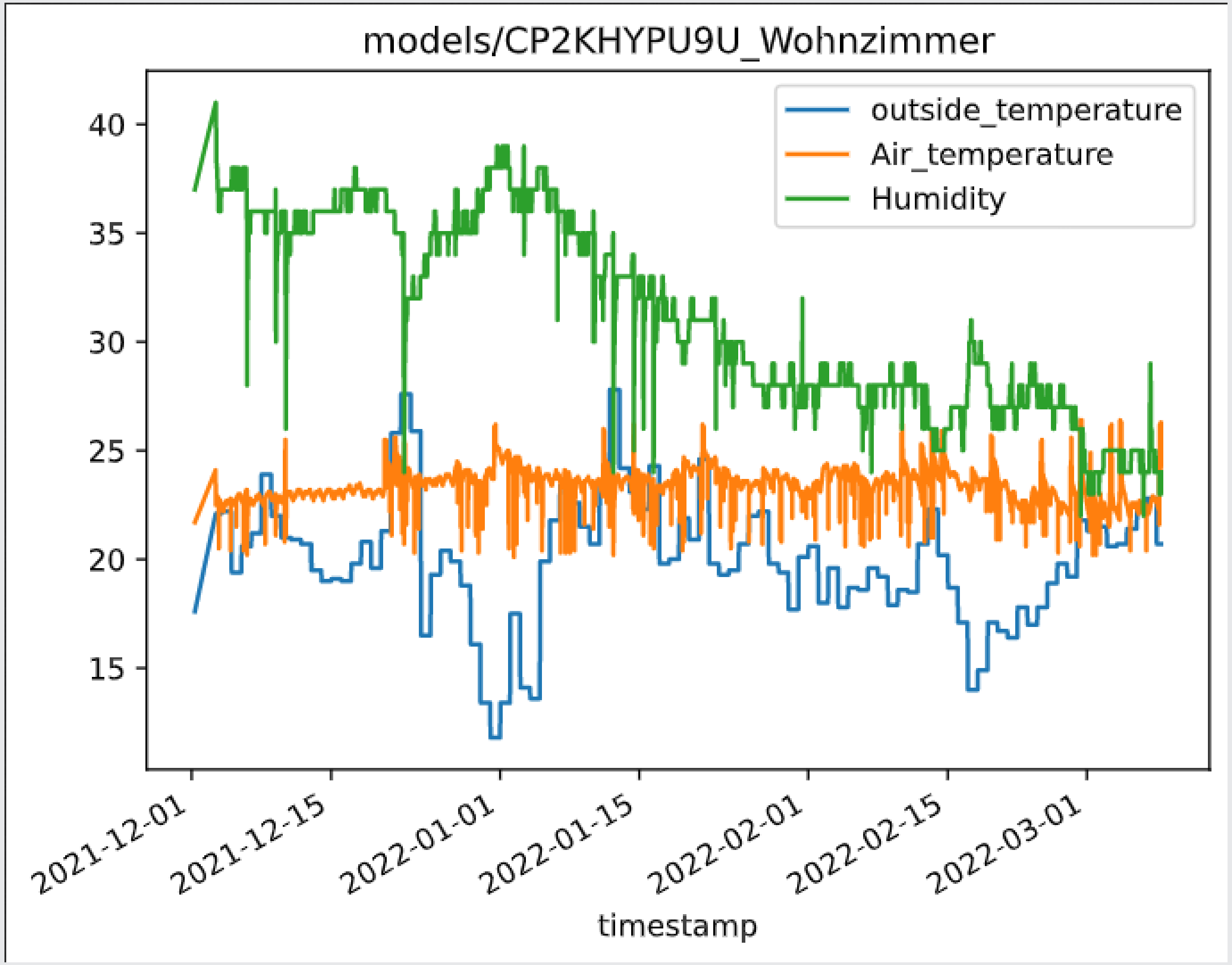
2022-01-08
timestamp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outside_temperature
Air_temperature
Humidity
40
35
30
25
20
15
2021-12-01
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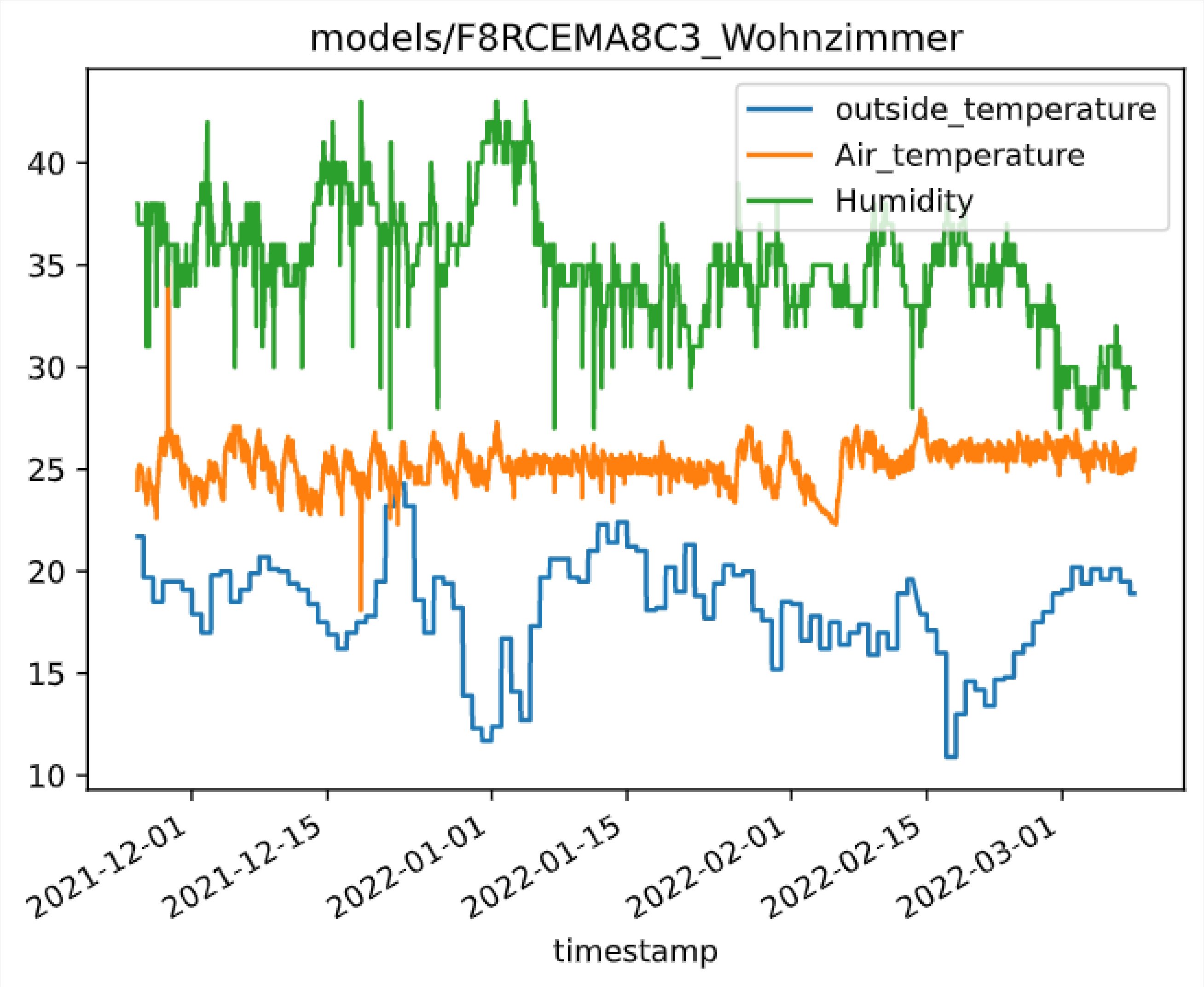
2022-02-15
2022-03-01
timestamp



models/F8RCEMA8C3_Wohnzimmer
outside_temperature
Air_temperature
Humidity
40
35
30
25
20
15
10
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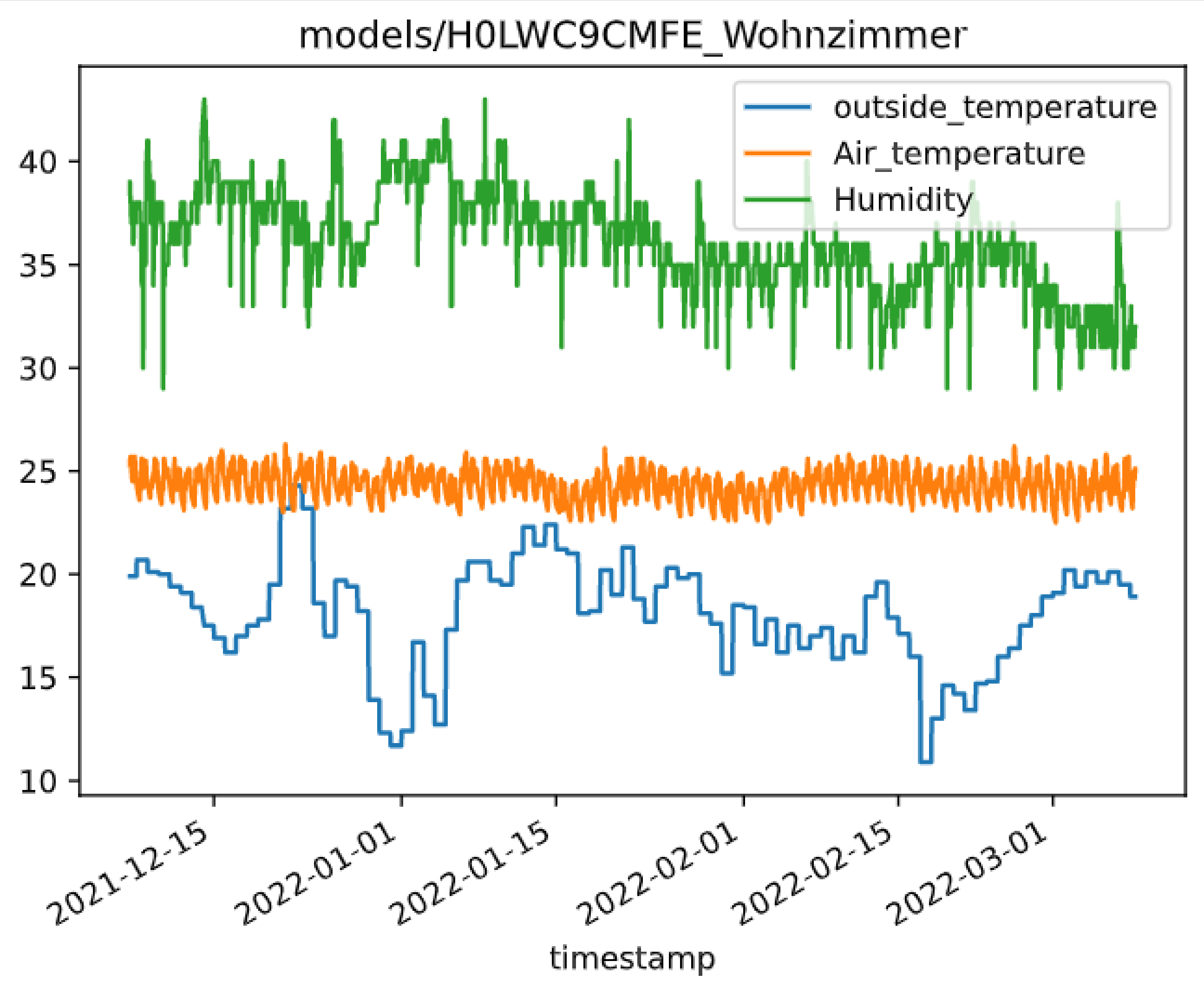
2022-03-01
timestamp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outside_temperature
Air_temperature
Humidity
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35
30
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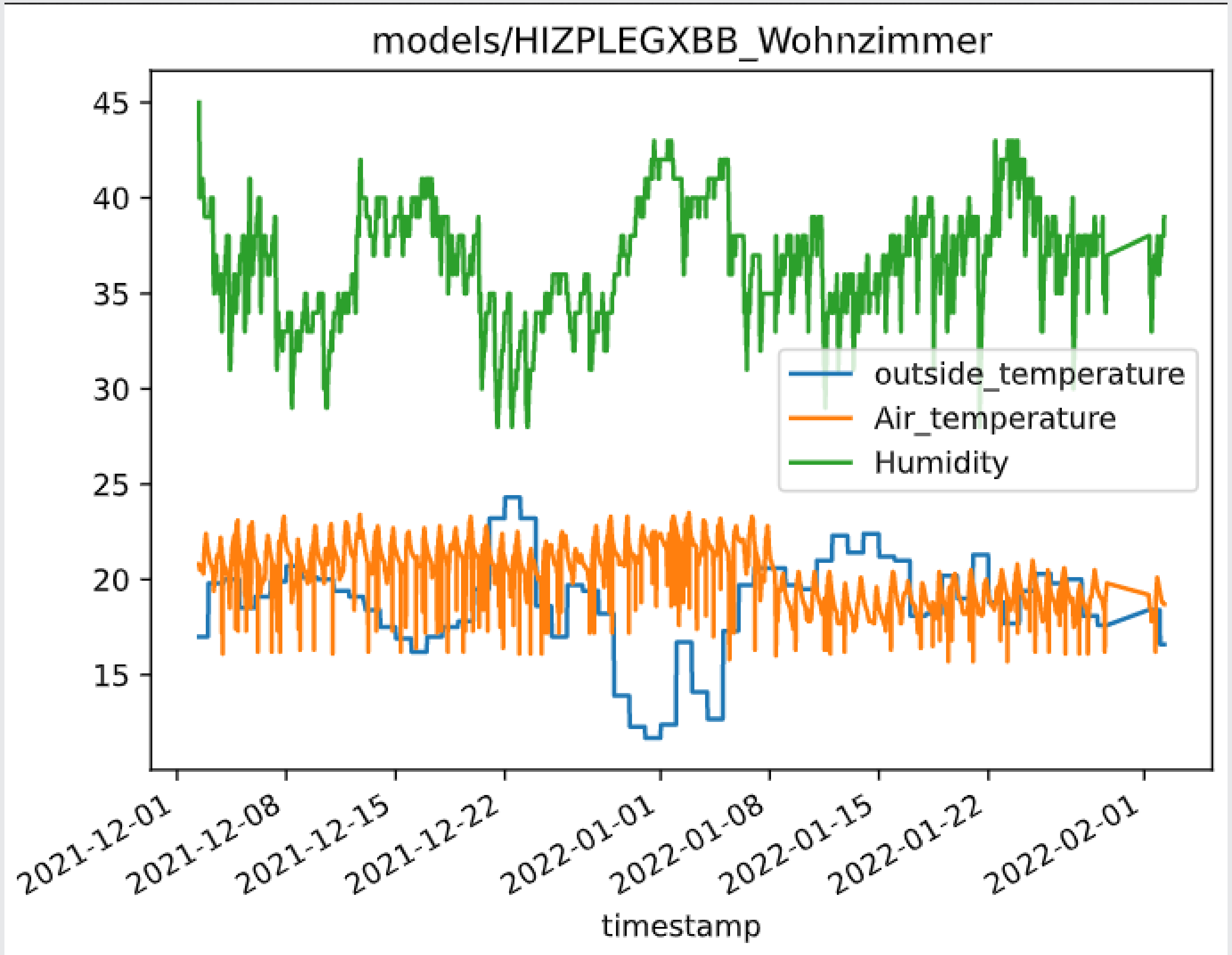
2022-02-01
2022-02-15
2022-03-01
timestamp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45
40
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outside_temperature
Air_temperature
Humidity
2021-12-01
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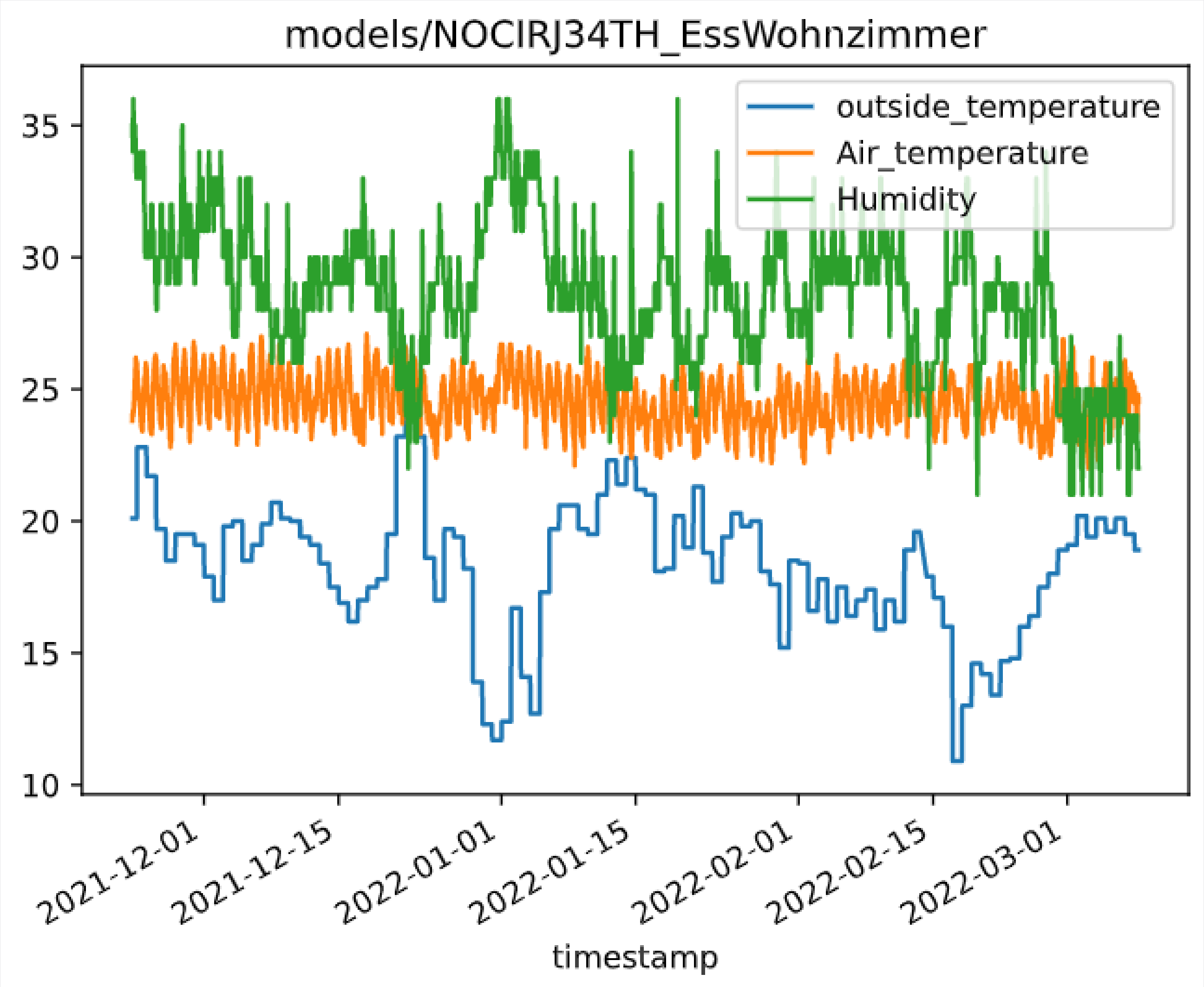
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outside_temperature
Air_temperature
Humidity
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30
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10
2021-12-01
2021-12-15
2022-01-01
2022-01-15
2022-02-01
2022-02-15
2022-03-01
timestamp

Some comments about our experience...

More sensor for Humidity measurements

Fill with data some measurements

Sensoring of the data more homogeneus (Fix hours)

Add sensors to the heating system

Keep investigating into this subject due to its importance

Sleeping times

AI Project

Content

- Topic justification
- Data analysis
- Trained models
- Improvements
- Feedback

Topic justification

Sleep is increasingly recognized as a critical component of healthy development and overall health.

Table 1

Sleep duration recommendations in the US and Canada

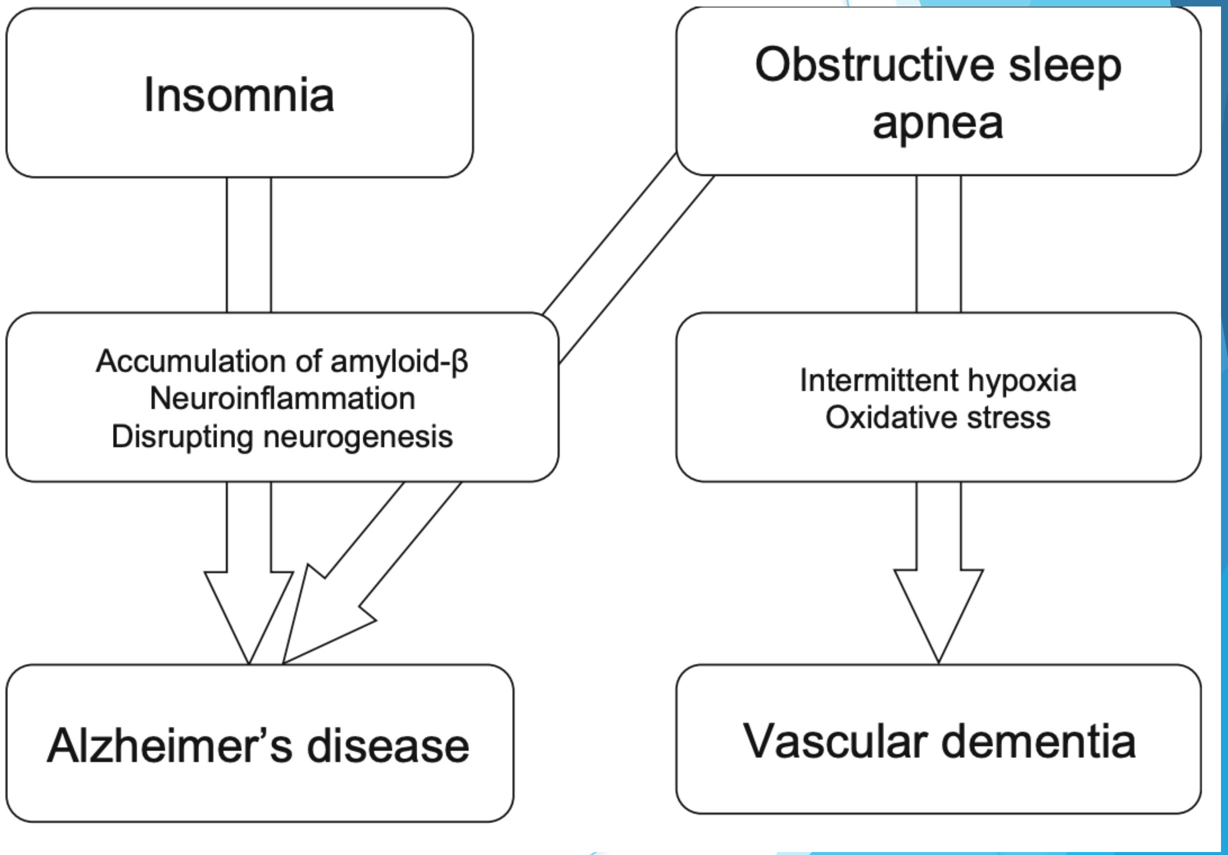
National sleep foundation (US)		AASM/SRS (US)		24-hour movement guidelines (Canada)	
Age group	**Recommendation**	**Age group**	**Recommendation**	**Age group**	**Recommendation**
Newborns (0–3 months)	14–17 hours	Newborns (0–3 months)	Not included	Newborns (0–3 months)	14–17 hours
Infants (4–11 months)	12–15 hours	Infants (4–11 months)	12–16 hours	Infants (4–11 months)	12–16 hours
Toddlers (1–2 years)	11–14 hours	Toddlers (1–2 years)	11–14 hours	Toddlers (1–2 years)	11–14 hours
Preschoolers (3–5 years)	10–13 hour	Preschoolers (3–5 years)	10–13 hours	Preschoolers (3–4 years)	10–13 hours
Children (6–13 years)	9–11 hours	Children (6–12 years)	9–12 hours	Children (5–13 years)	9–11 hours
Teenagers (14–17 years)	8–10 hours	Teenagers (13–17 years)	8–10 hours	Teenagers (14–17 years)	8–10 hours
Young adults (18–25 years)	7–9 hours	Adults (18–60 years)	≥7 hours	Adults (18–64 years)	In development
Adults (26–64 years)	7–9 hours			Older adults (≥65 years)	In development
Older adults (≥65 years)	7–8 hours				

Topic justification

There could be a connection between obstructive sleep anea (OSA) or insomnia AND dementia

OSA patients have a large tendency to develop Alzheimer or vascular dementia

"treating sleep disorders in elderly patients prevented or delayed the onset of dementia, mitigating the progression of symptoms in patients who already manifested dementic symptoms“



Topic justification
Sources

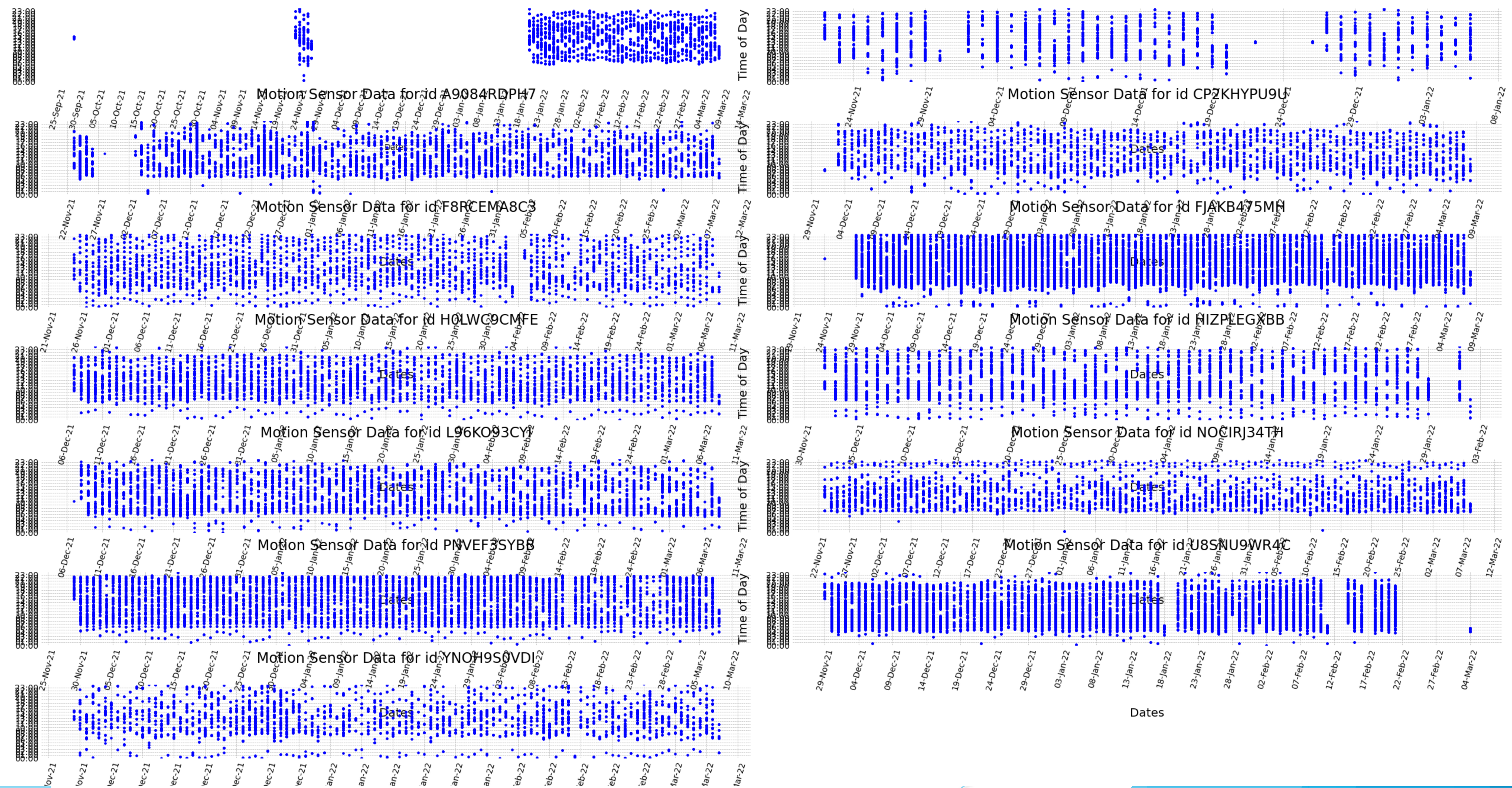
Chaput JP, Dutil C, Sampasa-Kanyinga H. Sleeping hours: what is the ideal number and how does age impact this? Nat Sci Sleep. 2018 Nov 27;10:421-430. doi: 10.2147/NSS.S163071. PMID: 30568521; PMCID: PMC6267703.

Kitamura, T., Miyazaki, S., Sulaiman, H.B. et al. Insomnia and obstructive sleep apnea as potential triggers of dementia: is personalized prediction and prevention of the pathological cascade applicable?. EPMA Journal 11, 355–365 (2020). https://doi.org/10.1007/s13167-020-00219-w

Data analysis

To work with the data we had to know what exactly we are working with.

- 13 different Ids
- Entries from the end of September until the middle of March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Motion Sensor Data for id CP2KHYPU9U
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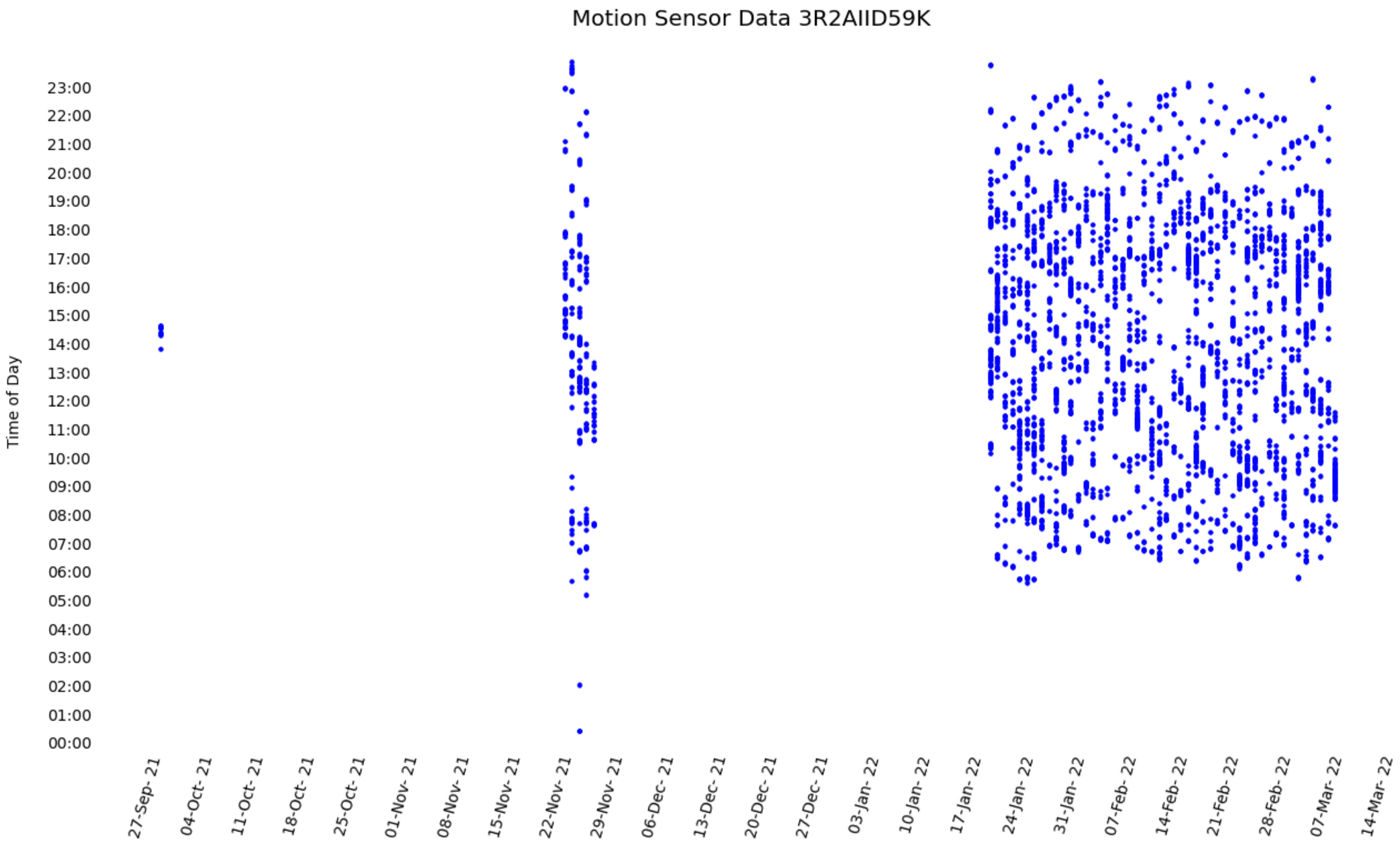
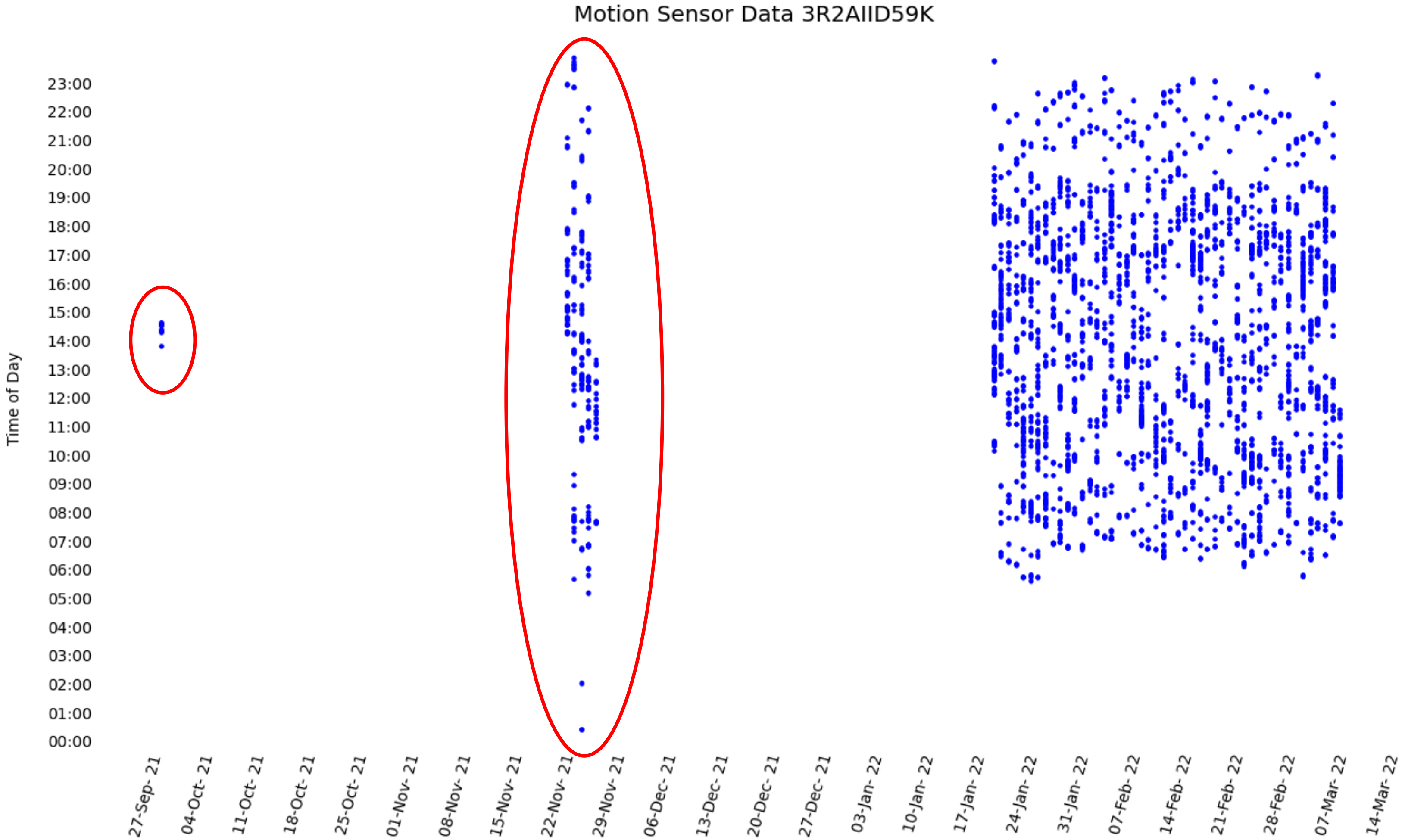
Motion Sensor Data for id FJAKB475MH
Motion Sensor Data for id H0LWC9CMFE
Motion Sensor Data for id HIZPLEGXBB
Motion Sensor Data for id L96KO93CYI
Motion Sensor Data for id NOCIRJ34TH
Motion Sensor Data for id PNVEF3SYBB
Motion Sensor Data for id U8SNU9WR4C
Motion Sensor Data for id YNOH9S0VDI
Time of Day
Dates

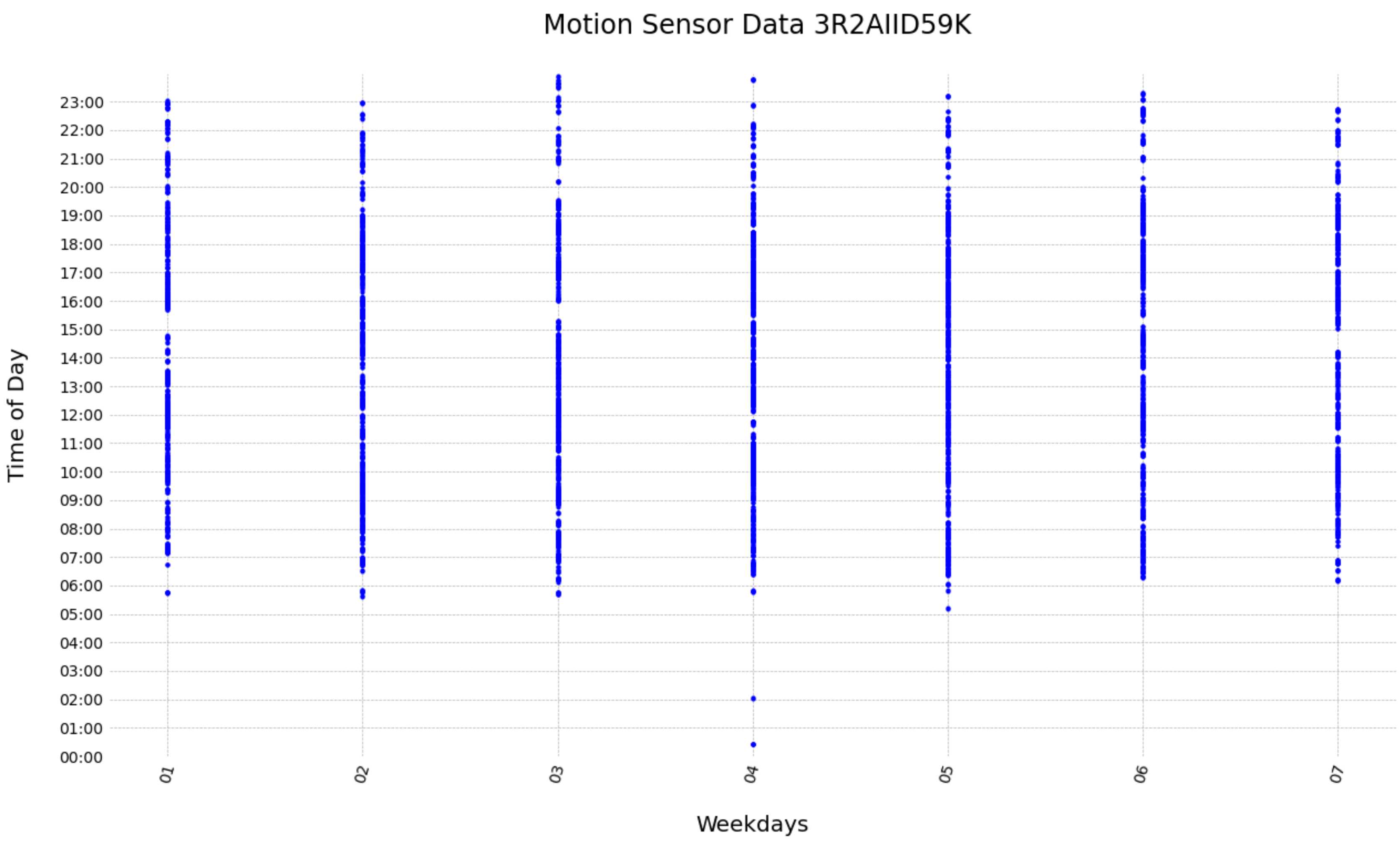
Data analysis



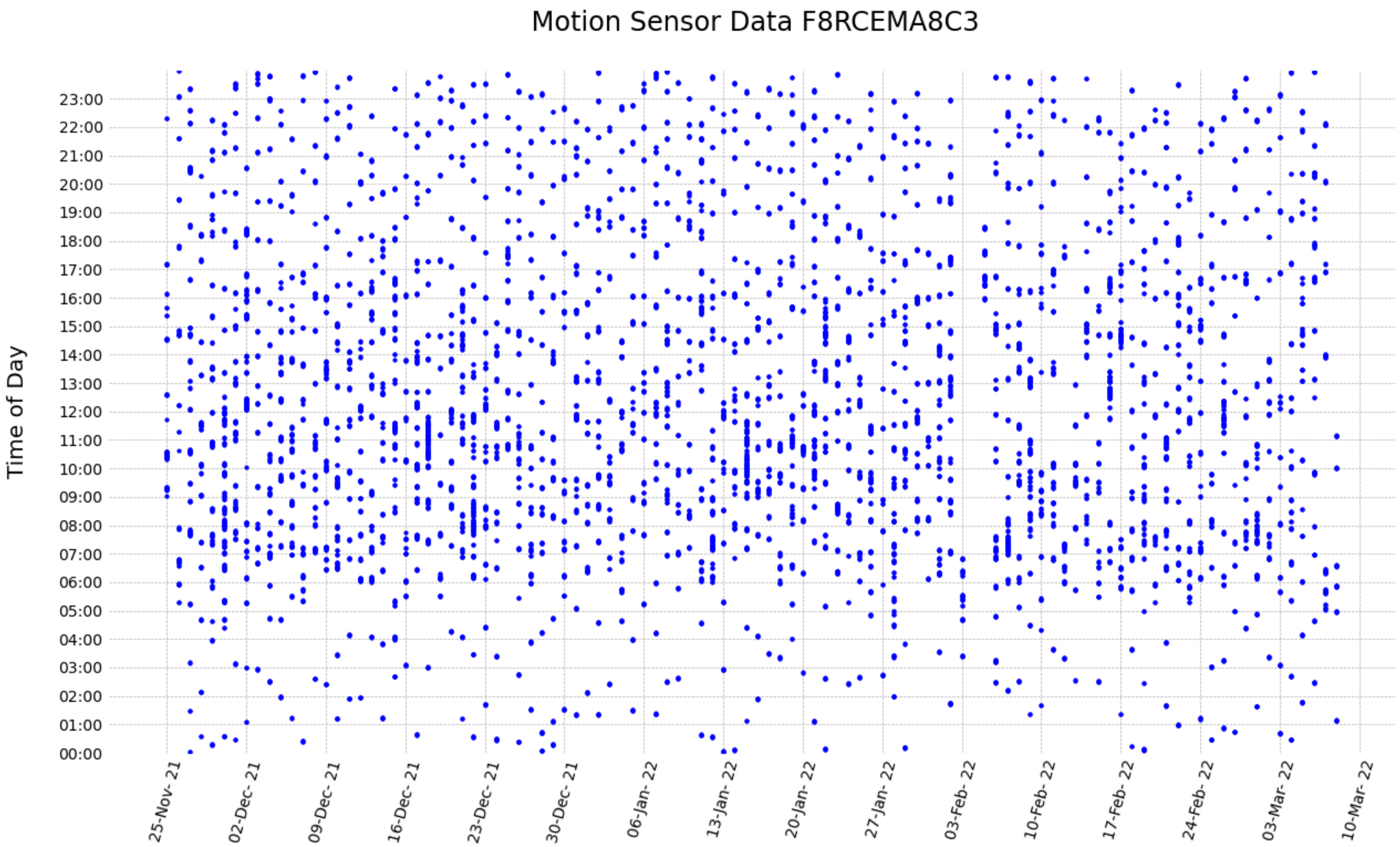
Data analysis



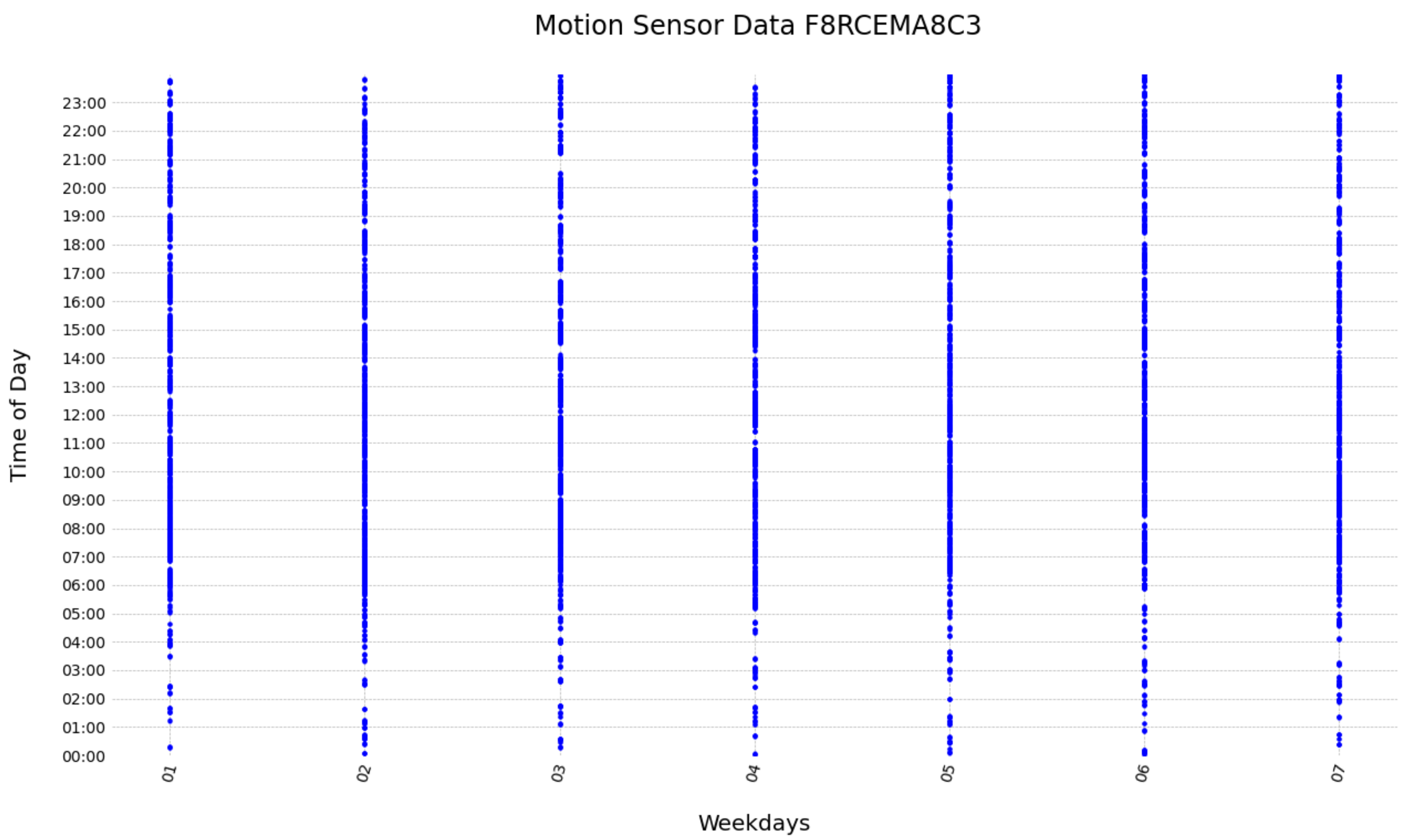
Data analysis



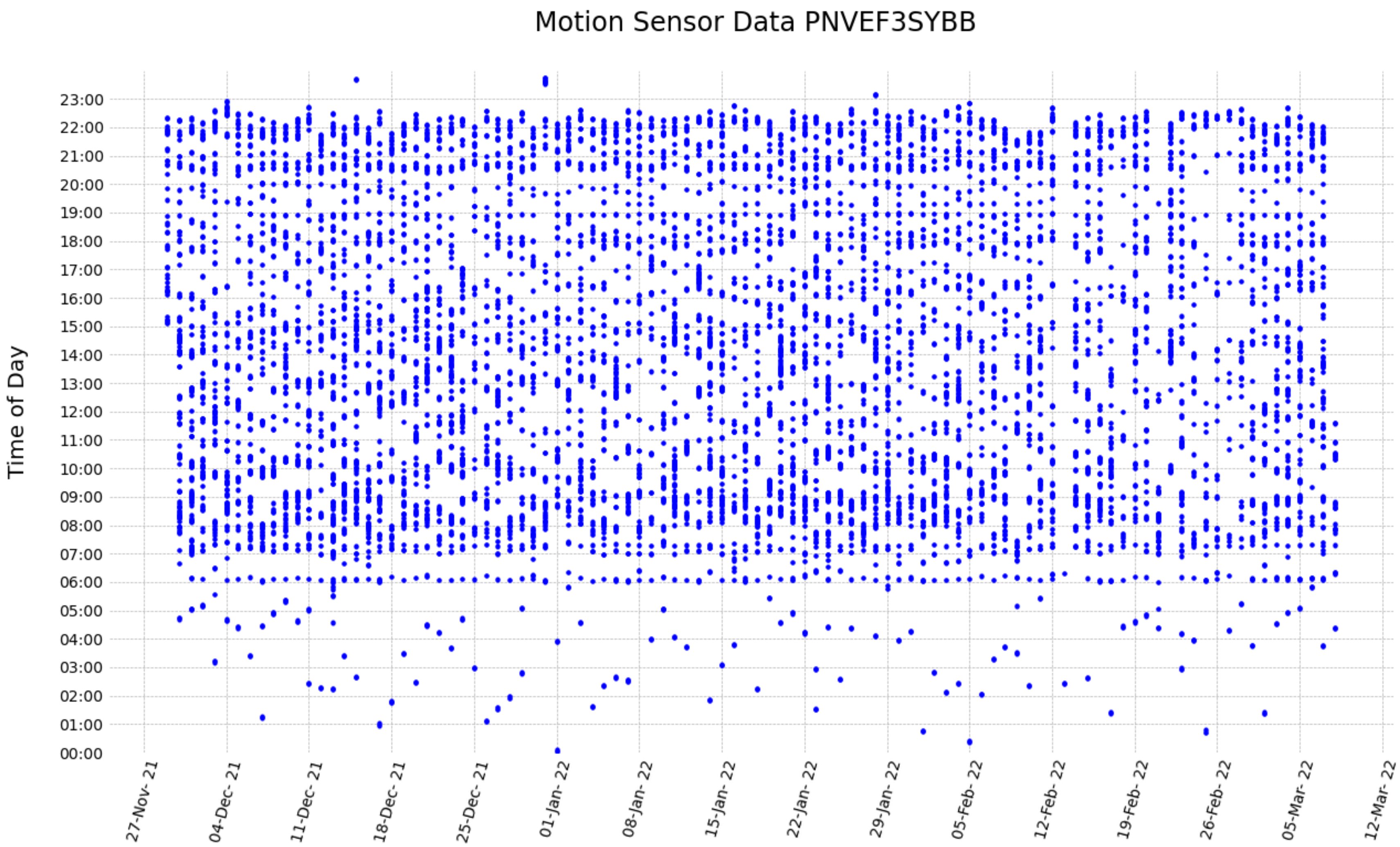
Data analysis



Data analysis



Data analysis



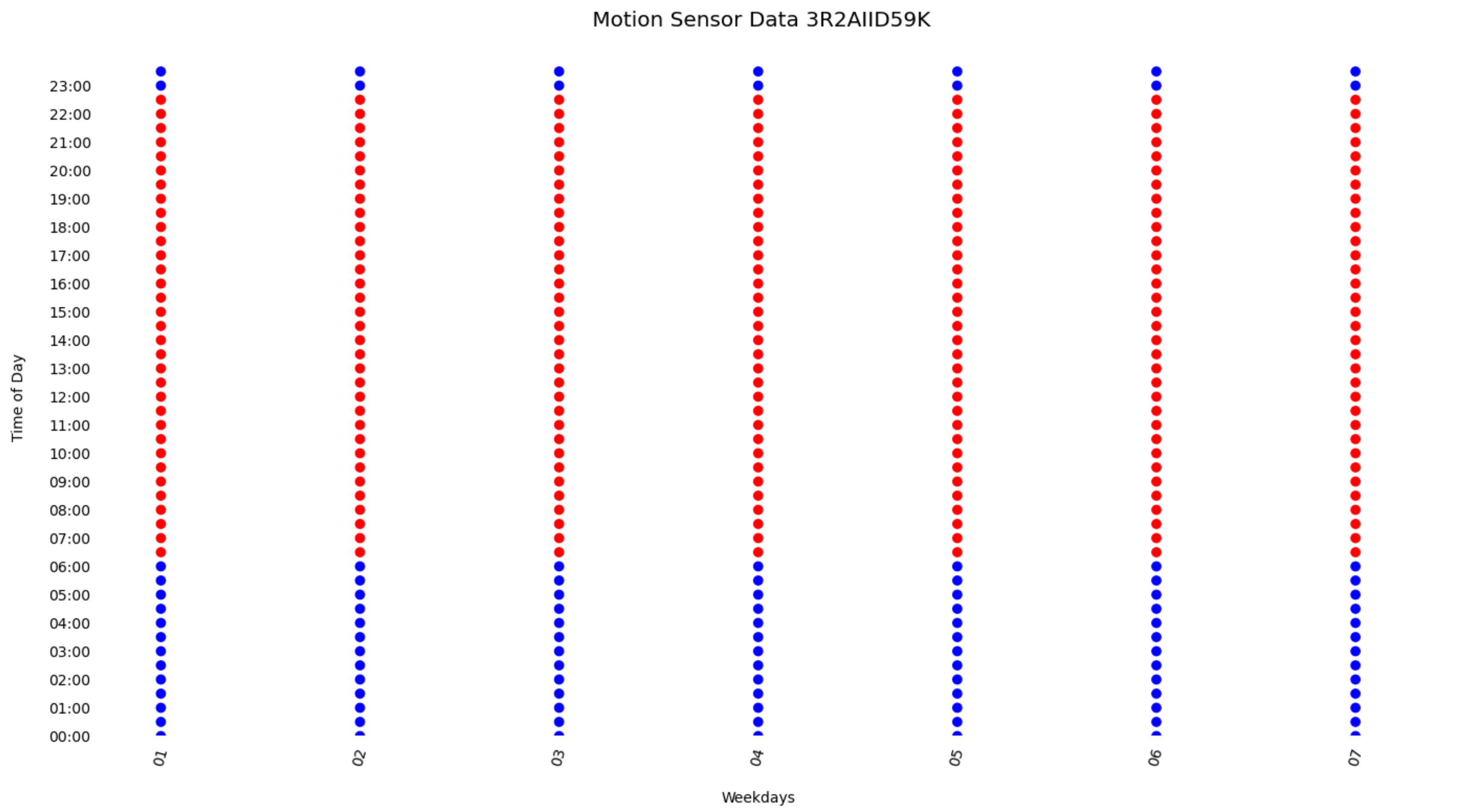
Data analysis
Summary

- Some data entries should be removed
- For most Ids there is some sleeping pattern visible
  - The pattern was often weekday specific
- Data cant be used as is to train a model
  - Date is split into weekday and time

Trained models

To train models we created training data.

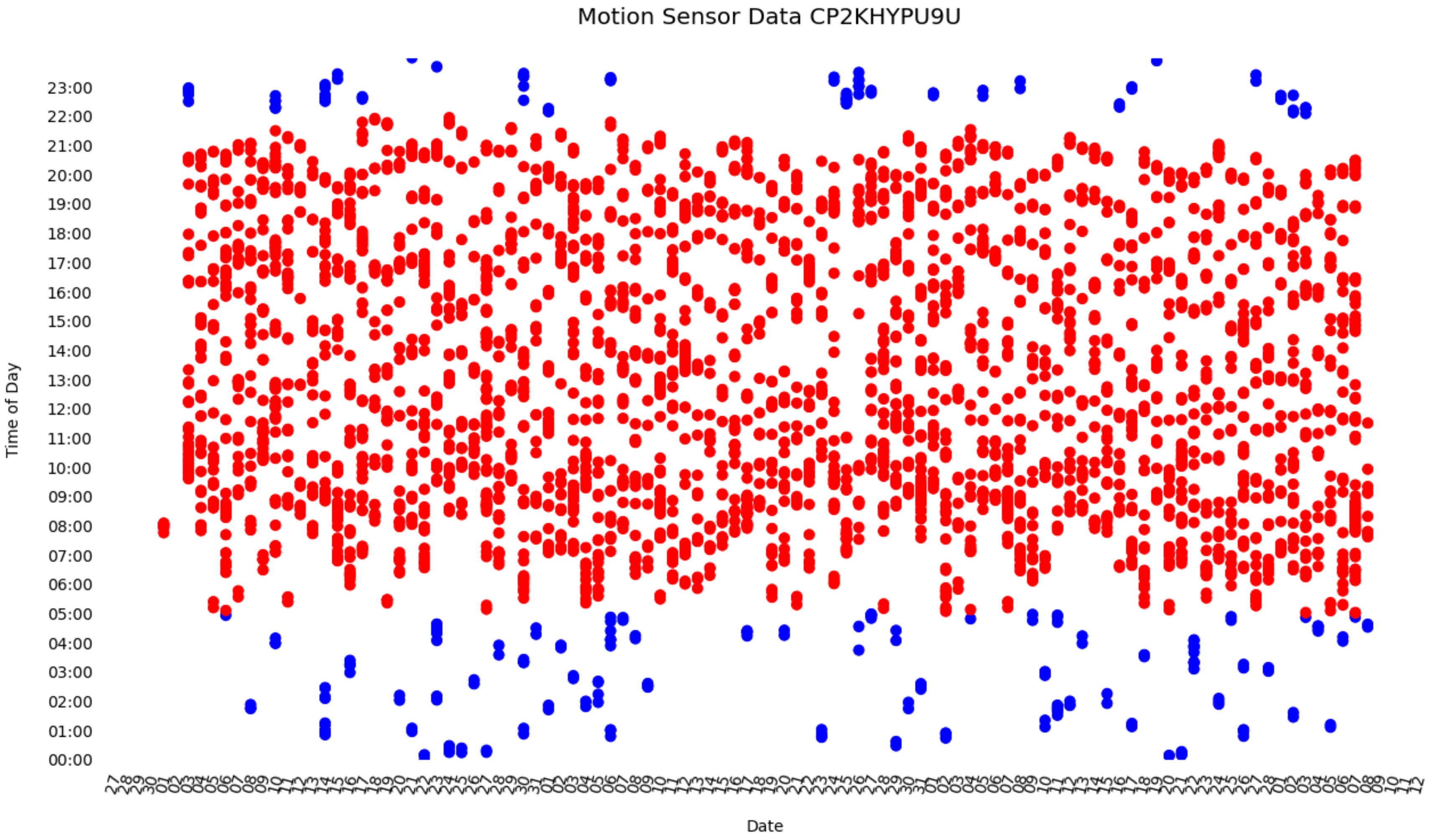
Trained models



Trained models

What was also done was to classify the original data.

Trained models



Trained models
KNN

- Trained on the created data
- Tested on the original data

Trained models

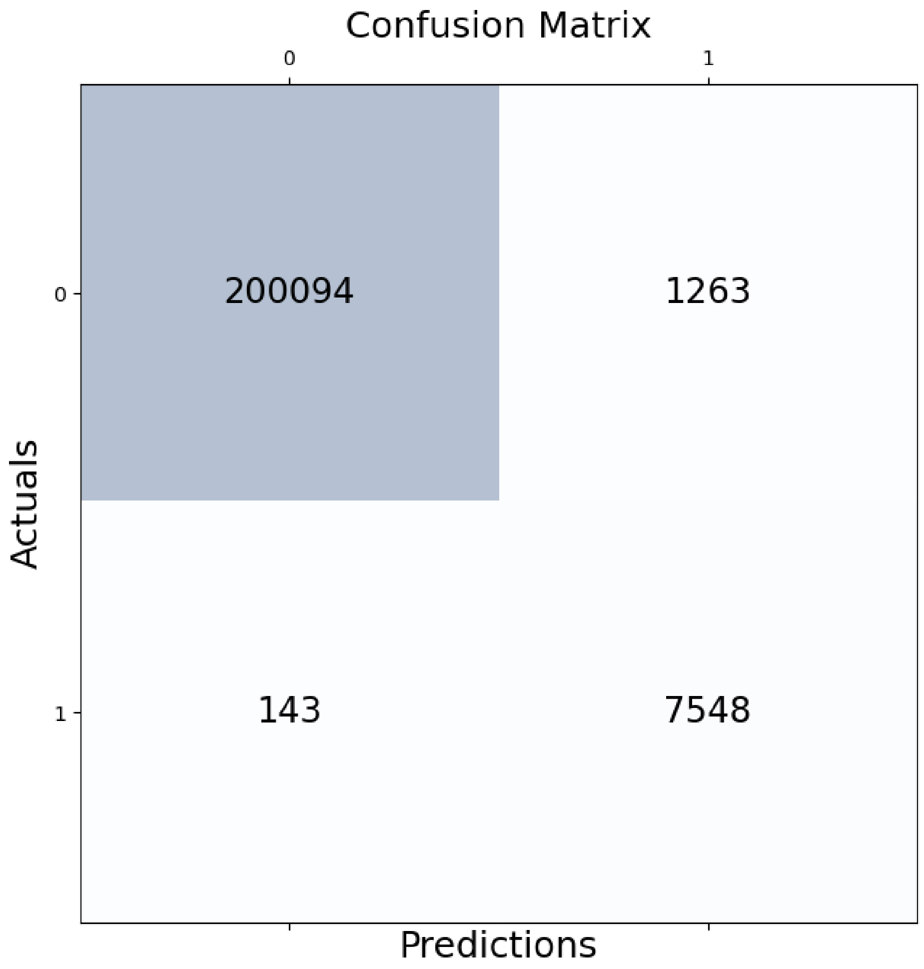
KNN

Precision

	precision	recall	f1-score	support
0	1.00	0.99	1.00	201357
1	0.86	0.98	0.91	7691
accuracy			0.99	209048
macro avg	0.93	0.99	0.96	209048
weighted avg	0.99	0.99	0.99	209048

Trained models

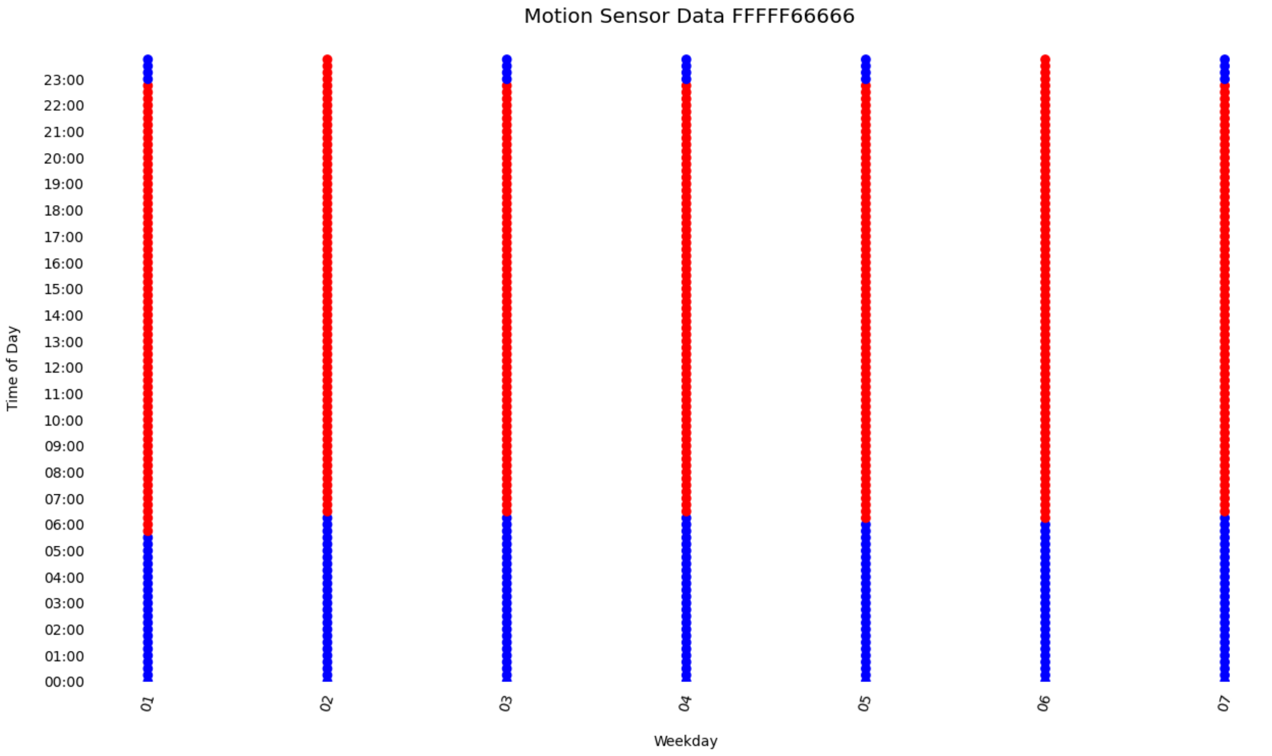
KNN



Trained models

KNN

Classifying of unknown ID



Trained models
Logistic regression

- Trained on the created data
- Tested on the original data

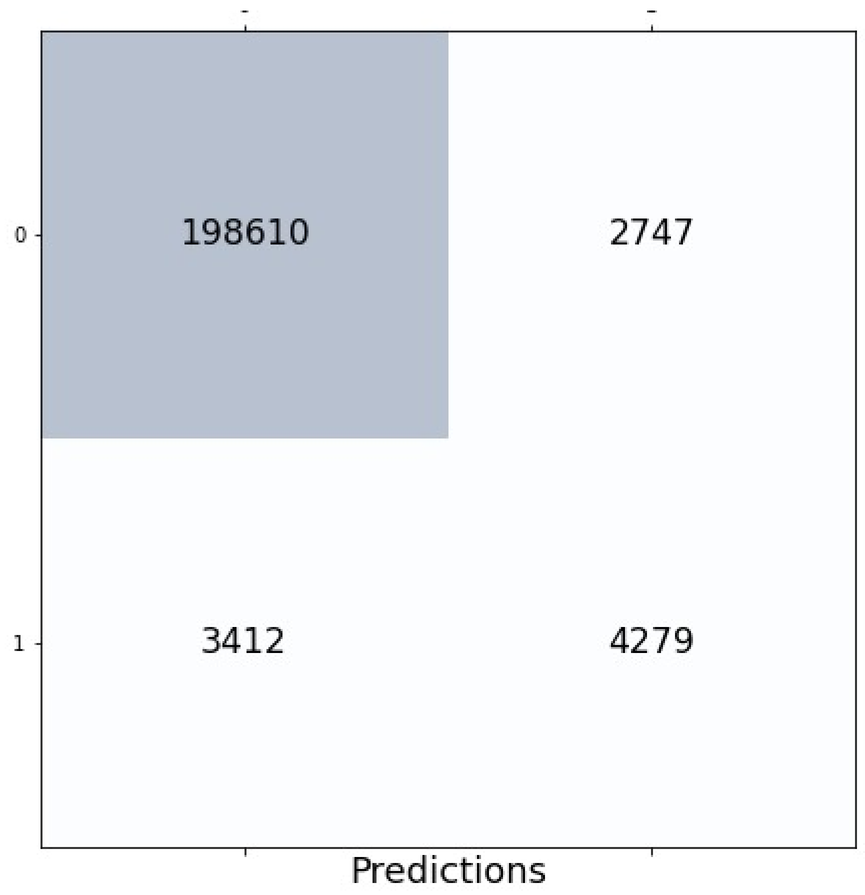
Trained models
Logistic regression

Precision

	precision	recall	f1-score	support
0	0.98	0.99	0.98	201357
1	0.61	0.56	0.58	7691
accuracy			0.97	209048
macro avg	0.80	0.77	0.78	209048
weighted avg	0.97	0.97	0.97	209048

Trained models
Logistic regression

Confusion matrix



Trained models
AutoSklearn

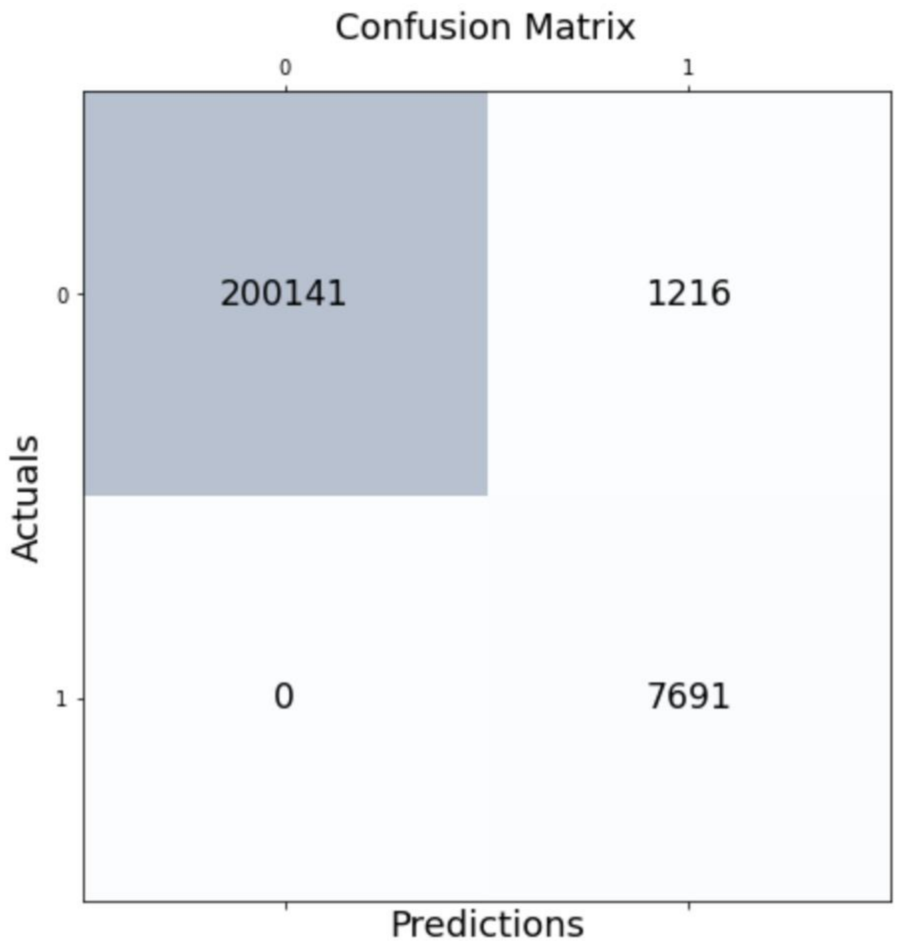
- Trained on the created data
- Tested on the original data

Trained models
AutoSklearn

Precision

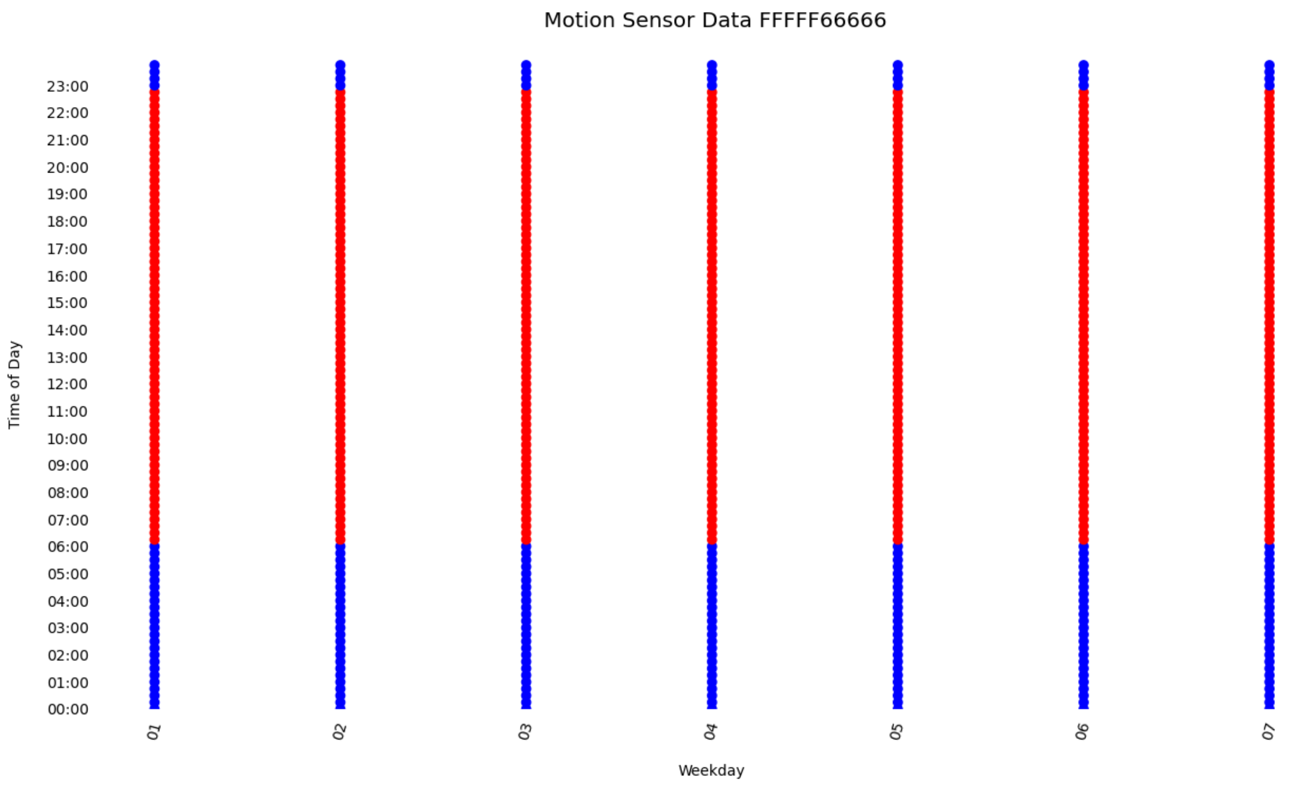
	precision	recall	f1-score	support
0	1.00	0.99	1.00	201357
1	0.86	1.00	0.93	7691
accuracy			0.99	209048
macro avg	0.93	1.00	0.96	209048
weighted avg	0.99	0.99	0.99	209048

Trained models
AutoSklearn



Trained models
AutoSklearn

Classifying of unknown ID



Improvements

Currently the models only look at the current time. It would be possible to make the following adjustments:

- Take a look at the last day, when was the last activity?
- Take a look at the lat privious activity, was he inactive long enough to be sleeping?

Improvements

The data currently only has entries for winter months. It would have to be looked into the sleeping behaviour in other seasons.

Summer might cause quite the change with the longer days.

Feedback

- Quite a few sensors werent labeled
- Pets might tamper with the motion sensor data