

# Visualization Term Project

20141087 Ryeongyang Kim      20161206 Jaewoong Lee

December 3, 2019

# Contents

<b>1</b>	<b>Introduction</b>	<b>4</b>
<b>2</b>	<b>Materials</b>	<b>4</b>
2.1	Building Layout . . . . .	4
2.1.1	Main Layout . . . . .	4
2.1.2	Energy Zone Layout . . . . .	4
2.1.3	Prox Zone Layout . . . . .	4
<b>3</b>	<b>Methods</b>	<b>4</b>
3.1	Python Packages . . . . .	4
3.1.1	Scikit-learn: Machine Learning in Python . . . . .	4
3.1.2	Matplotlib . . . . .	5
3.1.3	Pandas . . . . .	5
3.1.4	SciPy . . . . .	5
3.1.5	Pillow . . . . .	5
3.2	JavaScript . . . . .	5
3.2.1	Plotly . . . . .	5
3.3	TSNE . . . . .	5
3.4	Standardization . . . . .	5
<b>4</b>	<b>Results</b>	<b>5</b>
4.1	Question 1 . . . . .	5
4.1.1	General Information of prox Data . . . . .	5
4.1.2	Workflow . . . . .	7
4.1.3	Movement Direction and Distance . . . . .	7
4.1.4	Department Distribution . . . . .	7
4.1.5	Typical Patterns in prox Data . . . . .	9
4.1.6	Typical Day Look for GAStech employees . . . . .	9
4.2	Question 2 . . . . .	9
4.2.1	General Information of General Building Data . . . . .	9
4.2.2	Workflow . . . . .	9
4.2.3	Correlation within General Building Data . . . . .	9
4.2.4	Plots of General Building Data . . . . .	11
4.2.5	Interesting Patterns . . . . .	13
4.3	Question 3 . . . . .	15
4.3.1	General Information of Hazium Concentration . . . . .	15
4.3.2	Workflow . . . . .	15
4.3.3	Abnormality in General Building Data . . . . .	15
4.3.4	Score of Classification of Abnormality . . . . .	15
4.3.5	Column for Abnormality . . . . .	16
4.3.6	Danger for Building Operation . . . . .	16
4.4	Question 4 . . . . .	18
4.4.1	Frequency of prox Data . . . . .	18
4.4.2	Workflow . . . . .	18
4.4.3	. . . . .	18
4.4.4	Correlation between General Building Data and prox Data . . . . .	18
4.4.5	Cause and Effect for the Correlation . . . . .	18
<b>5</b>	<b>Discussion</b>	<b>18</b>

## List of Tables

1	Basic Statistics Data within Movement Distance . . . . .	6
2	Minimum Moving Employees . . . . .	6
3	Maximum Moving Employees . . . . .	6
4	Department Information by Quartiles . . . . .	9
5	Basic Statistics of R-Values . . . . .	10
6	Minimum Values of R-Values . . . . .	11
7	Maximum Values of R-Values . . . . .	11

8	Basic Statistics Data with the peak in the Second-quarter . . . . .	13
9	Basic Statistics Data with the under-peak in the Fourth-quarter . . . . .	13
10	Scores of Classification of Abnormality . . . . .	16
11	Basic Statistics Data with the Differences of Mean Values . . . . .	16
12	Basic Statistics Data with the Frequency of prox Data . . . . .	18

## List of Figures

1	Main Layout of the building . . . . .	4
2	Energy Zone of the Building . . . . .	4
3	Prox zone of the Building . . . . .	5
4	Distribution of Movement Distance . . . . .	6
5	Workflow for Question 1 . . . . .	7
6	Movement Direction/Distance on First Floor . . . . .	7
7	Movement Direction/Distance on Second Floor . . . . .	8
8	Movement Direction/Distance on Third Floor . . . . .	8
9	Pie Plot of Department Distribution by Quartiles . . . . .	9
10	TSNE for General Building Data . . . . .	10
11	Workflow for Question 2 . . . . .	10
12	Correlation Heatmap within General Building Data . . . . .	10
13	R-value Distribution within General Building Data . . . . .	10
14	Plots of the Lowest R-values . . . . .	12
15	Plots of General Building Data . . . . .	12
16	Cyclic Plots on First-quarters . . . . .	12
17	Peak in the Second-quarter . . . . .	13
18	Cyclic Plots on Third-quarters . . . . .	14
19	Under-peak in the Fourth-quarter . . . . .	14
20	Hazium Data from Different Data Sources . . . . .	15
21	Workflow for Question 3 . . . . .	15
22	Abnormality in General Building Data by Timeline . . . . .	15
23	Distribution of Differences between Mean Value . . . . .	16
24	Heatmap of R-values between General Building Data and Hazium Data . . . . .	17
25	Heatmap of R-values with Higher and Lower General Building Data . . . . .	17
26	Scatter Plot between General Building Data and Hazium Data . . . . .	17
27	Distribution with Frequency of prox Data . . . . .	18
28	Timeline with Frequency of prox Data . . . . .	18
29	Daily Cycle of prox Data . . . . .	19
30	Workflow for Question 4 . . . . .	19

## 1 Introduction

In this term project, we have to answer several question with virtual building data.

## 2 Materials

## 2.1 Building Layout

To analyzing movement data, we should find corresponding coordinate with zone data. To find matching coordinate, we calculate the approximate center of all zones, and consider the approximate center coordinate as representative of its zone.

### 2.1.1 Main Layout



Figure 1: Main Layout of the building

The main layout of this building is as figure 1.

### 2.1.2 Energy Zone Layout



Figure 2. Energy zones of the Building

The energy zone of this building is as figure 2.

### 2.1.3 Tax Zone Layout

The prox zone of this building is as figure 3.

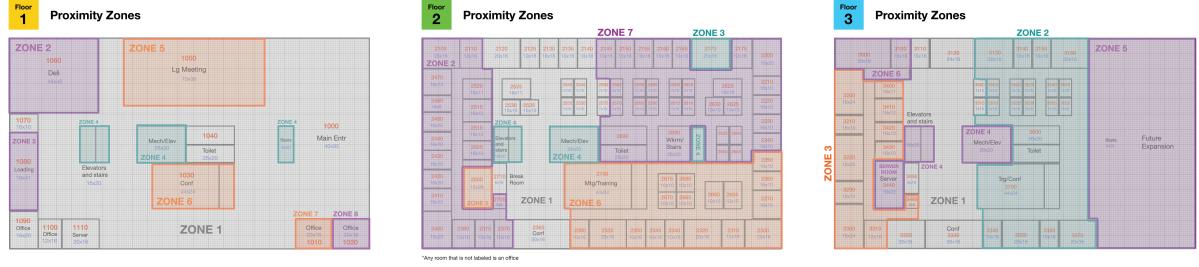
### 3 Methods

### 3.1 Python Packages

To analyze data, we used Python programming language. Also, we adopt many Python modules as hereinafter.

### 3.1.1 Scikit-learn: Machine Learning in Python

*Scikit-learn* is a Python module integrating a wide range of state-of-the-art machine learning algorithms for medium-scale supervised and unsupervised problems [1].



(a) First Floor

(b) Second Floor

(c) Third Floor

Figure 3: Prox zone of the Building

### 3.1.2 Matplotlib

*Matplotlib* is a Python 2D plotting library which produces publication quality figures in a variety of hardcopy formats and interactive environments across platforms [2].

### 3.1.3 Pandas

*Pandas* is a Python library of rich data structures and tools for working with structured data sets common to statistic, finance, social sciences, and many other fields [3].

### 3.1.4 SciPy

*SciPy* is a Python-based ecosystem of open-source software for mathematics, science, and engineering [4].

### 3.1.5 Pillow

*Pillow* is the Python Imaging Library. [5]

## 3.2 JavaScript

For implementing interactive plots in web, we used JavaScript for showing plots.

### 3.2.1 Plotly

*Plotly* is a high-level, declarative charting library. *plotly.js* ships with over 40 chart types, including 3D charts, statistical graphs, and SVG maps. [6]

## 3.3 TSNE

T-distributed Stochastic Neighbor Embedding (TSNE) is a machine learning algorithm for visualization high-dimensional data in a low-dimensional space [7].

## 3.4 Standardization

Note that, in this analysis, all values are standardized. In other words, all values are adjusted for the mean value is zero, and standard deviation is 1. If all values in one columns are same, then the column will be discarded.

## 4 Results

### 4.1 What are the typical patterns in the prox card data? What does a typical day look like for GAStech employees?

#### 4.1.1 General Information of prox Data

First of all, we drew the distribution of movement distance as figure 4. Also, the basic statistics values, such as minimum, maximum, and average, of movement distance is in table 1.

Furthermore, the extreme value of moving information is in tables 2 and 3.

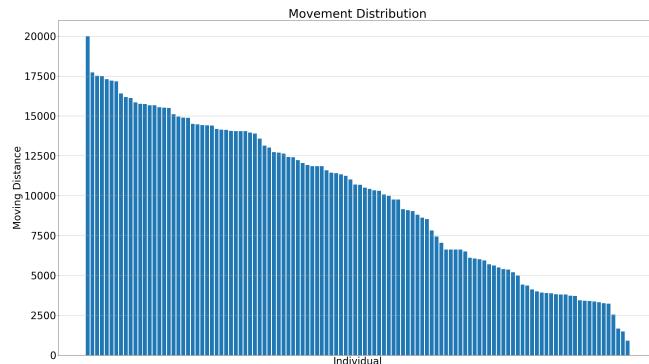


Figure 4: Distribution of Movement Distance

Table 1: Basic Statistics Data within Movement Distance

Item	Minimum	Maximum	Mean	q1	Median	q3	Standard Deviation
Value	902.44	19999.38	10083.95	5642.54	10688.57	14134.16	4750.46

Table 2: Minimum Moving Employees

Moving Distance	ID
902.4411338142776	earpa
1482.4411338142788	vawelon
1667.820095117141	jfrost
2550.198060545332	ibarranco
3233.4833039729083	cstaley

Table 3: Maximum Moving Employees

Moving Distance	ID
19999.386059326014	chawelon
17719.3756100877	hmies
17507.957735800737	eminto
17478.788651971503	monda
17302.863257165674	ldedos

#### 4.1.2 Workflow

With the general information of prox data, we have decided our workflow for question 1 as figure 5.

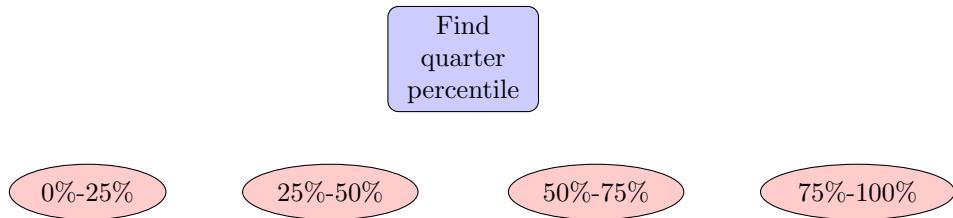


Figure 5: Workflow for Question 1

#### 4.1.3 Movement Direction and Distance

We drew the plot about movement direction and distance with each sub-group as figures 6, 7, and 8. Note that the darkness of arrow is proportioned with number of duplicates.

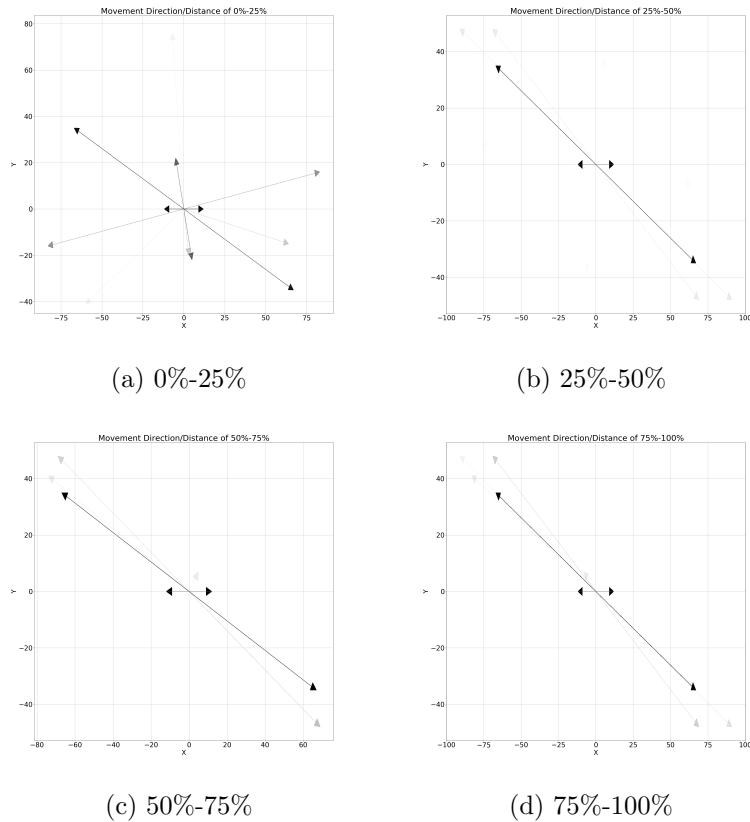


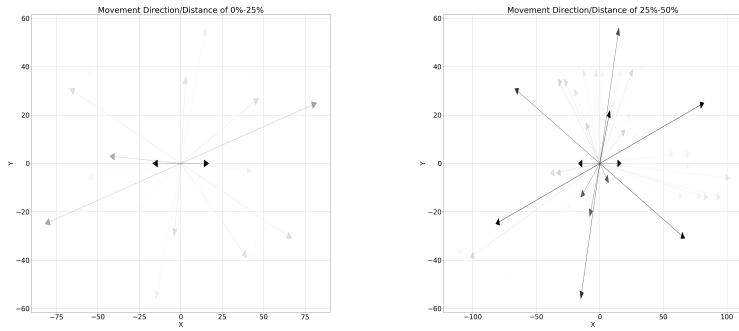
Figure 6: Movement Direction/Distance on First Floor

The movement direction and distance on the first floor is shows as figure 6. In figure 6-(b, c, d), you can see two arrows: one is left-upward arrow, the other is right-downward arrow.

#### 4.1.4 Department Distribution

There are seven departments in the data as followings: (in alphabetical)

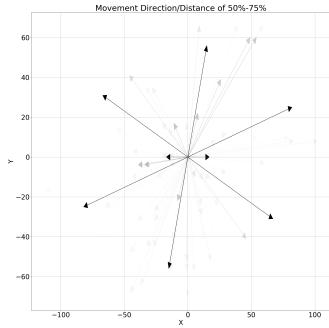
1. Administration
2. Engineering
3. Executive
4. Facilities



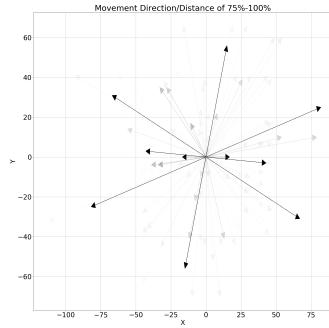
(a) 0%-25%



(b) 25%-50%

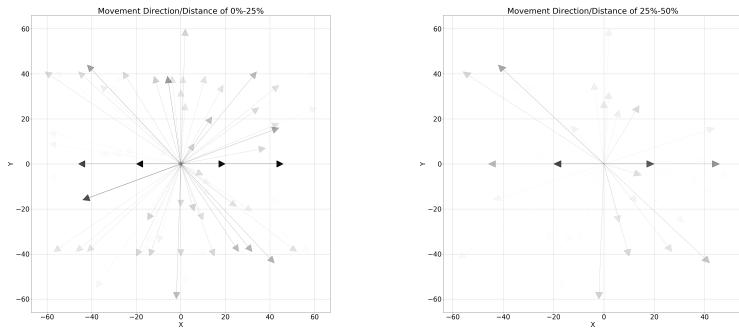


(c) 50%-75%

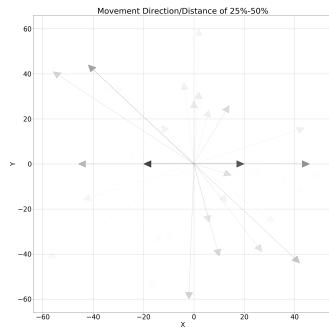


(d) 75%-100%

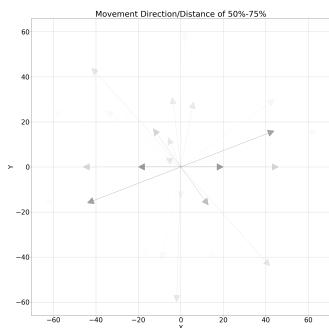
Figure 7: Movement Direction/Distance on Second Floor



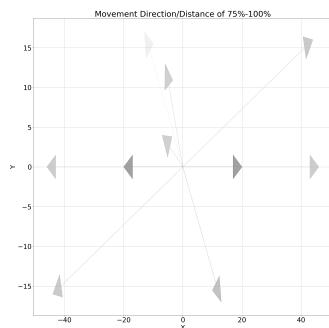
(a) 0%-25%



(b) 25%-50%



(c) 50%-75%



(d) 75%-100%

Figure 8: Movement Direction/Distance on Third Floor

- 5. HR
- 6. Information Technology
- 7. Security

Table 4 shows the distribution of department by quartiles. Also, with the data in table 4, we drew the four pie plots as 9.

Table 4: Department Information by Quartiles

Quartiles	Department	Counts
q1 (Minimum 25%)	Administration	8
	Executive	7
	Facilities	6
	HR	3
q2	Engineering	11
	Security	8
	Administration	6
	Information Technology	2
	Facilities	1
q3	Information Technology	12
	Engineering	7
	Facilities	5
	Security	2
q4 (Maximum 25%)	Engineering	15
	Facilities	9
	Information Technology	3
	Security	1

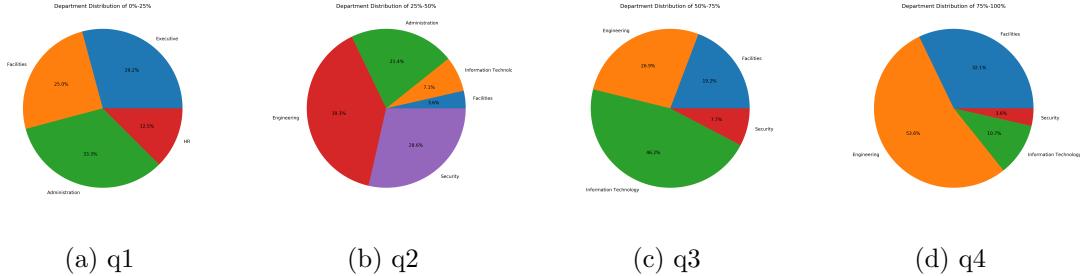


Figure 9: Pie Plot of Department Distribution by Quartiles

#### 4.1.5 Typical Patterns in prox Data

#### 4.1.6 Typical Day Look for GAStech employees

### 4.2 Describe up to five of the most interesting patterns that appear in the building data. Describe what is notable about the pattern and explain its possible significance.

#### 4.2.1 General Information of General Building Data

First of section 4.2, we should find about the distribution of general building data. With TSNE technique, we can draw the TSNE plot of general building data as figure 10.

#### 4.2.2 Workflow

#### 4.2.3 Correlation within General Building Data

We made the correlation heatmap within the general building data to find two columns which have strong positive or negative correlation. The correlation heatmap is as figure 12. Moreover, the R-value distribution with the data which are used in figure 12 is as shown as figure 13.

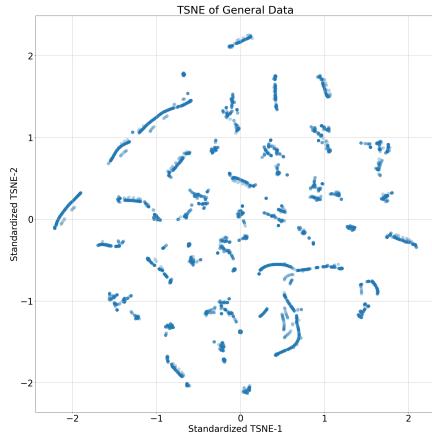


Figure 10: TSNE for General Building Data

Figure 11: Workflow for Question 2

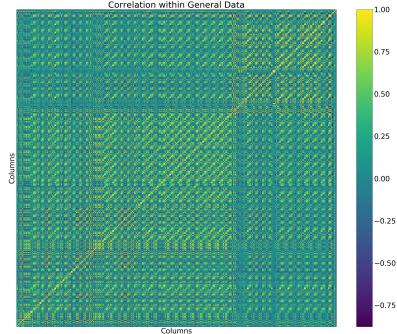


Figure 12: Correlation Heatmap within General Building Data

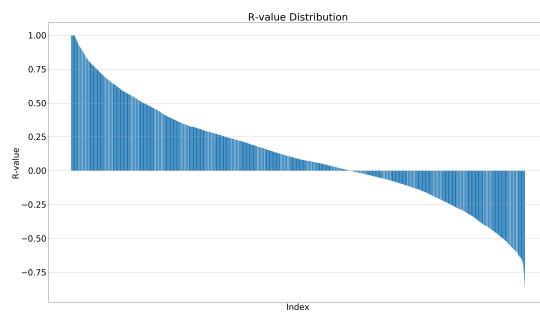


Figure 13: R-value Distribution within General Building Data

Table 5: Basic Statistics of R-Values

Item	Minimum	Maximum	Mean	q1	Median	q3	Standard Deviation
Value	-0.88	1.0	0.11	-0.12	0.08	0.34	0.37

The basic statistics of these R-values are in table 5.

Furthermore, the extreme values of R-values are in tables 6 and 7.

Table 6: Minimum Values of R-Values  
Column1      Column2

Column1	Column2	R-Value
F_3_Z_11C: Thermostat Temp	F_3_Z_11B VAV REHEAT Damper Position	-0.877076318455652
F_3_Z_11C: Thermostat Temp	F_3_Z_11B SUPPLY INLET Mass Flow Rate	-0.8770746421685551
Supply Side Inlet Temperature	F_3_Z_6: Equipment Power	-0.8764301266869379
Supply Side Inlet Temperature	F_3_Z_6: Lights Power	-0.8764301266869379
Supply Side Inlet Temperature	F_1_Z_4: Lights Power	-0.8743564507417133

Table 7: Maximum Values of R-Values  
Column1      Column2

Column1	Column2	R-Value
Water Heater Tank Temperature	Supply Side Outlet Temperature	1.0
F_3_Z_7: Thermostat Heating Setpoint	F_3_Z_3: Thermostat Heating Setpoint	1.0
F_3_Z_7: Thermostat Heating Setpoint	F_3_Z_2: Thermostat Heating Setpoint	1.0
F_3_Z_7: Thermostat Heating Setpoint	F_3_Z_11B: Thermostat Heating Setpoint	1.0
F_3_Z_7: Thermostat Heating Setpoint	F_3_Z_11A: Thermostat Heating Setpoint	1.0
F_3_Z_7: Thermostat Heating Setpoint	F_3_Z_10: Thermostat Heating Setpoint	1.0
F_3_Z_7: Thermostat Cooling Setpoint	F_3_Z_3: Thermostat Cooling Setpoint	1.0
F_3_Z_7: Thermostat Cooling Setpoint	F_3_Z_2: Thermostat Cooling Setpoint	1.0
F_3_Z_7: Thermostat Cooling Setpoint	F_3_Z_11B: Thermostat Cooling Setpoint	1.0
F_3_Z_7: Thermostat Cooling Setpoint	F_3_Z_11A: Thermostat Cooling Setpoint	1.0
F_3_Z_7: Thermostat Cooling Setpoint	F_3_Z_10: Thermostat Cooling Setpoint	1.0
F_3_Z_6: Thermostat Heating Setpoint	F_3_Z_5: Thermostat Heating Setpoint	1.0
F_3_Z_6: Thermostat Cooling Setpoint	F_3_Z_5: Thermostat Cooling Setpoint	1.0
F_3_Z_6: Lights Power	F_3_Z_6: Equipment Power	1.0
F_3_Z_5: Lights Power	F_3_Z_5: Equipment Power	1.0
F_3_Z_3: Thermostat Heating Setpoint	F_3_Z_2: Thermostat Heating Setpoint	1.0
F_3_Z_3: Thermostat Heating Setpoint	F_3_Z_11B: Thermostat Heating Setpoint	1.0
F_3_Z_3: Thermostat Heating Setpoint	F_3_Z_11A: Thermostat Heating Setpoint	1.0
F_3_Z_3: Thermostat Heating Setpoint	F_3_Z_10: Thermostat Heating Setpoint	1.0
F_3_Z_3: Thermostat Cooling Setpoint	F_3_Z_2: Thermostat Cooling Setpoint	1.0
F_3_Z_3: Thermostat Cooling Setpoint	F_3_Z_11B: Thermostat Cooling Setpoint	1.0
F_3_Z_3: Thermostat Cooling Setpoint	F_3_Z_11A: Thermostat Cooling Setpoint	1.0
F_3_Z_3: Thermostat Cooling Setpoint	F_3_Z_10: Thermostat Cooling Setpoint	1.0
F_3_Z_3: Lights Power	F_3_Z_3: Equipment Power	1.0
(omitted...)	(omitted...)	(omitted...)

As table 6, no combination of columns make R-value to -1; but, there are many combinations of columns make R-value 1. In other words, many columns have strong positive correlation with others rather than negative correlation. However, in table 7, most of combination are (Thermostat Heating Setpoint), (Thermostat Cooling Setpoint), or (Lights Power & Equipment power). Also, not all Thermostat Setpoints in same floor have strong correlation; but, Thermostat Setpoints in different floor do not have strong correlation.

Furthermore, we draw plot between three general building data which have the lowest R-values as figure 14. In the figure 14, the R-values are about 0.88, so the R-squared values ( $R^2$ ) will be about 0.77. Therefore, in figure 14, we can argue that they have negative correlation, but it is not *strong* negative correlation.

#### 4.2.4 Plots of General Building Data

In the figure 15, there are two plots: Figure 15-(a) is stacked plot about all columns, and figure 15-(b) has basic statistics plot of general building data. In figure 15-(b), we can see that the pattern of general building data is changing by quarters: in first-quarters, the cyclic pattern is shown; in second-quarters, rapidly increasing can be detected; in third-quarters, many general building data jump and hold a while; and, in fourth-quarters, general building data are suddenly decreasing.

In the first-quarter, we find that the general building data make a cycle every 288 indices as figure 16. The general building data are reported on every 5 minutes, so the general building data make a cycle every 1440 minutes or every 24 hours or every 1 day.

In the second-quarter, we calculated the peak in every columns in general building data. With figure 17-(a), the distribution of peak width is shown; and, with figure 17-(b), you can know that where is peak in general

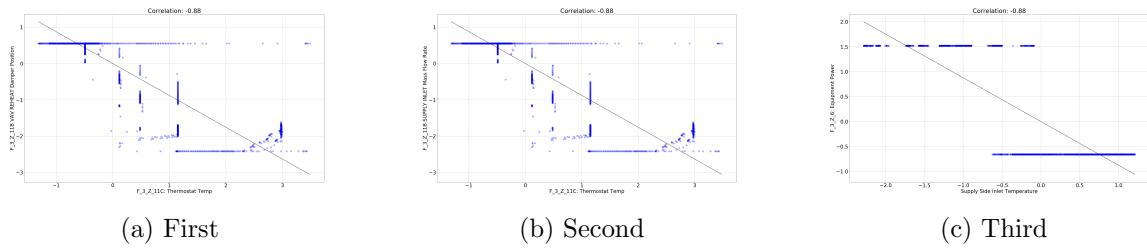


Figure 14: Plots of the Lowest R-values

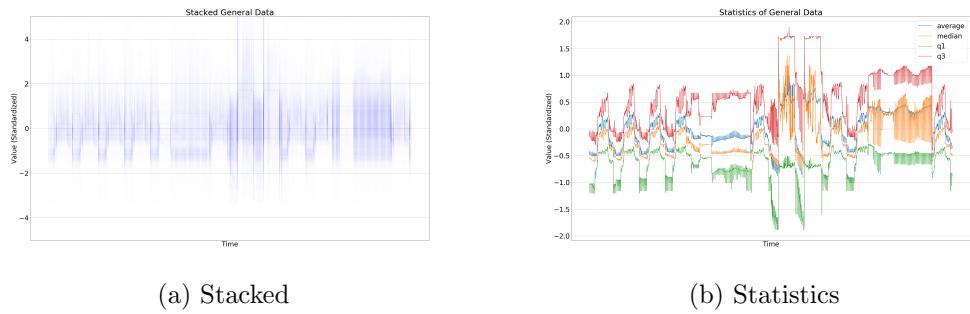


Figure 15: Plots of General Building Data

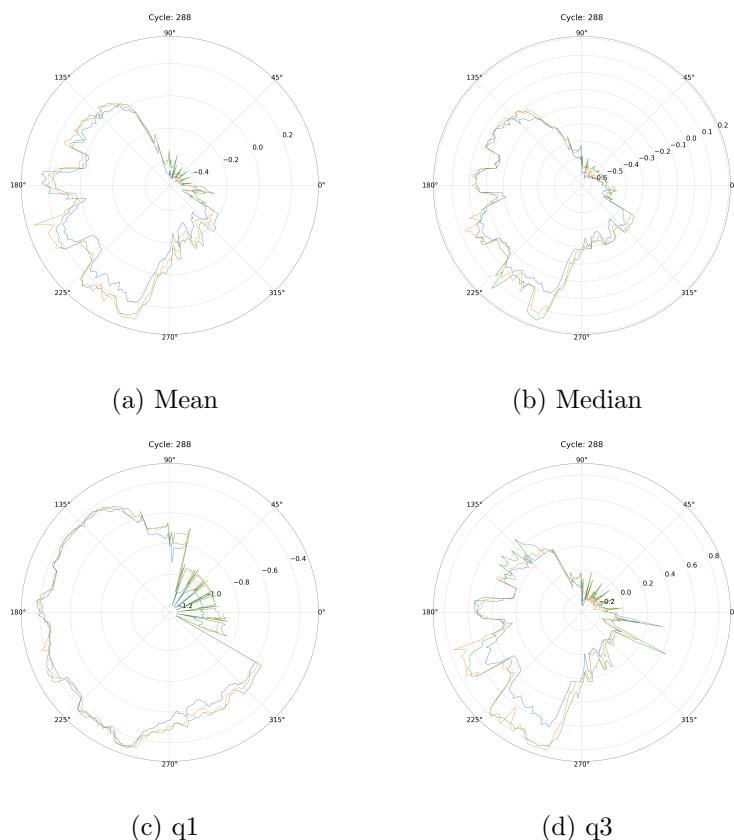
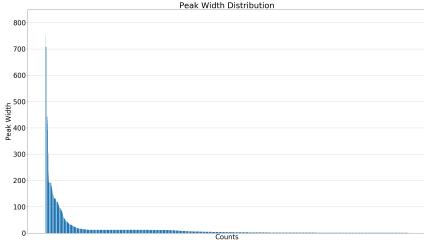


Figure 16: Cyclic Plots on First-quarters

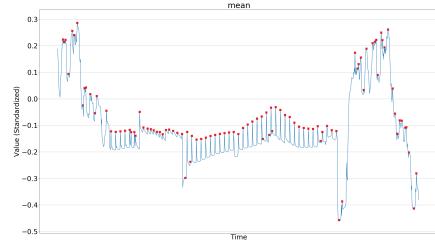
building data. Also, table 8 displays basic statistics value of peak width. With the data in figure 17 and table 8, we can know that the general building data are suddenly increasing about *15 indices*; in other words, the general building data has steeps every *75 minutes*.

Table 8: Basic Statistics Data with the peak in the Second-quarter

Item	Minimum	Maximum	Mean	q1	Median	q3	Standard Deviation
Value	1.0	808.45	15.98	1.51	3.71	12.0	55.36



(a) Peak Width Distribution



(b) Peak in Mean Column

Figure 17: Peak in the Second-quarter

As figure 16, we drew the cyclic plots of the third-quarters of general building data as figure 18. As the first-quarters, the period is *288 indices*, *24 hours*, or *1 day*. Therefore, there are two days which has increased general building data.

In the fourth-quarter, we calculated the under-peak in every columns in general building data. As figure 17, with figure 19-(a), the distribution of under-peak width is displayed; and, with figure 19-(b), you can know that where is under-peak in general building data. Moreover, table 9 shows basic statistics value of under-peak width. Amongst the data in figure 19 and table 9, we can know that the general building data are rapidly decreasing about *16 indices*; in other words, the general building data has under-steeps every *80 minutes*.

Table 9: Basic Statistics Data with the under-peak in the Fourth-quarter

Item	Minimum	Maximum	Mean	q1	Median	q3	Standard Deviation
Value	1.0	850.54	16.36	1.11	2.77	11.68	69.86

#### 4.2.5 Interesting Patterns

According to these fact, we can know followings:

1. *Thermostat Setpoint* is controlled by floor. Someone can adjust specific zone in floor, but the default value is sets on floor. (Table 7)
2. Some zone only have *lights* for power consumption. (Table 7)
3. No *strong* negative correlation exist. (Figure 14)
4. In the first-quarter, the general building data make a cycle everyday. (Figure 16)
5. In the second-quarter, the general building data are suddenly increasing about every *75 minutes*. (Table 8 and Figure 17)
6. There are two days which are increasing whole usage of the general building data. (Figure 18)
7. In the fourth-quarter, the general building data are dramatically decreasing about every *80 minutes*. (Table 9 and Figure 19)

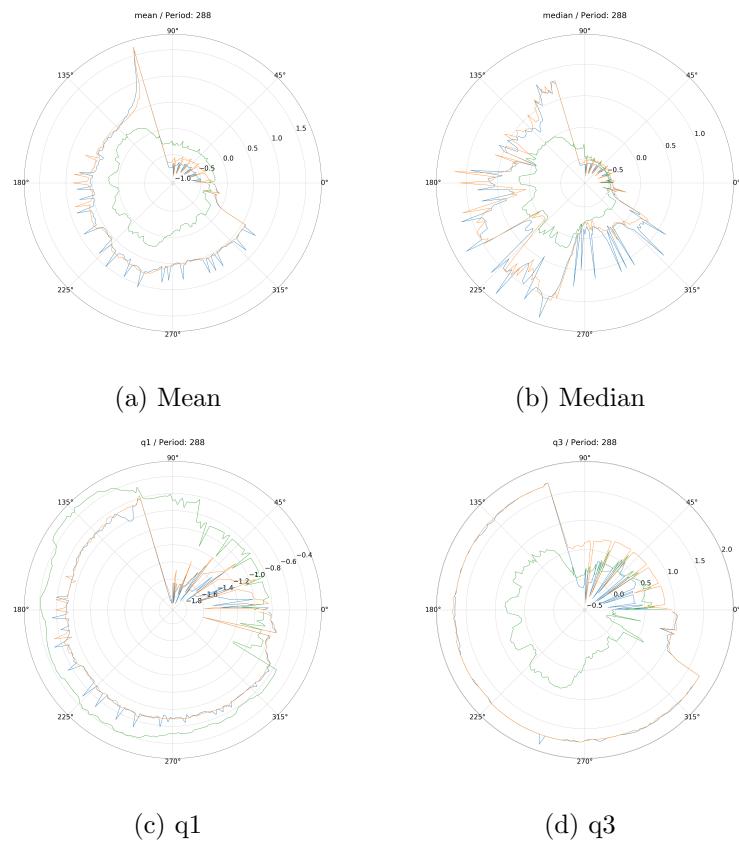


Figure 18: Cyclic Plots on Third-quarters

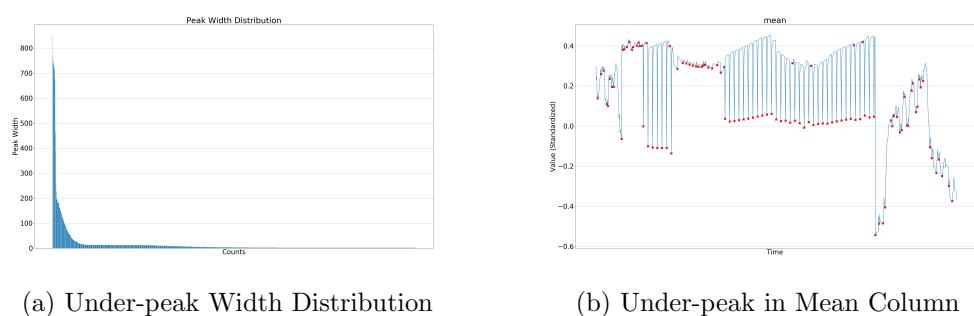


Figure 19: Under-peak in the Fourth-quarter

**4.3 Describe up to five notable anomalies or unusual events you see in the data. Prioritize those issue that are most likely to represent a danger or a serious issue for building operations.**

#### 4.3.1 General Information of Hazium Concentration

In the question 2 or section 4.2, we need to find a danger or a serious issue for building data. Hence, we suppose that a danger will be related with Hazium concentration. In other words, if there are some danger in building operation, then the Hazium data will be increased along.

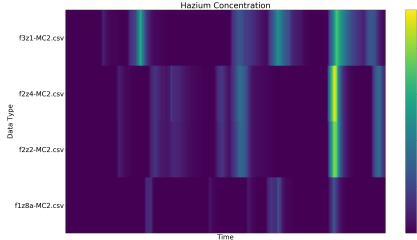


Figure 20: Hazium Data from Different Data Sources

In the figure 20, we can see Hazium concentration of many sources.

#### 4.3.2 Workflow

Figure 21: Workflow for Question 3

#### 4.3.3 Abnormality in General Building Data

To find patterns which appear in the building data, we should find that normality/abnormality in the building data. However, there are over 400 columns in the general building data; therefore, it is almost impossible to find abnormality column-by-column by human. Hence, we used these four algorithms which are included in scikit-learn: *EllipticEnvelope* [8], *OneClassSVM*, *IsolationForest* [9, 10], and *LocalOutlierFactor* [11].

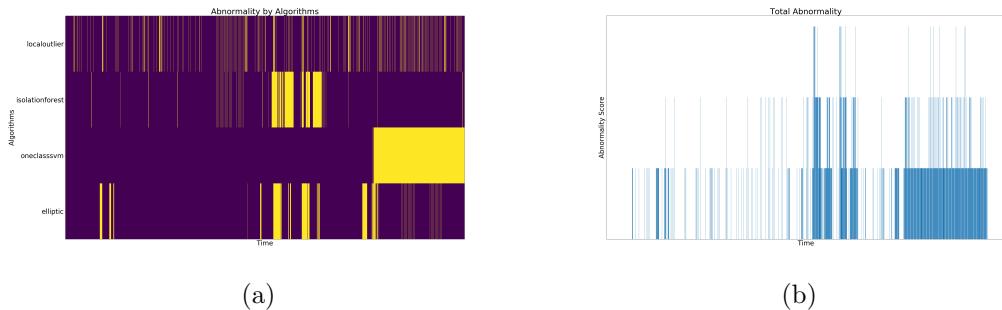


Figure 22: Abnormality in General Building Data by Timeline

Moreover, we can display the timeline of abnormality as figure 22. In the figure 22-(a), we can know that which algorithm consider specific time as abnormal events (yellow marked is abnormal); and, in the figure 22-(b), we can realize that how many algorithms consider specific time as abnormal events.

#### 4.3.4 Score of Classification of Abnormality

To decide the best algorithm for find abnormality, we use these five classifier algorithms for scoring: *KNeighbor*, *SVC* [12, 13], *DecisionTree* [14, 15, 16], *RandomForest* [16], and *AdaBoost* [17, 18]. The scores are in table 10; the highest score is 0.9938 on *LocalOutlier* algorithm. Therefore, we choose *LocalOutlier* algorithm for finding abnormality. Note that the train data and the test data are randomly selected with 0.8 : 0.2 ratio, and the seed is specified for repeated result.

Table 10: Scores of Classification of Abnormality

	Elliptic	OneClassSVM	IsolationForest	LocalOutlier
KNeighbor	0.995	0.991	0.929	0.988
SVC	0.994	0.993	0.919	0.985
DecisionTree	0.988	0.989	0.948	0.999
RandomForest	0.993	0.995	0.942	0.999
AdaBoost	0.986	0.985	0.937	0.999
Mean	0.9911	0.9906	0.9351	0.9938

#### 4.3.5 Column for Abnormality

Now, we know that when is abnormal in general building data, and the general building data *per se*. Therefore, we can calculate the difference of mean value for each columns in general building data. In other words, we can measure that which column in general building data most differ between normal and abnormal timing.

The distribution of differences between mean values for whole columns of general building data is figure 23; also, the basic statistics values of differences between mean values are in table 11.

Table 11: Basic Statistics Data with the Differences of Mean Values

Item	Minimum	Maximum	Mean	q1	Median	q3	Standard Deviation
Value	0.00058	1.05075	0.159379	0.05347	0.1097855	0.1756	0.171869

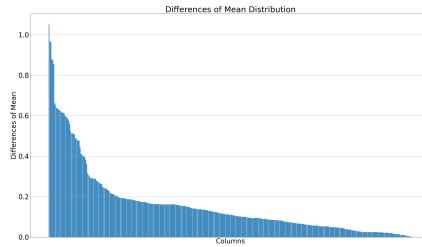


Figure 23: Distribution of Differences between Mean Value

#### 4.3.6 Danger for Building Operation

Figure 24 display two heatmap about R-values: figure 24-(a) is consist with the data which marked as *normal*; and, figure 24-(b) contains the data which marked as *abnormal*. However, as shown as figure 24, the R-values are not significant; in other words, R-squared values are too small to give confidence for correlation. Therefore, we divided the abnormal data with comparing the general building data and Hazium data directly. As we mentioned herein-above, all of values are standardized, so we can compare two values one-by-one.

Figure 25 contains two heatmap plot of divided abnormal data. Figure 25-(a) is drawn with the data which has higher general building data than Hazium data; and also, figure 25-(b) is written with the data which has lower general building data. With comparing figure 24 and figure 25, the R-values in 25 is bigger than the R-values in 24. In other words, in the (General Building Data)–(Hazium Data) plot, the scatter data are aligned near the X-axis and Y-axis.

With the data in figure 25, we can select the column which has the highest sum of R-values. In this data, combination of the column (*F\_2\_Z\_16 SUPPLY INLET Temperature*) and the data set (*f2z2-MC2.csv*) has the highest value. Figure 26 is written with this combination. As we mentioned herein-above, many points are along the X-axis or the Y-axis.

$\therefore$  Hence, if the data (*F\_2\_Z\_16 SUPPLY INLET Temperature*) is decreasing, then the Hazium concentration of Zone 2 on Floor 2 will be increasing; and *vice versa*. Many other combinations exist; but, we only display this combination which has the highest R-values.

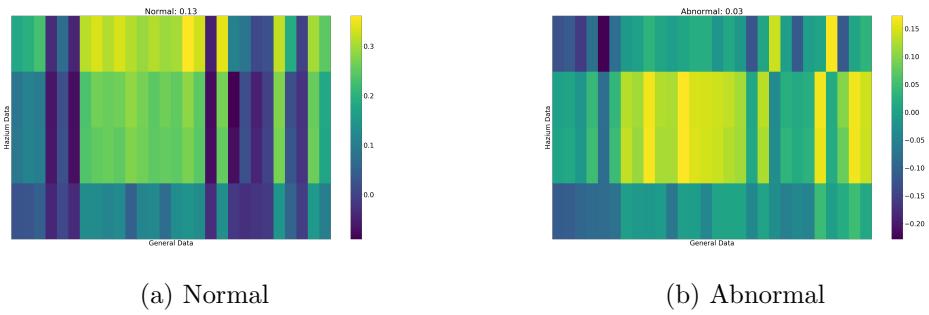


Figure 24: Heatmap of R-values between General Building Data and Hazium Data

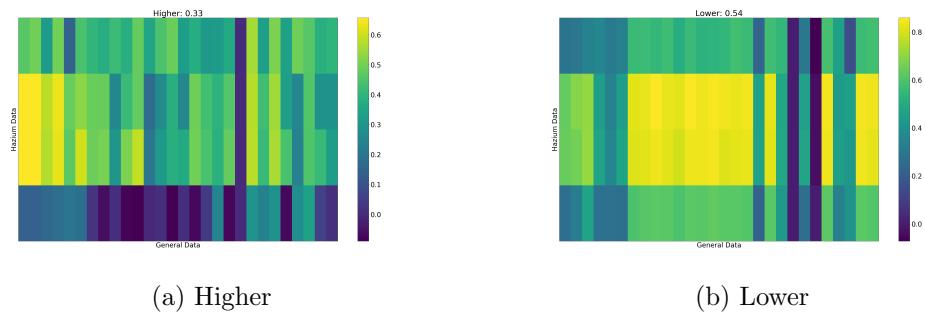


Figure 25: Heatmap of R-values with Higher and Lower General Building Data

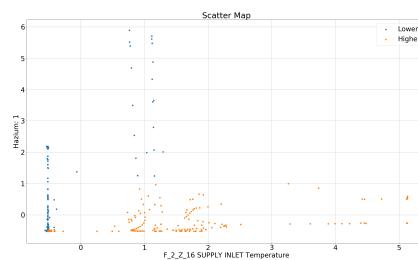


Figure 26: Scatter Plot between General Building Data and Hazium Data

**4.4 Describe up to three observed relationships between the proximity card data and building data elements. If you find a causal relationship, describe your discovered cause and effect, the evidence you found the support it, and your level of confidence in your assessment of the relationship.**

#### 4.4.1 Frequency of prox Data

The general building data has been reported every five minutes; however, prox data is a kind of movement data, so prox data has no cycle pattern at all. Therefore, we should gather and count prox data for comparing with general building data. In this manner, table 12 and figure 27 have the distribution information about frequency of prox data.

Table 12: Basic Statistics Data with the Frequency of prox Data

Item	Minimum	Maximum	Mean	q1	Median	q3	Standard Deviation
Value	0	141	8.014	0	0	10	15.35

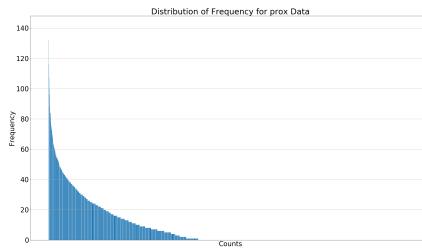


Figure 27: Distribution with Frequency of prox Data

Moreover, with figure 28, there are some peaks in the prox data. Also, the five peaks in the row, we can have reasonable doubt about weekday and weekend.

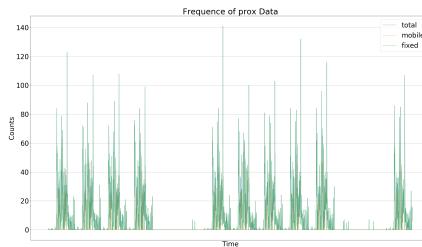


Figure 28: Timeline with Frequency of prox Data

With the reasonable doubt from figure 28, we can draw the cycle plot with daily as figure 29. With figure 29, we can know what the employees look like such as their attendance time.

#### 4.4.2 Workflow

#### 4.4.3

#### 4.4.4 Correlation between General Building Data and prox Data

#### 4.4.5 Cause and Effect for the Correlation

## 5 Discussion

## References

- [1] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, *et al.*, “Scikit-learn: Machine learning in python,” *Journal of machine learning research*, vol. 12, no. Oct, pp. 2825–2830, 2011.

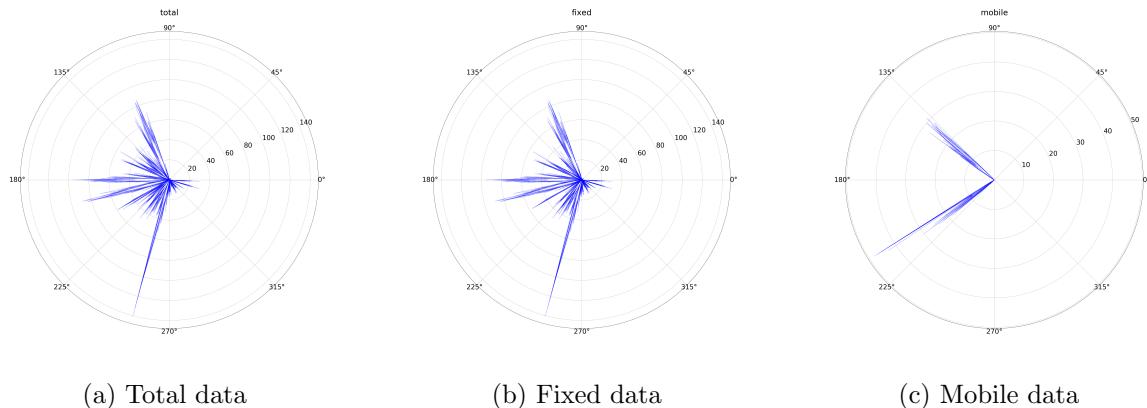


Figure 29: Daily Cycle of prox Data

Figure 30: Workflow for Question 4

- [2] J. D. Hunter, “Matplotlib: A 2d graphics environment,” *Computing in science & engineering*, vol. 9, no. 3, p. 90, 2007.
  - [3] W. McKinney, “pandas: a foundational python library for data analysis and statistics,” *Python for High Performance and Scientific Computing*, vol. 14, 2011.
  - [4] E. Jones, T. Oliphant, P. Peterson, *et al.*, “Scipy: Open source scientific tools for python,” 2001.
  - [5] A. Clark, “Pillow (pil fork) documentation,” 2015.
  - [6] C. Sievert, C. Parmer, T. Hocking, S. Chamberlain, K. Ram, M. Corvellec, and P. Despouy, “plotly: Create interactive web graphics via ‘plotly.js’,” *R package version*, vol. 4, no. 1, p. 110, 2017.
  - [7] L. v. d. Maaten and G. Hinton, “Visualizing data using t-sne,” *Journal of machine learning research*, vol. 9, no. Nov, pp. 2579–2605, 2008.
  - [8] P. J. Rousseeuw and K. V. Driessen, “A fast algorithm for the minimum covariance determinant estimator,” *Technometrics*, vol. 41, no. 3, pp. 212–223, 1999.
  - [9] F. T. Liu, K. M. Ting, and Z.-H. Zhou, “Isolation forest,” in *2008 Eighth IEEE International Conference on Data Mining*, pp. 413–422, IEEE, 2008.
  - [10] F. T. Liu, K. M. Ting, and Z.-H. Zhou, “Isolation-based anomaly detection,” *ACM Transactions on Knowledge Discovery from Data (TKDD)*, vol. 6, no. 1, p. 3, 2012.
  - [11] M. M. Breunig, H.-P. Kriegel, R. T. Ng, and J. Sander, “Lof: identifying density-based local outliers,” in *ACM sigmod record*, vol. 29, pp. 93–104, ACM, 2000.
  - [12] C.-C. Chang and C.-J. Lin, “Libsvm: A library for support vector machines,” *ACM transactions on intelligent systems and technology (TIST)*, vol. 2, no. 3, p. 27, 2011.
  - [13] J. Platt *et al.*, “Probabilistic outputs for support vector machines and comparisons to regularized likelihood methods,” *Advances in large margin classifiers*, vol. 10, no. 3, pp. 61–74, 1999.
  - [14] L. Breiman, *Classification and regression trees*. Routledge, 2017.
  - [15] T. Hastie, R. Tibshirani, and J. Friedman, *The elements of statistical learning: data mining, inference, and prediction*. Springer Science & Business Media, 2009.
  - [16] L. Breiman, “Random forests,” *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.
  - [17] Y. Freund and R. E. Schapire, “A decision-theoretic generalization of on-line learning and an application to boosting,” *Journal of computer and system sciences*, vol. 55, no. 1, pp. 119–139, 1997.
  - [18] T. Hastie, S. Rosset, J. Zhu, and H. Zou, “Multi-class adaboost,” *Statistics and its Interface*, vol. 2, no. 3, pp. 349–360, 2009.