Visualization Term Project

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1 Introduction

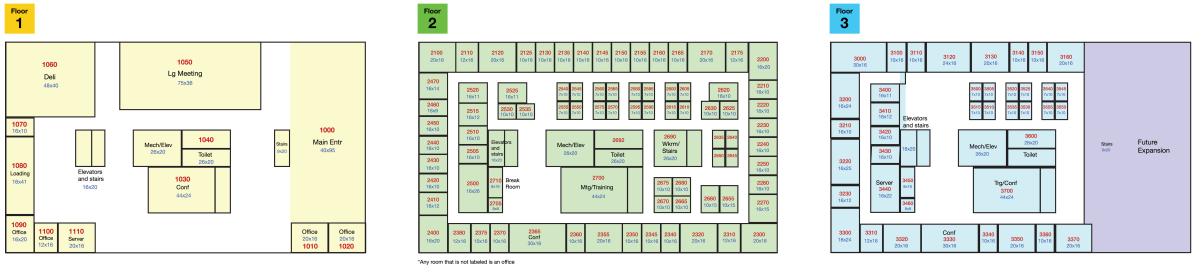
In this term project, we have to answer several question with virtual building data.

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

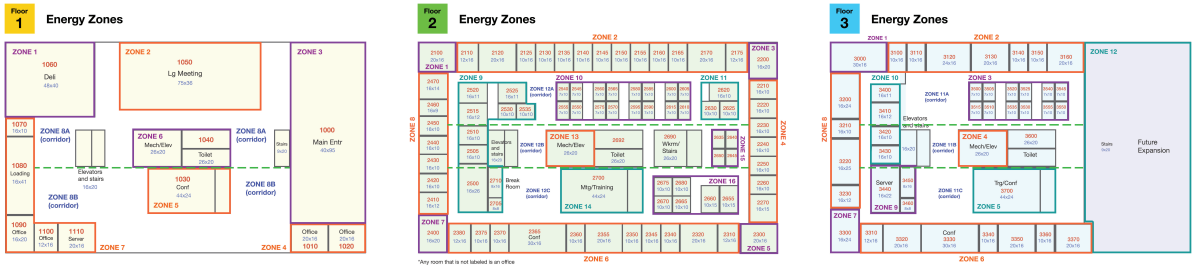


(a) First Floor (b) Second Floor (c) Third Floor

Figure 1: Main Layout of the building

The main layout of this building is as figure 1.

2.1.2 Energy Zone Layout



(a) First Floor (b) Second Floor (c) Third Floor

Figure 2: Energy Zone of the Building

The energy zone of this building is as figure 2.

2.1.3 Prox Zone Layout

The prox zone of this building is as figure 3.

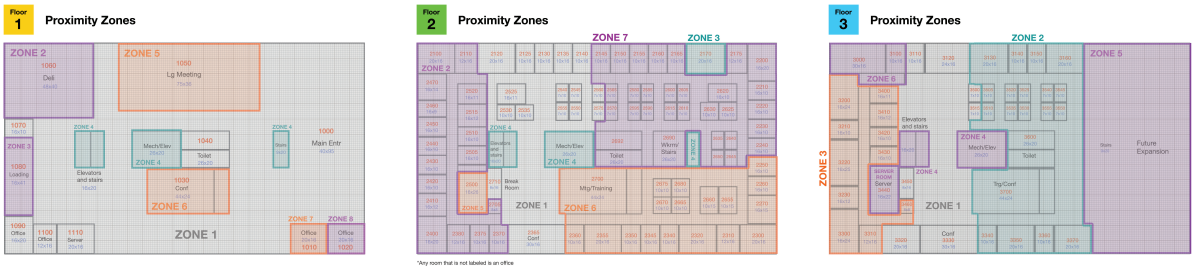
3 Methods

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 TSNE

T-distributed Stochastic Neighbor Embedding (TSNE) is a machine learning algorithm for visualization high-dimensional data in a low-dimensional space [6].

3.3 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.

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

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

4.1.2 Workflow

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

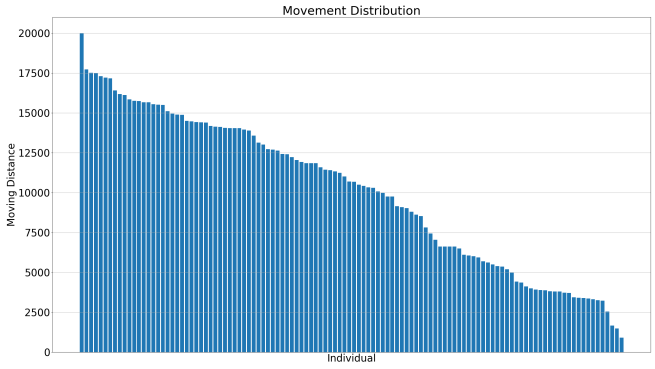


Figure 4: Distribution of Movement Distance

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

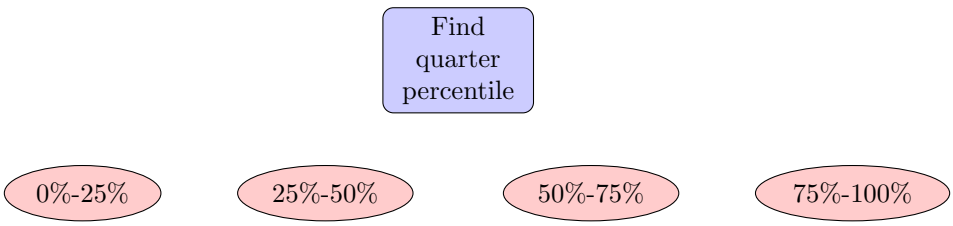
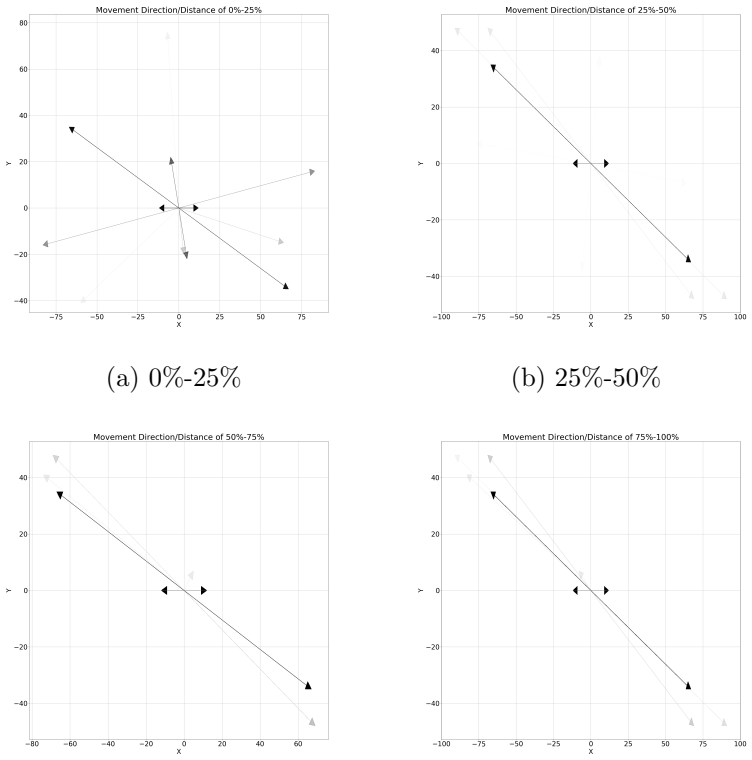


Figure 5: Workflow for Question 1

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.



(a) 0%-25%

(b) 25%-50%

(c) 50%-75%

(d) 75%-100%

Figure 6: Movement Direction/Distance on First Floor

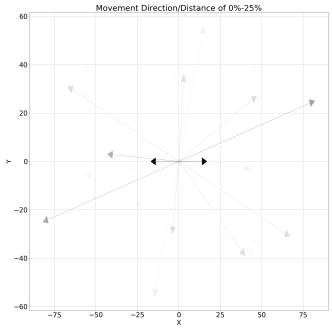
The movement direction and distance on the first floor is shows as figure 6. In figure 6-(b, c, d), you can see two arrows: one is left-upward arrow, the other is right-downward arrow.

4.1.4 Department Distribution

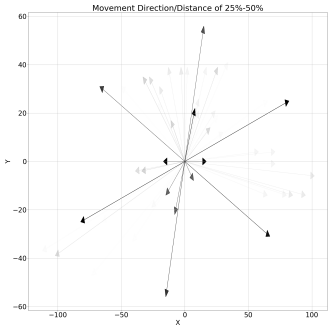
There are seven departments in the data as followings: (in alphabetical)

1. Administration
2. Engineering
3. Executive
4. Facilities
5. HR
6. Information Technology
7. Security

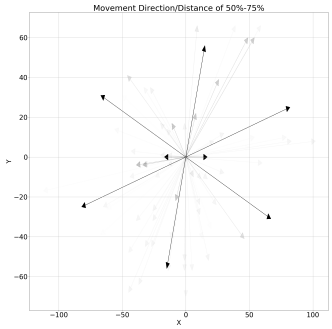
Table 4 shows the distribution of department by quartiles. Also, with the data in table 4, we drew the four pie plots as 9.



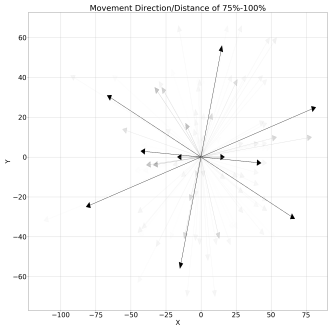
(a) 0%-25%



(b) 25%-50%

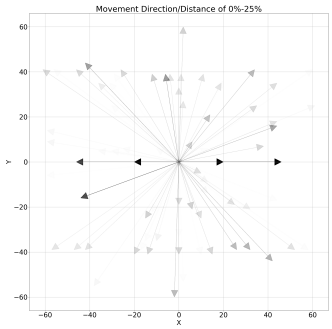


(c) 50%-75%

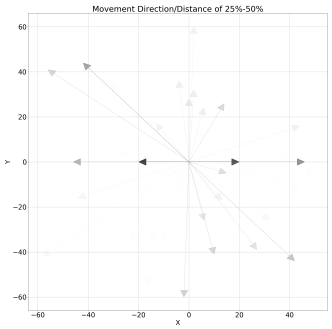


(d) 75%-100%

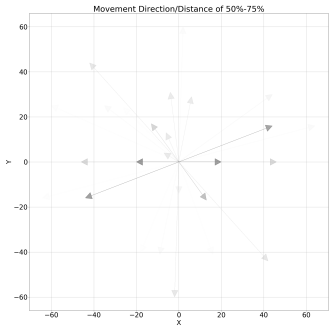
Figure 7: Movement Direction/Distance on Second Floor



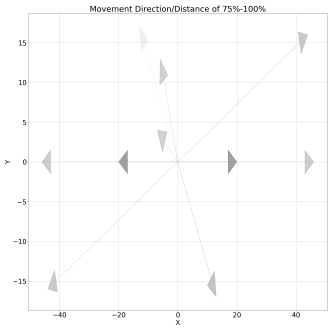
(a) 0%-25%



(b) 25%-50%



(c) 50%-75%

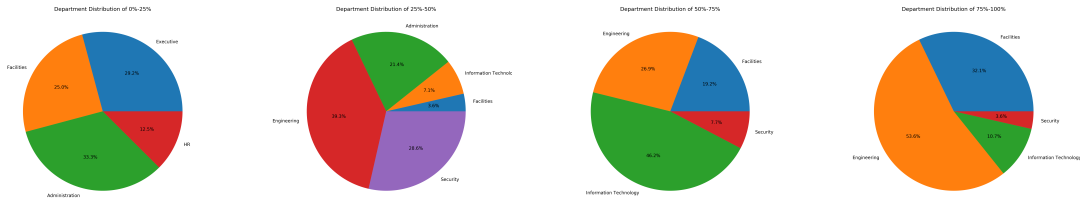


(d) 75%-100%

Figure 8: Movement Direction/Distance on Third Floor

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



(a) q1 (b) q2 (c) q3 (d) q4

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.

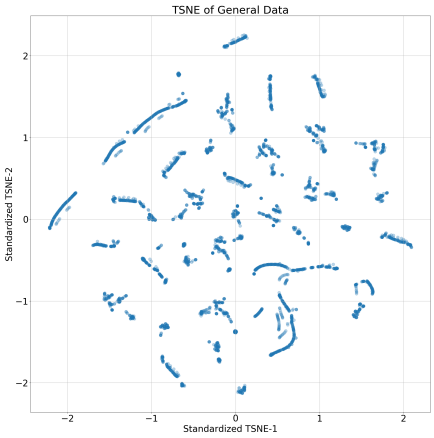


Figure 10: TSNE for General Building Data

4.2.2 Workflow

Figure 11: Workflow for Question 2

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.

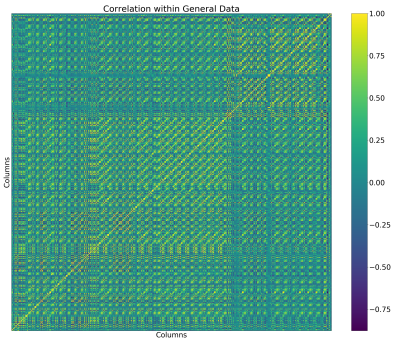


Figure 12: Correlation Heatmap within General Building Data

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

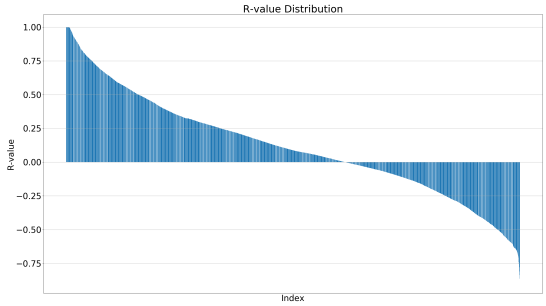


Figure 13: R-value Distribution within General Building Data

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

Table 6: Minimum Values of R-Values

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

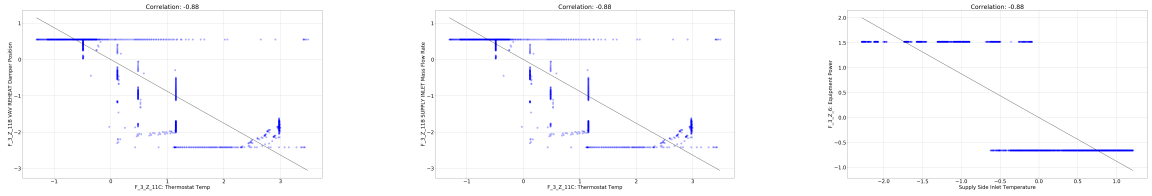
Table 7: Maximum Values of R-Values

Column1	Column2	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...)

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

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.

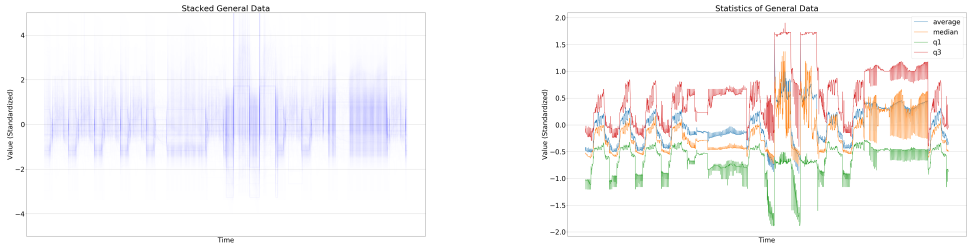


(a) First (b) Second (c) Third

Figure 14: Plots of the Lowest R-values

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.



(a) Stacked (b) Statistics

Figure 15: Plots of General Building Data

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*.

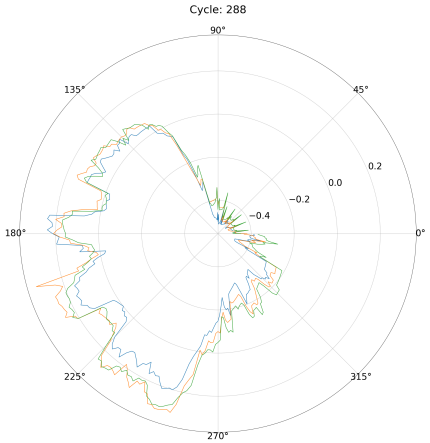
In the second-quarter, we calculated the peak in every columns in general building data. With figure 17-(a), the distribution of peak width is shown; and, with figure 17-(b), you can know that where is peak in general building data. Also, table 8 displays basic statistics value of peak width. With the 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

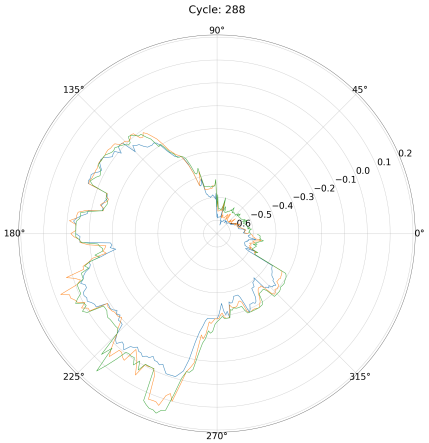
Item	Minimum	Maximum	Mean	q1	Median	q3	Standard Deviation
Value	1.0	808.45	15.98	1.51	3.71	12.0	55.36

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.

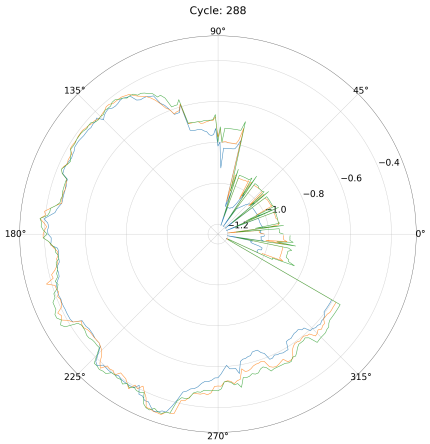
In the fourth-quarter, we calculated the under-peak in every columns in general building data. As figure 17, with figure 19-(a), the distribution of under-peak width is displayed; and, with figure 19-(b), you can know



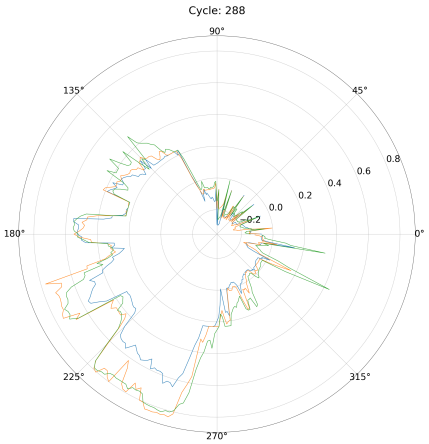
(a) Mean



(b) Median

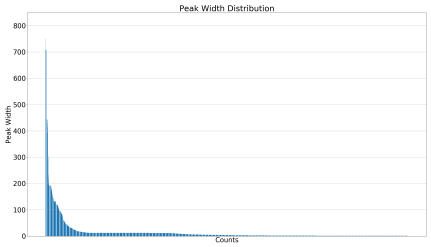


(c) q1

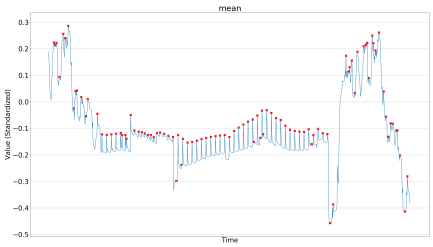


(d) q3

Figure 16: Cyclic Plots on First-quarters

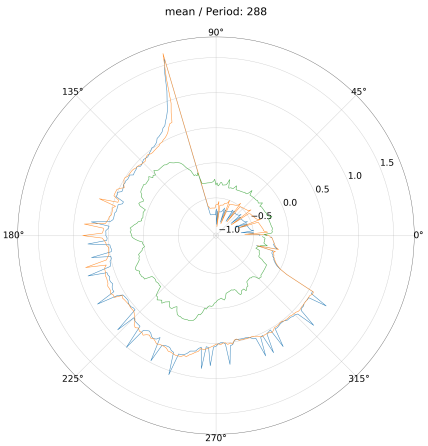


(a) Peak Width Distribution

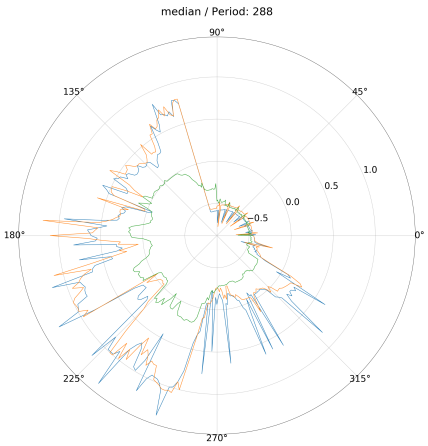


(b) Peak in Mean Column

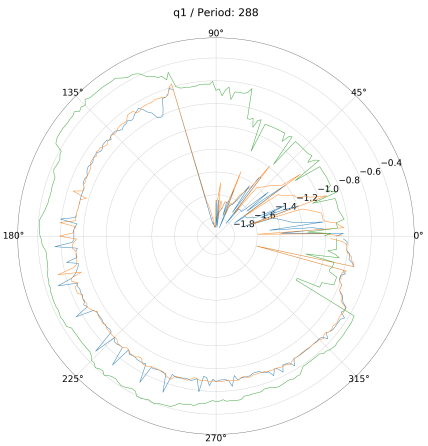
Figure 17: Peak in the Second-quarter



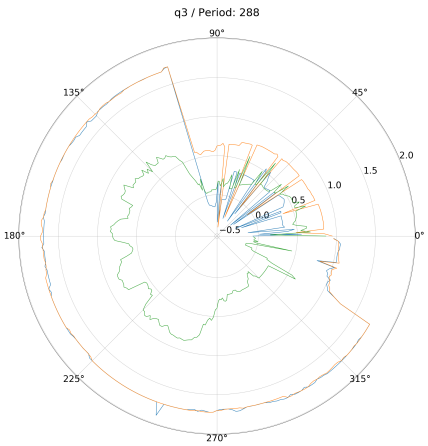
(a) Mean



(b) Median



(c) q1



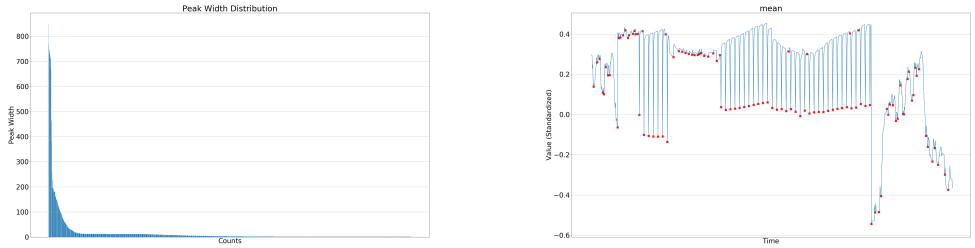
(d) q3

Figure 18: Cyclic Plots on Third-quarters

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



(a) Under-peak Width Distribution (b) Under-peak in Mean Column

Figure 19: Under-peak in the Fourth-quarter

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)

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.

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

4.3.2 Workflow

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* [7], *OneClassSVM*, *IsolationForest* [8, 9], and *LocalOutlierFactor* [10].

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.

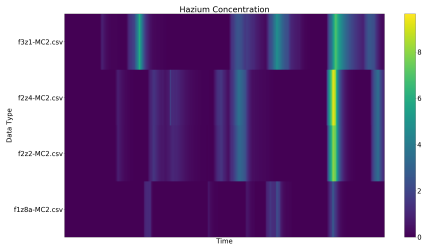


Figure 20: Hazium Data from Different Data Sources

Figure 21: Workflow for Question 3

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* [11, 12], *DecisionTree* [13, 14, 15], *RandomForest* [15], *AdaBoost* [16, 17]. 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.

4.3.5 Danger for Building Operation

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. Furthermore, we only choose columns which has the difference between mean values is bigger than *0.5*. With this process, only 28 columns are selected amongst 387 columns.

(a) (b)

Figure 22: Abnormality in General Building Data by Timeline

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

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

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 General Information of Moving Mean for General Building Data

4.4.2 Workflow

4.4.3 Frequency of prox Data

4.4.4 Correlation between General Building Data and prox Data

4.4.5 Cause and Effect for the Correlation

5 Discussion

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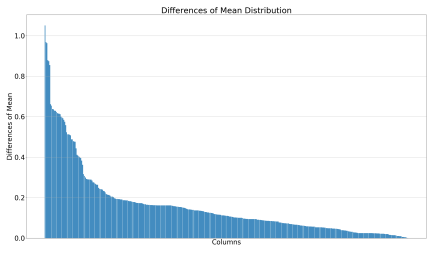

Figure 23: Distribution of Differences between Mean Value

Figure 24: Workflow for Question 4

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