Analysis of MFC location in Seoul

Data Mining Application Team Project

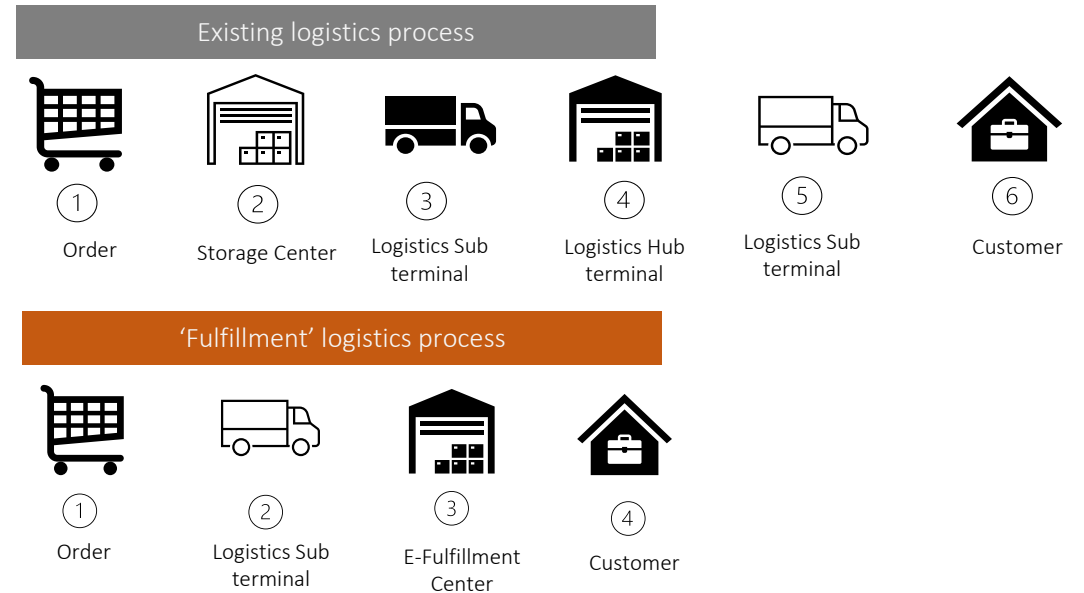201800302 강대경 201801158 김 찬 201802033 신 용 201904193 김나연

CONTENTS

Benefits of MFC Installation

Small Urban distribution center 'Micro Fulfillment Center'

'Fulfillment' refers to a service of all processes of product delivery to customer such as product storage, selection and delivery
Existing distribution centers are generally located outside the city

MFCs are located the city and if the product is stored in MFC in advance by predicting consumer preferences
➡ The time between ordering and delivery can be greatly reduced

Existing logistics process

①	②	③	④	⑤	⑥
Order	Storage Center	Logistics Sub terminal	Logistics Hub terminal	Logistics Sub terminal	Customer

'Fulfillment' logistics process

①	②	③	④
Order	Logistics Sub terminal	E-Fulfillment Center	Customer

MFC and Oil station

: Discussion of the need for MFC in the city

But Where?

: It is difficult to secure a new location in Seoul

Expected change in oil station

: Anticipation of changes in places

Judging that 'Gas station' and 'MFC' features are similar
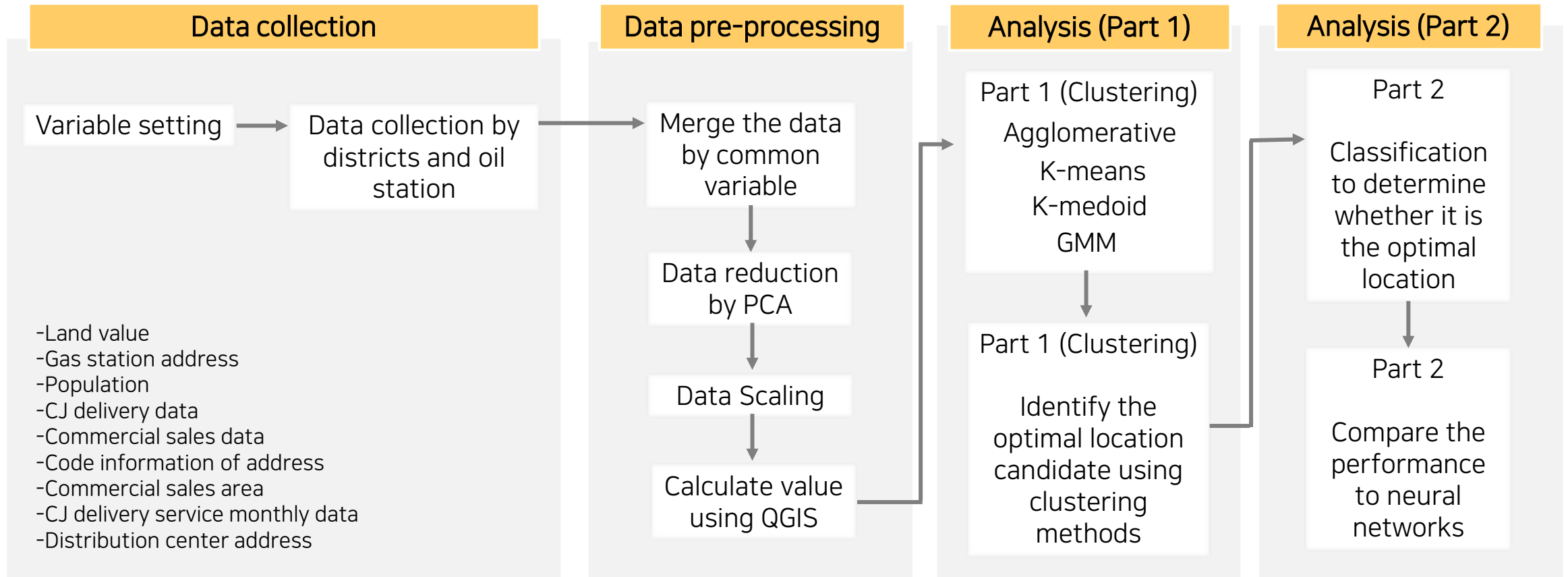
① Decrease in demand for gas stations

② Distance from demand

③ Change the role of oil station

"CJ 대한통운 SK에너지, 주유소를 도심 물류센터로" -조선 비즈-

01. Topic selection background

Procedure

Data collection	Data pre-processing	Analysis (Part 1)	Analysis (Part 2)

Data collection

Variable setting → Data collection by districts and oil station

-Land value
-Gas station address
-Population
-CJ delivery data
-Commercial sales data
-Code information of address
-Commercial sales area
-CJ delivery service monthly data
-Distribution center address

Data pre-processing

Merge the data by common variable
↓
Data reduction by PCA
↓
Data Scaling
↓
Calculate value using QGIS

Analysis (Part 1)

Part 1 (Clustering)

Agglomerative
K-means
K-medoid
GMM
↓
Part 1 (Clustering)

Identify the optimal location candidate using clustering methods

Analysis (Part 2)

Part 2

Classification to determine whether it is the optimal location
↓
Part 2

Compare the performance to neural networks

Pre-processing

Variables Used for Clustering

Variable	Contents
DRIVEN_EFF	Operational efficiency; 서울특별시 빅데이터 캠퍼스 > CJ택배 운행량 월별 통계.csv
TOTAL_LOGIS	Delivery volume by region; 서울 열린 데이터 광장 > 주민등록인구.csv
POP2040	Number of Producible Populations; 서울 열린 데이터 광장 > 주민등록인구.csv
TOTAL_SALES	Off-line commercial sales; 서울 열린 데이터 광장 > 서울시 상권 매출액.csv
NUM_STORE	Size of offline commercial area; 서울 열린 데이터 광장 > 서울시 우리마을가게 상권분석 서비스
ESTATE	Official land price; 서울특별시 빅데이터 캠퍼스 > CJ택배 운행량 월별 통계.csv

The following is a preprocessing of collected data for clustering
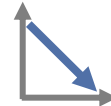
Preprocessed data						
	DISTRICT	DRIVEN_EFF	TOTAL_LOGIS	POP2040	TOTAL_SALES	NUM_STORE	ESTATE
0	동대문구	0.027219	2400374	166805	4.447564e+12	66655	5198000
1	용산구	0.131360	2250955	112398	6.805869e+12	62840	10079000
2	구로구	0.054334	2442377	184583	2.806535e+12	69651	4109000
3	노원구	0.026526	2507172	215172	1.834499e+12	57391	3911000
4	서초구	0.159699	2165093	185381	6.456707e+12	117682	11141000

Generate derivable attribute : Driving Efficiency

Data used to obtain Driving Efficiency							
	운행년월 (DRIVEN_YM)	주소(구) (ADDR)	운행거리(평균) (DRIVEN_AVR)	운행거리(총거리) (DRIVEN_SUM)	운행대수 (DRIVEN_CNT)	운행_총시간 (DRIVEN_TIME)	경유지_총건 수(VIA_CNT)
0	202011	동대문	10.706256	52579.968458	7122	109180824	402530
1	202006	용산구	12.758485	85058.221296	3671	66316795	375971
2	202007	구로구	12.307220	76255.048379	5280	79544164	299260

$$\text{Driving Efficiency} = \left(\frac{Driven\_Sum}{Driven\_Time}\right) * \left(\frac{VIA\_CNT}{Driven\_CNT}\right)$$

Operation efficiency is proportional to the speed of operation and the number of transit points.

Operational efficiency is inversely proportional to the number of operations.

" **Areas with high operational efficiency already have high delivery efficiency** "

Standard Scaling

If the data is scaled differently by characteristics, machine learning may not work well, so data scaling ensures that the range of all characteristics is the same

Preprocessed data

	DISTRICT	DRIVEN_EFF	TOTAL_LOGIS	POP2040	TOTAL_SALES	NUM_STORE	ESTATE
0	동대문구	0.027219	2400374	166805	4.447564e+12	66655	5198000
1	용산구	0.131360	2250955	112398	6.805869e+12	62840	10079000
2	구로구	0.054334	2442377	184583	2.806535e+12	69651	4109000
3	노원구	0.026526	2507172	215172	1.834499e+12	57391	3911000
4	서초구	0.159699	2165093	185381	6.456707e+12	117682	11141000

Standard Scaling

	DRIVEN_EFF	TOTAL_LOGIS	POP2040	TOTAL_SALES	NUM_STORE	ESTATE
0	-1.136150	0.227904	-0.197550	0.290781	-0.345691	-0.461560
1	1.346835	-0.703058	-1.124559	1.234272	-0.450148	0.939167
2	-0.489647	0.489605	0.105360	-0.365747	-0.263659	-0.774076
3	-1.152681	0.893314	0.626548	-0.754631	-0.599345	-0.830897

PCA Analysis

PCA Analysis : high-dimensional data → low-dimensional data
There is no need to proceed with PCA because the 6 variables are small enough, but we did. Select the number of PCA with a described variance of 0.7 or greater and a cumulative rate of 80% or greater.

PCA Analysis Results

	Explained variance	Explained variance ratio	Cumulative ratio
pca1	2.960610	0.473698	0.473698
pca2	1.562628	0.250021	0.723718
pca3	1.034192	0.165471	0.889189
pca4	0.526031	0.084165	0.973354
pca5	0.125891	0.020143	0.993496
pca6	0.040648	0.006504	1.000000

The variance of PCA 3 is greater than 0.7 and the cumulative rate is greater than 80%.
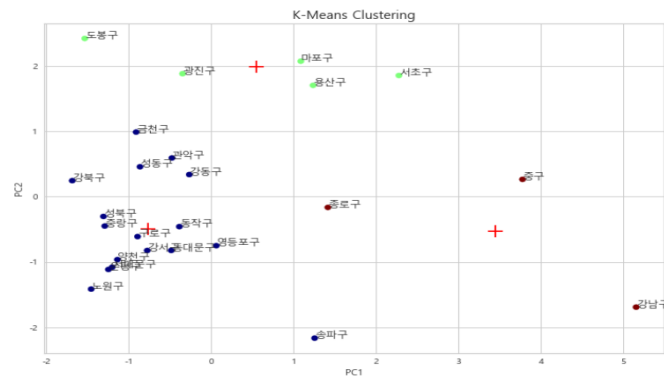
" **PCA3** is suitable "

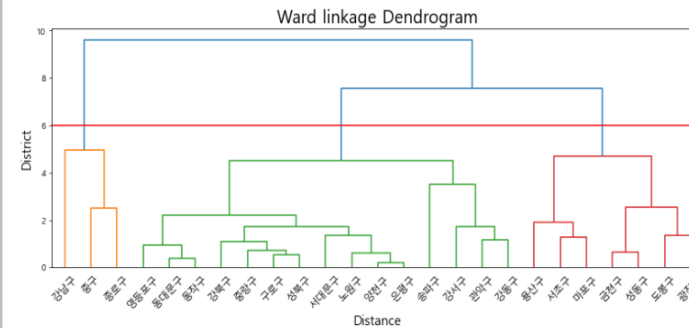## Clustering : Using 4 Techniques

Results of each clustering methods and selected districts are suitable for MFC location
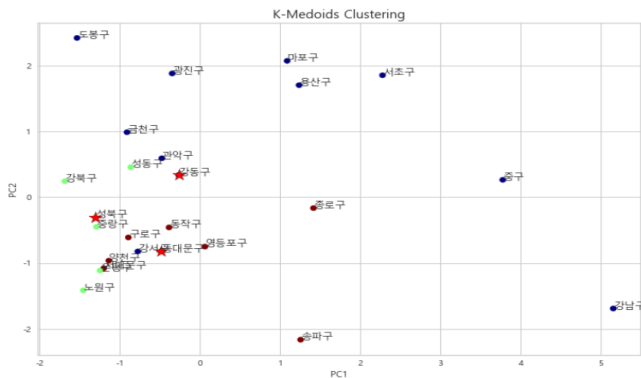
1. K-means

Each cluster is marked as the center of the cluster and must be sensitive to outliers and specify the number of clusters k.
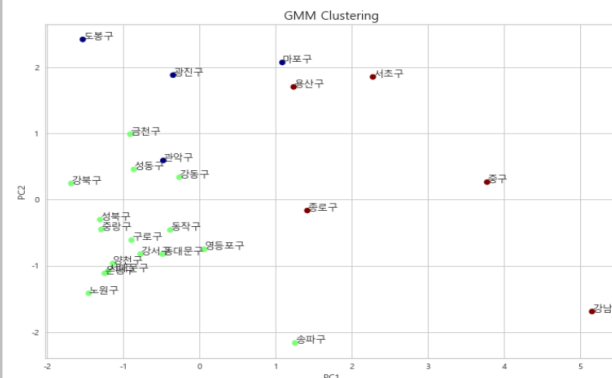
3. Agglomerative

Cluster results can vary depending on distance measurements and do not require setting a value for k.

2. K-medoids

Using midpoints instead of means is less sensitive than k-means clustering, but it takes a long time because all distances are calculated repeatedly.

4. GMM

Even if the variance is not constant, clustering can be well generated, but it has computational complexity and good results cannot be expected if it does not fit the Gaussian distribution assumption.

K-means

Step 1

Choose the number of cluster k

① Eblow method
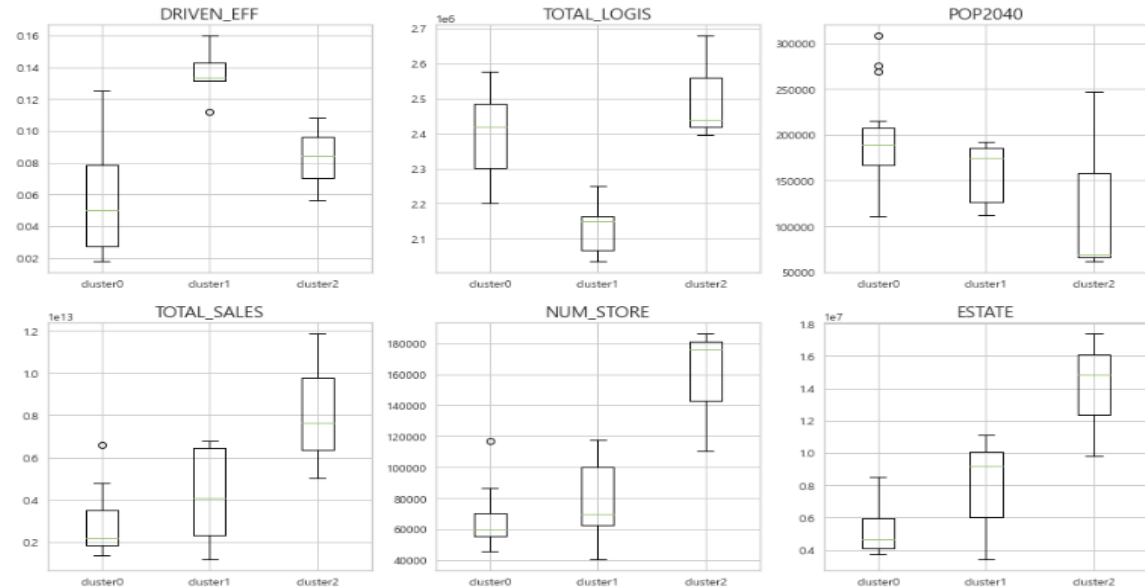: Use the turning point in the curve of sum of within cluster variance

Elbow for K-Means clustering
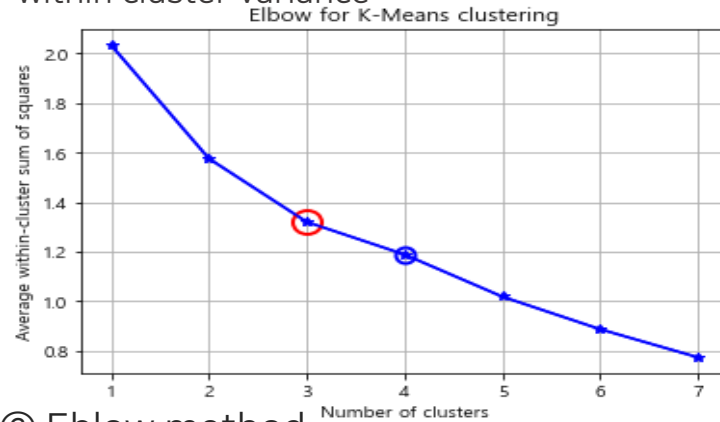
② Eblow method
: Decompose data objects into a several levels of nested partitioning

Ward linkage Dendrogram
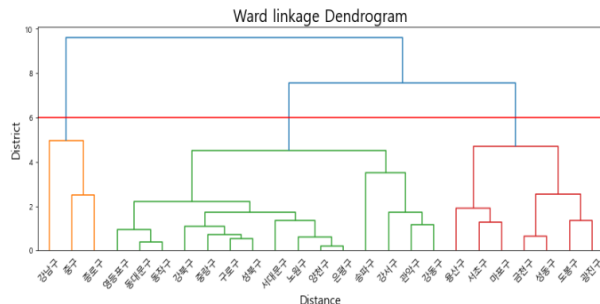
Step 2

Interpret each cluster and determine suitable or not

Cluster 0 ✔

- The logistics and population are high
- The population is large, but the size of the commercial is small, so we can expect untact consumption
- The lowest land estate and driven efficiency

→ Cluster 0 is suitable

Cluster 1

- The lowest logistics
- Since the driven efficiency is the highest, the logistics service rate is already high
- The commercial and consumption are adequate

→ Cluster 1 is not suitable

Cluster 2

- The highest total logistics
- The highest commercial and consumption power relative to the population
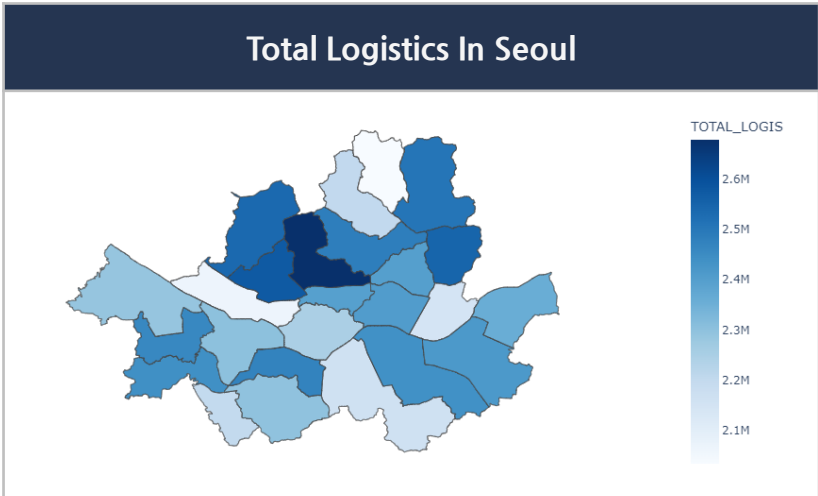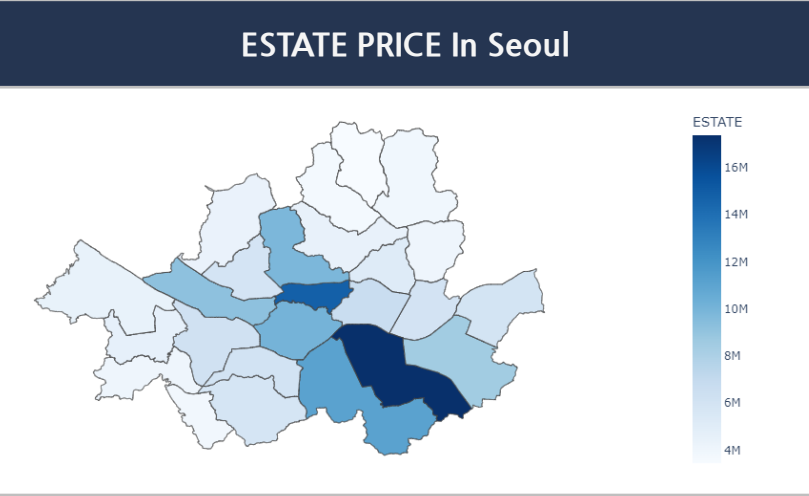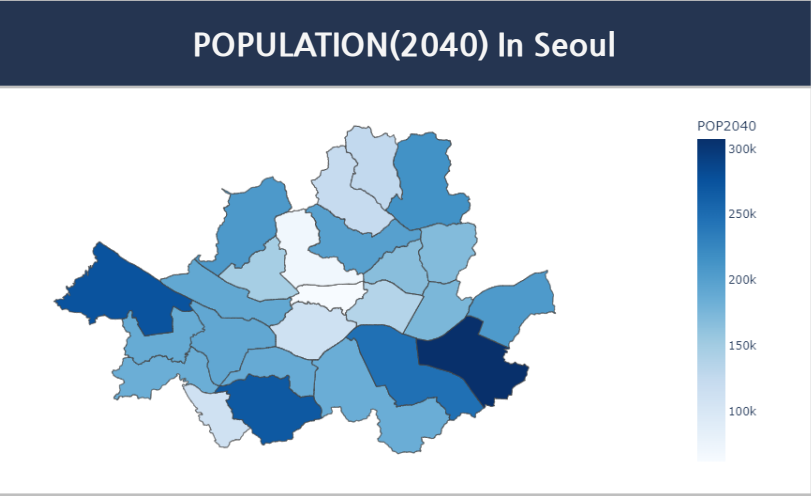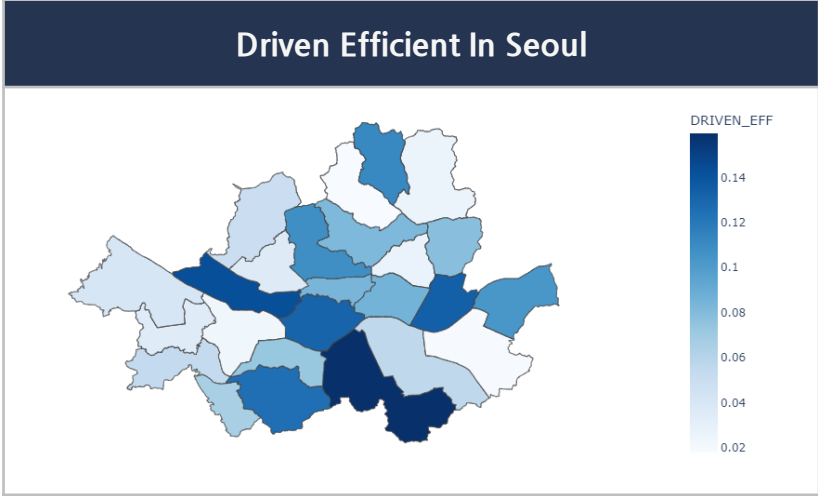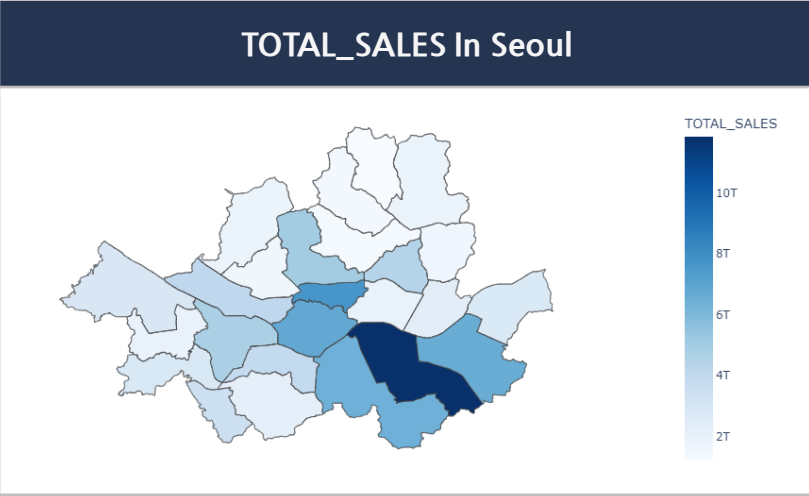- But the highest land estate

→ Cluster 2 is not suitable

Consensus

By combining all four method results , MFC is most needed has been selected

The areas where the final MFC is most needed : 동대문구, 양천구, 동작구, 송파구, 구로구, 서대문구, 영등포구
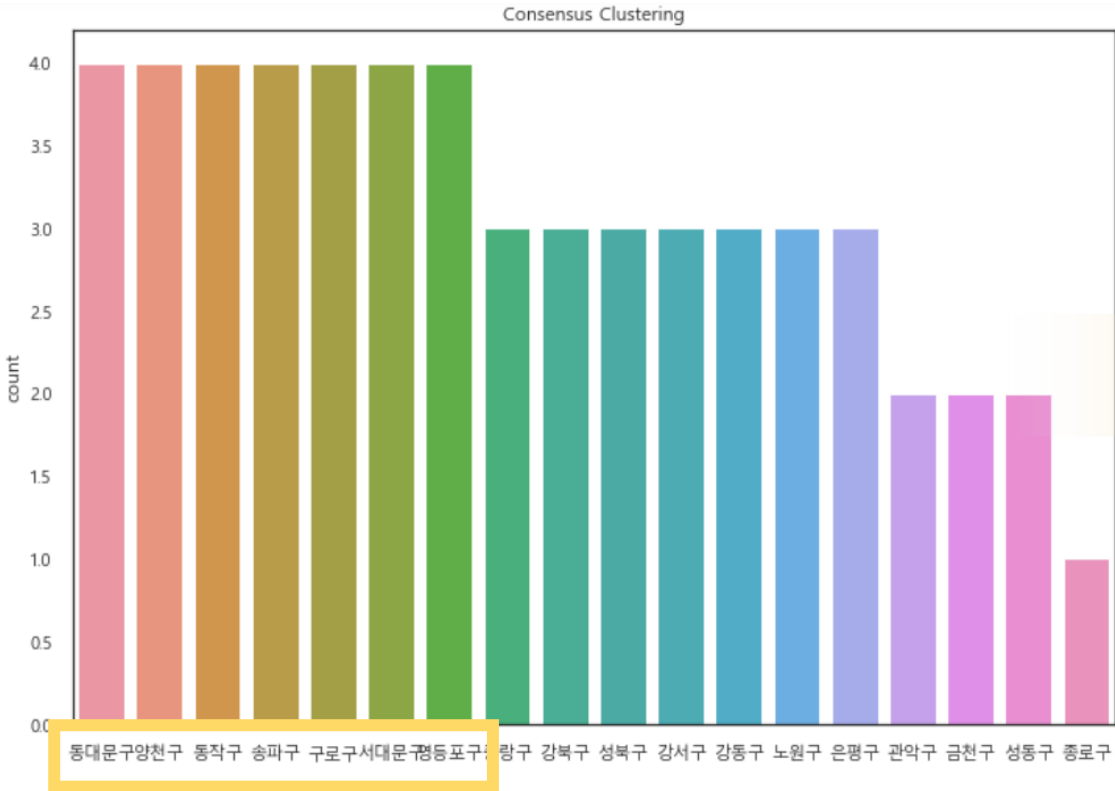
EDA

Independent variables : Population

```python
from sklearn.neighbors import KNeighborsClassifier

oilbank = pd.read_excel('서울시주유소_위경도.xlsx')
oilbank.rename(columns = {'LATITUDE': '위도', 'LONGITUDE':'경도'}, inplace = True)
x_train = df[['위도', '경도']]
y_train = df['wkt_geom']

neigh = KNeighborsClassifier(n_neighbors = 1)
neigh.fit(x_train, y_train)

x_test = oilbank.loc[:, ['위도', '경도']]
labels = neigh.predict(x_test)
oilbank['wkt_geom'] = labels
import haversine

df_LEFT_JOIN['points'] = df_LEFT_JOIN[['위도', '경도']].values.tolist()
oilbank['points'] = oilbank[['위도', '경도']].values.tolist()
m = 1000
for i in range(len(oilbank)):
    print(i)
    oil_point = oilbank.loc[i, 'points']
    df_LEFT_JOIN['m'] = df_LEFT_JOIN['points'].apply(lambda x: haversine.haversine(oil_point, x, unit = 'm'))
    population = df_LEFT_JOIN[df_LEFT_JOIN['m'] <= m+1]['인구'].sum()
    oilbank.loc[i, 'population'] = population

result = oilbank.loc[:, ['GAS_STATION', '위도', '경도', 'DISTRICT', 'DONG', 'wkt_geom', 'population']]
result.to_excel('주유소 100m 반경 안 인구수 최종 파일.xlsx',index=False)
result
```
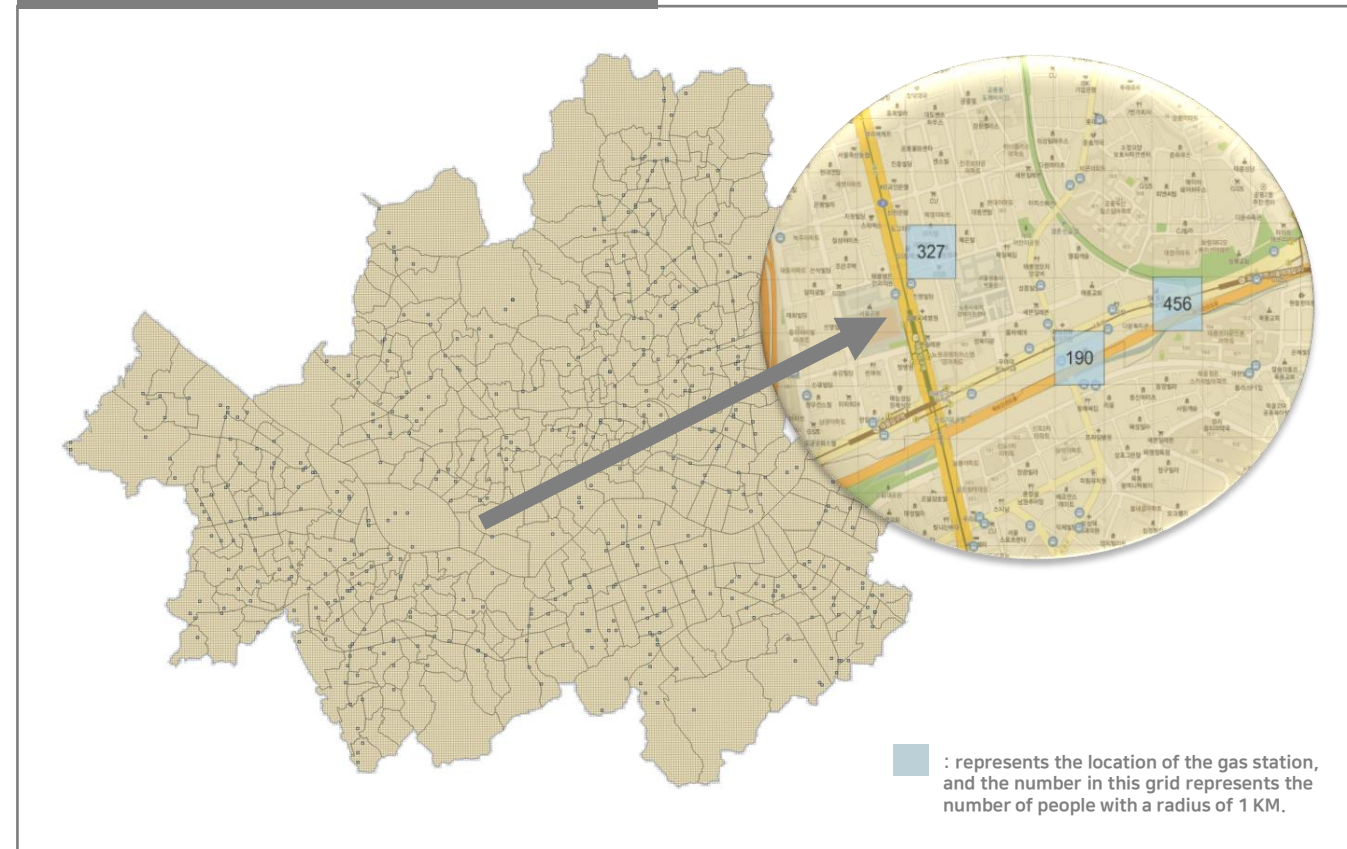
	GAS_STATION	위도	경도	DISTRICT	DONG	wkt_geom	population
0	현대오일뱅크(주) 직영소월길주유소	37.554409	126.977735	용산구	후암동	MultiPolygon (((126.97694474052541125 37.55358...	166.0
1	선익상사(주) 동자동주유소	37.550201	126.972418	용산구	동자동	MultiPolygon (((126.97130965709310146 37.54995...	349.0
2	현대오일뱅크㈜ 직영갈월동주유소	37.547029	126.972228	용산구	갈월동	MultiPolygon (((126.971335512071627592 37.54635...	251.0
3	서계주유소	37.552366	126.968994	용산구	서계동	MultiPolygon (((126.96790067781765288 37.55174...	102.0
4	㈜영원에너지 풍기주유소	37.535589	126.962709	용산구	원호로2가	MultiPolygon (((126.96235679690941822 37.53549...	186.0
...	...	...	...	...	...	...	...
467	현대오일뱅크㈜직영 도봉현대셀프주유소	37.688374	127.045327	도봉구	도봉동	MultiPolygon (((127.04518659989290086 37.68816...	16.0
468	GS칼텍스㈜ 도봉주유소	37.684369	127.045522	도봉구	도봉동	MultiPolygon (((127.04521411792508445 37.68366...	180.0
469	(주)송만에너지 도봉제일주유소	37.674474	127.044067	도봉구	도봉동	MultiPolygon (((127.04300674510970737 37.67373...	465.0
470	노원교주유소	37.679015	127.049751	도봉구	도봉동	MultiPolygon (((127.04864917541478064 37.67826...	55.0
471	오복주유소	37.662280	127.047441	도봉구	방학동	MultiPolygon (((127.0464798867402294 37.662036...	247.0

Data on the total population (personnel) were obtained from the SGIS statistical geographic information service, and the number of factors within a 1km radius of the gas station was extracted. This extracted data is then converted into a SHP file and visualized in QGIS.

Visualize 1KM Population Count with QGIS

: represents the location of the gas station, and the number in this grid represents the number of people with a radius of 1 KM.

Independent variables : School & Apart & Market

The Ministry of Land, Infrastructure and Transport obtained data on the number of schools, apartments, and markets within the range of Seoul, and obtained numbers within a 1KM radius based on each gas station with the data.

```python
import haversine
m = 1000
oilbank_df['point'] = oilbank[['LATITUDE', 'LONGITUDE']].values.tolist()
lst = ['school', 'apart', 'market']
for stat in lst:
    globals()[f'{stat}_df']['point'] = globals()[f'{stat}'][['Latitude', 'Longitude']].values.tolist()
    for i in range(len(oilbank)):
        oil_point = oilbank_df.loc[i, 'point']

        globals()[f'{stat}_df']['stat_per_m'] = globals()[f'{stat}_df']['point'].apply(lambda x: haversine.haversine(x, oil_point, unit = 'm'))
        oilbank_df.loc[i, stat] = len(globals()[f'{stat}_df'][globals()[f'{stat}_df']['stat_per_m'] <= m+1])
```

	GAS_STATION	LATITUDE	LONGITUDE	point	school	apart	market
0	현대오일뱅크(주) 직영소월길주유소	37.554409	126.977735	[37.5544085670544, 126.977734582566]	5.0	1.0	58.0
1	선익상사(주) 동자동주유소	37.550201	126.972418	[37.5502005044121, 126.972417738531]	9.0	2.0	6.0
2	현대오일뱅크㈜ 직영갈월동주유소	37.547029	126.972228	[37.5470289447515, 126.9722284578290]	9.0	1.0	22.0
3	서계주유소	37.552366	126.968994	[37.5523662854224, 126.9689937005090]	5.0	2.0	4.0
4	㈜영원에너지 풍기주유소	37.535589	126.962709	[37.5355890312127, 126.9627089734190]	9.0	6.0	20.0
...	...	...	...	...	...	...	...
467	현대오일뱅크㈜직영 도봉현대셀프주유소	37.688374	127.045327	[37.6883740291887, 127.045327229383]	4.0	1.0	0.0
468	GS칼텍스㈜ 도봉주유소	37.684369	127.045522	[37.6843693792253, 127.045522281038]	4.0	1.0	0.0
469	(주)송만에너지 도봉제일주유소	37.674474	127.044067	[37.6744735831616, 127.044066665278]	0.0	0.0	4.0
470	노원교주유소	37.679015	127.049751	[37.679014779402, 127.049750654086]	3.0	1.0	2.0
471	오복주유소	37.662280	127.047441	[37.6622801187124, 127.047441496273]	4.0	3.0	4.0

Visualize 1KM School & Apart & Market Count with QGIS

One **red grid** represents the location of one gas station, and the number in this grid represents the number of schools within a radius of 1 KM.

One **orange grid** represents the location of one gas station, and the number in this grid represents the number of Aparts within a radius of 1 KM.
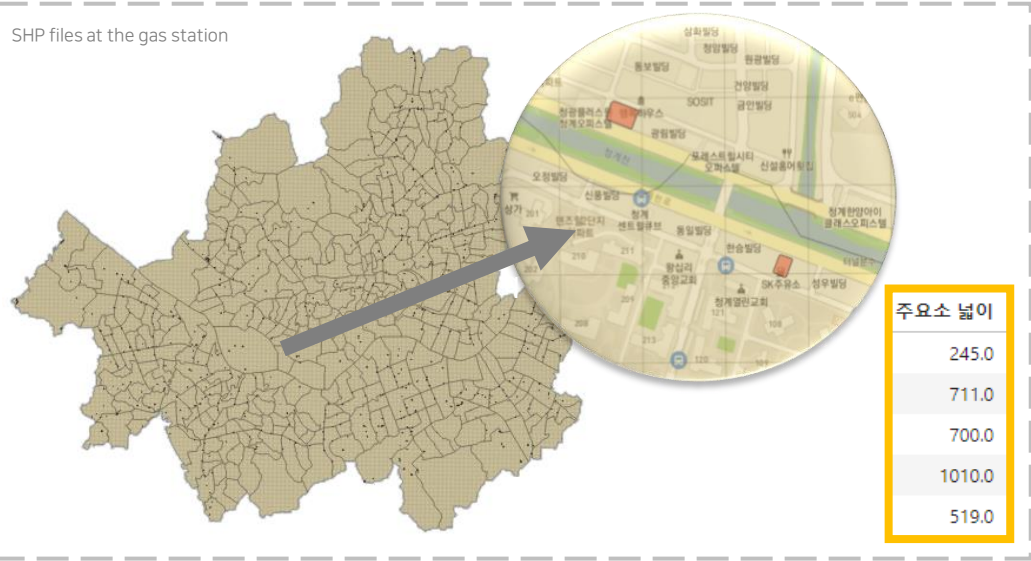
One **blue grid** represents the location of one gas station, and the number in this grid represents the number of markets within a radius of 1 KM.

Independent variables : Area & Land price

Use the '$AREA' function of the QGIS program to find the area of each gas station in the polygon form of the gas station shp file.

SHP files at the gas station

| 주요소 넓이 |
|---|
| 245.0 |
| 711.0 |
| 700.0 |
| 1010.0 |
| 519.0 |

The individual publicly announced land price at gas stations was selected as an independent variable because it was related to rent incurred when entering MFC.

	주유소명	공시지가(원/㎡)
0	현대오일뱅크(주) 직영소월길주유소	8280000.0
1	선익상사(주) 동자동주유소	18850000.0
2	현대오일뱅크㈜ 직영갈월동주유소	15050000.0

Independent variables : Coverable distance

The distance to each terminal was calculated based on each gas station.

Variable	Definition
dist_eastDC	the streets from the east to the terminal
dist_westDC	the streets from west to terminal
dist_koreaDC	Streets to Korea Terminal

WEST TERMINAL ② ← GAS STATION → ① EAST TERMINAL

KOREA TERMINAL ③

① dist_eastDC
② dist_westDC
③ dist_kroeaDC
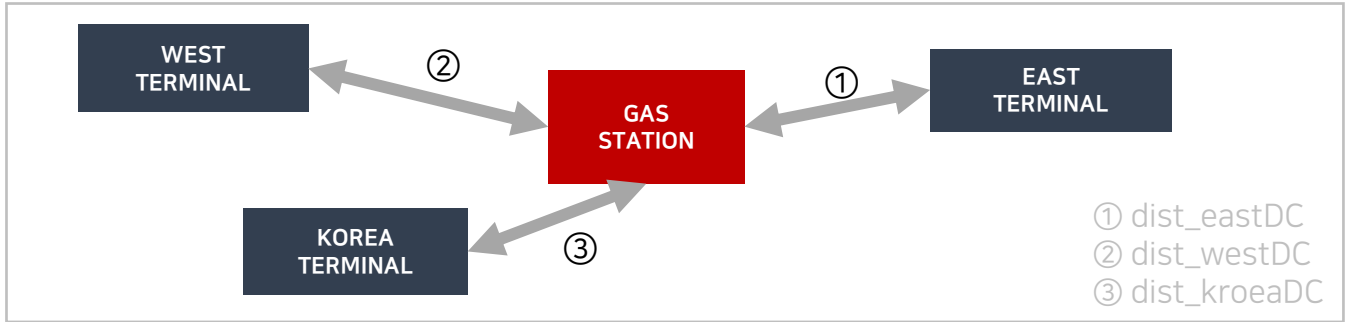
```
from haversine import haversine
from tqdm import notebook

distance_compare_list = []
for i in notebook.tqdm(range(df_DC.shape[0])):
    for j in range(df_gas.shape[0]):
        DC = (df_DC.Latitude[i], df_DC.Longitude[i])
        oil = (df_gas.LATITUDE[j], df_gas.LONGITUDE[j])
        result = haversine(DC, oil, unit='km')
        distance_compare_list.append(result)
```

| GAS_STATION	DIST_EASTDC	DIST_WESTDC	DIST_KOREADC
현대오일뱅크(주) 직영소월길주유소	8.970251	13.202286	11.678968
선익상사(주) 동자동주유소	9.568763	12.593357	11.494239
현대오일뱅크㈜ 직영갈월동주유소	9.713120	12.454393	11.199948

EDA

The following graph shows that not all values of the independent variable are null values.

Visualize that data has no null value
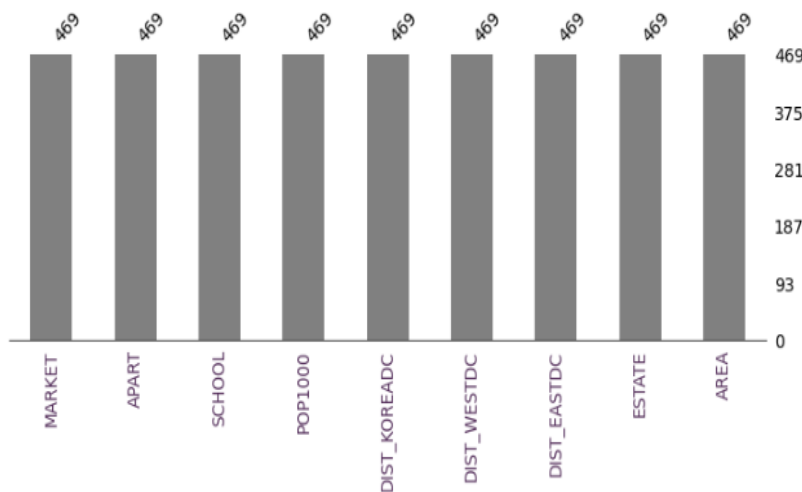
Although there is no missing value, outliers exist for each variable, so outliers were removed.
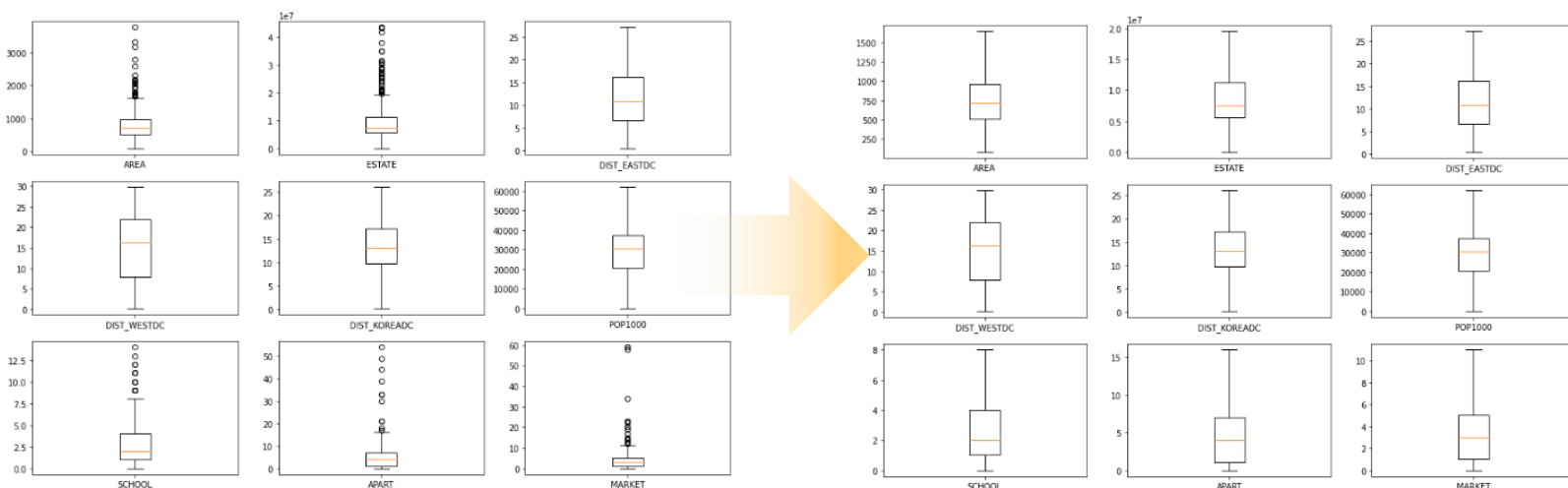
Rather than removing the abnormal value, the lower limit (25%) and the upper limit (75%) were determined, and if it is less than the lower limit, it was replaced with a lower limit value, and if it is greater than the upper limit, it was replaced with an upper limit value.

Numeric Features Distribution
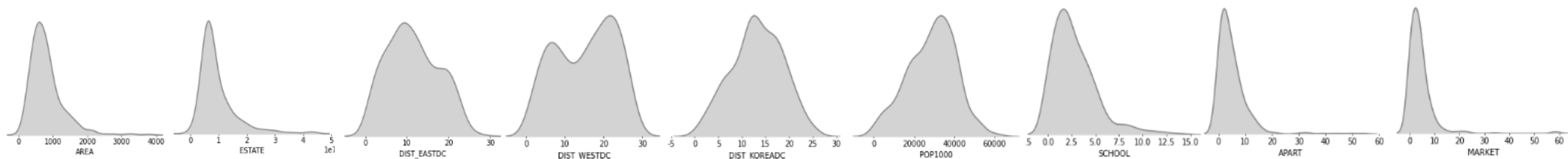
Set Dependent variable : Using AHP method

Using the AHP(Analytic Hierarchy Process) to calculate the weights of the independent variables of the location score function

척도	정의
1	equal importance
3	moderate importance
5	strong importance
7	very strong importance
9	absolute importance
2,4,6,8	위 값들의 중간값

Pairwise Comparison Matrix

	AREA	ESTATE	DISTANCE	POPULATION	SCHOOL	APARTMENT	MARKET
AREA	1	1/2	3	1/3	9	7	5
ESTATE	2	1	3	3	9	7	6
DISTANCE	1/3	1/3	1	1/3	9	5	3
POPULATION	3	1/3	3	1	9	6	5
SCHOOL	1/9	1/9	1/9	1/9	1	1/3	1/4
APARTMENT	1/7	1/7	1/5	1/6	3	1	1
MARKET	1/5	1/6	1/3	1/5	4	1	1

AREA	0.198
ESTATE	0.327
DISTANCE	0.124
POPULATION	0.244
SCHOOL	0.020
APARTMENT	0.040
MARKET	0.048

$$SCORE = (AREA * 0.198) - (ESTATE * 0.327) - (DIST\_EASTDC * 0.0413) - (DIST\_WESTDC * 0.0413) - (DIST\_KOREADC * 0.0413) + (POP1000 * 0.244) + (SCHOOL * 0.020) + (APART * 0.040) + MARKET * 0.048)$$

After minmax scaling and calculate location score

	AREA	ESTATE	DIST_EASTDC	DIST_WESTDC	DIST_KOREADC	POP1000	SCHOOL	APART	MARKET	SCORE
0	0.043427	0.189831	0.318940	0.438800	0.443422	0.253190	0.357143	0.018519	0.983051	0.013764
1	0.169609	0.432974	0.341411	0.418207	0.436269	0.411800	0.642857	0.037037	0.101695	-0.037691
2	0.166631	0.345562	0.346831	0.413507	0.424874	0.435364	0.642857	0.018519	0.372881	0.008770
3	0.250571	0.236987	0.349078	0.411788	0.450253	0.489771	0.357143	0.037037	0.067797	0.053482
4	0.117620	0.305306	0.395409	0.373522	0.403165	0.442966	0.642857	0.111111	0.338983	0.016702

Multi-class Classification

Using qcut(), Generate categorical variable "SCORE_CAT"

	AREA	ESTATE	DIST_EASTDC	DIST_WESTDC	DIST_KOREADC	POP1000	SCHOOL	APART	MARKET	SCORE_CAT
0	245.0	8280000.0	8.970251	13.202286	11.678968	15660	5	1	58	부적합
1	711.0	18850000.0	9.568763	12.593357	11.494239	25467	9	2	6	매우부적합
2	700.0	15050000.0	9.713120	12.454393	11.199948	26924	9	1	22	부적합
3	1010.0	10330000.0	9.772973	12.403577	11.855362	30288	5	2	4	적합
4	519.0	13300000.0	11.006969	11.272070	10.639303	27394	9	6	20	부적합

SCORE	Category
(-0.296, -0.00108]	매우 부적합 (Most Unsuitable)
(-0.00108, 0.0432]	부적합 (Unsuitable)
(0.0432, 0.0825]	적합 (Suitable)
(0.0825, 0.184]	매우 적합 (Most Suitable)
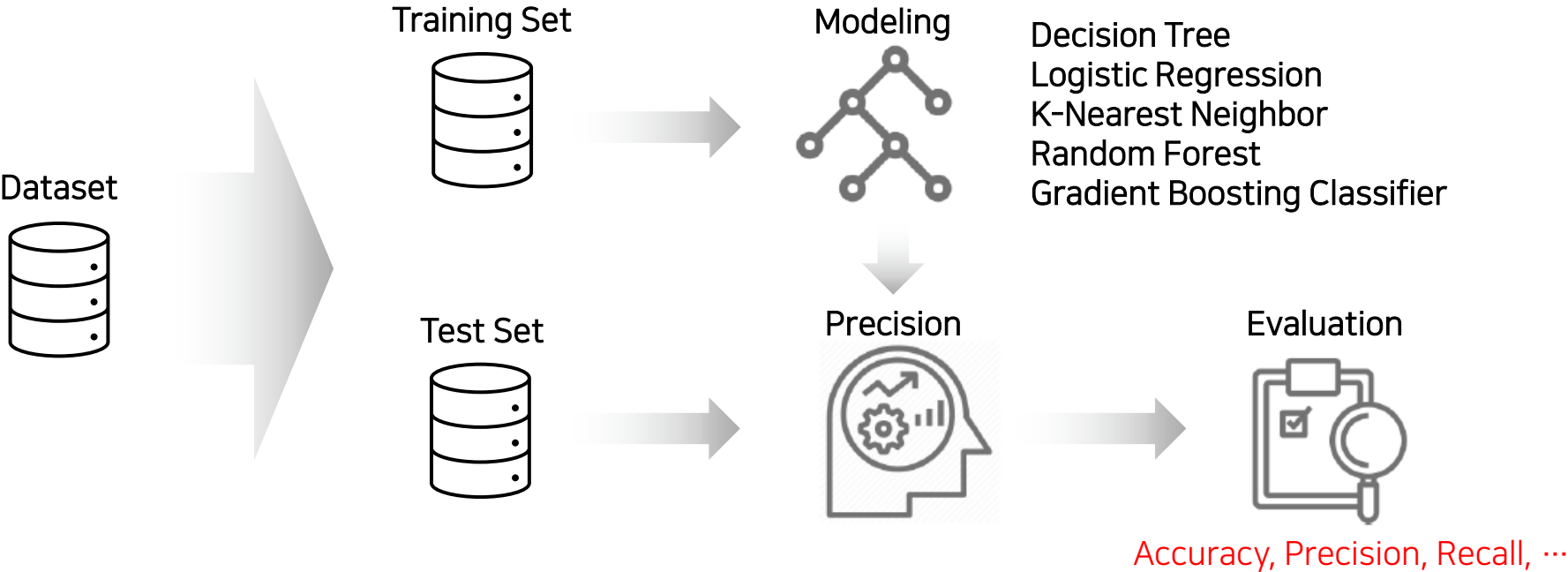
Training Set

Modeling

Decision Tree
Logistic Regression
K-Nearest Neighbor
Random Forest
Gradient Boosting Classifier

Dataset

Test Set

Precision

Evaluation

Accuracy, Precision, Recall, …

Multi-class Classification

Model Evaluation	
Model	Accuracy
DT	0.7518
LR	0.6667
KNN	0.6667
RF	0.7589
GBC	0.766

Model Evaluation		Precision	Recall	F-1 Score	Accuracy
Random Forest	Most Unsuitable	0.86	0.82	0.84	0.7589
	Unsuitable	0.61	0.63	0.62	
	Suitable	0.69	0.65	0.67	
	Most Suitable	0.82	0.89	0.85	
Gradient Boosting Classifier	Most Unsuitable	0.88	0.84	0.86	0.766
	Unsuitable	0.59	0.63	0.61	
	Suitable	0.67	0.71	0.69	
	Most Suitable	0.88	0.83	0.85	
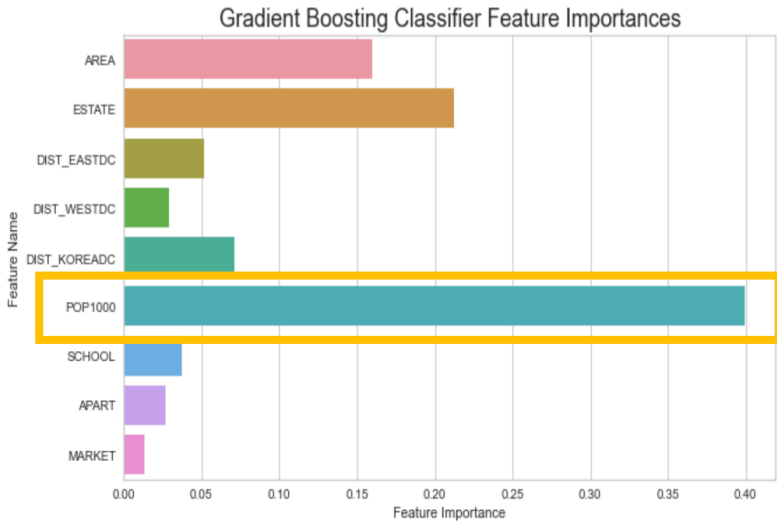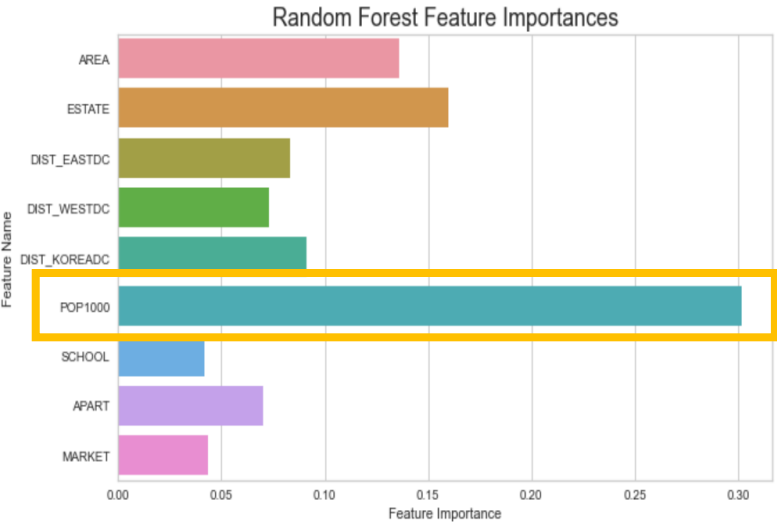
"Population" is the most important feature in RF & GBC.

Random Forest Feature Importances

Gradient Boosting Classifier Feature Importances

Multi-Class-Neural Network : 4 Steps

The method is a technique for constructing a model needed to recognize unique patterns or structures in the data and proceeds to four steps.

1. Label Encoding for Multi-classification ANN

```python
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
le.fit(df['SCORE_CAT'])
label_encoded = le.transform(df['SCORE_CAT'])

label_df = pd.DataFrame(label_encoded,
                        columns = ['Score_label'])

label_df.head()
```

	Score_label
0	2
1	0
2	2
3	3
4	2

- 매우부적합(Most unsuitable) : 0

- 부적합(Unsuitable) : 2

- 적합(Suitable) : 3

- 매우적합(most Suitable) : 1

2. Data processed

```python
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1113)
```

```python
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```python
train_scaled, val_scaled, train_target, val_target = train_test_split(X_train_scaled, y_train, test_size=0.3, random_state=1113)
```

Train-test data split

Data scaling

Validation

2. Define the Neural Network Model

```
Model: "sequential"
_____
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 64)                640

dense_1 (Dense)              (None, 32)                2080

dense_2 (Dense)              (None, 8)                 264

dense_3 (Dense)              (None, 4)                 36

=================================================================
Total params: 3,020
Trainable params: 3,020
```

- 9 Indep. Variables -> input shape : 9

- 4 Dep. Variables -> Last Layer: 4

- Multi class -> Activation f(x) : Softmax

- Most popular optimizer -> 'Adam'

- Loss & Metrics -> 'Sparse_categorical'

4. Fit model

```
Epoch 144/1000
8/8 [==============================] - 0s 22ms/step - loss: 0.0954 - sparse_categorical_accuracy: 0.9869 - val_loss: 0.1826 - val_sparse_categorical_accuracy: 0.9091 - lr: 0.001

Epoch 145/1000
1/8 [==>...........................] - ETA: 0s - loss: 0.0882 - sparse_categorical_accuracy: 1.0000
Epoch 145: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
8/8 [==============================] - 0s 26ms/step - loss: 0.0991 - sparse_categorical_accuracy: 0.9694 - val_loss: 0.1741 - val_sparse_categorical_accuracy: 0.9293 - lr: 0.001
0
Epoch 145: early stopping
```
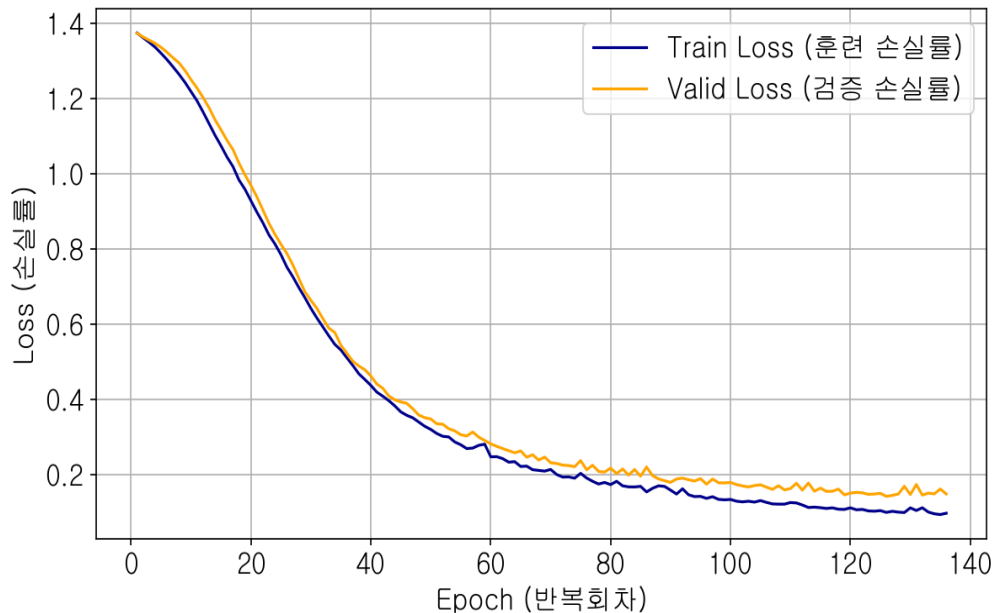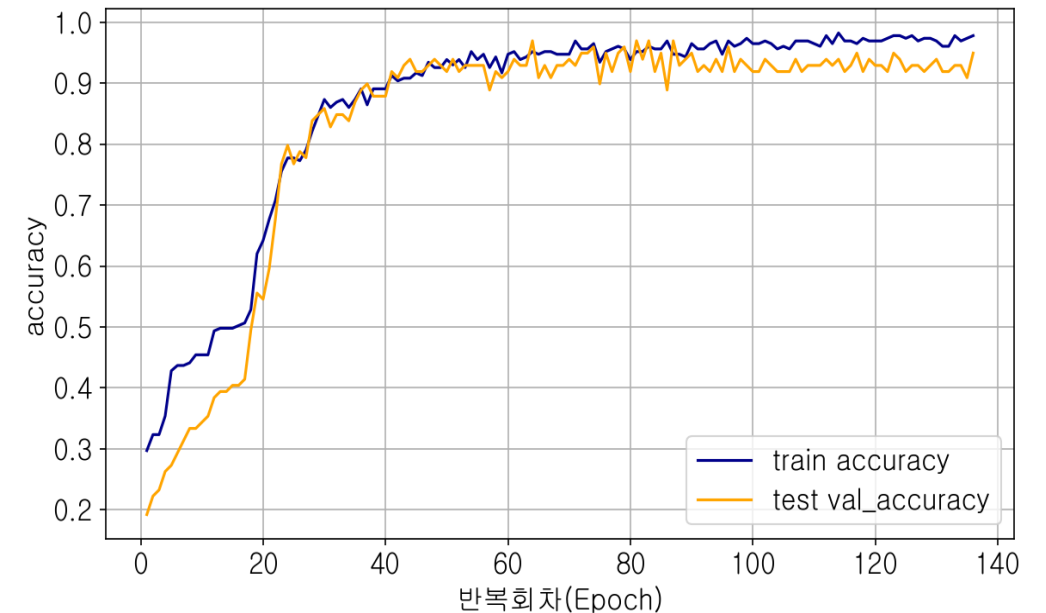
Multi-Class-Neural Network : Evaluation

After completing the 4 steps of the 'Multi-Class-Natural Network',
the training and verification loss rate and training and verification accuracy were evaluated.

Train & Valid Loss (훈련 및 검증 손실률)

Train & Valid Accuracy (훈련 및 검증 정확도)

Result   FINAL LOSS : 0.139630   FINAL ACCURACY : 0.957447

As a result of checking the loss rate and accuracy,
it can be confirmed that a high performance of 95% was achieved without overfitting.

Association Rule

Showing how often events happen together and how much they are related to each other.

Use Binning

Use binning to convert numeric variables into categorical variables, which are divided into binary variables greater than or less than the mean.

Name	Distribution	Mean
N AREA		805.6831
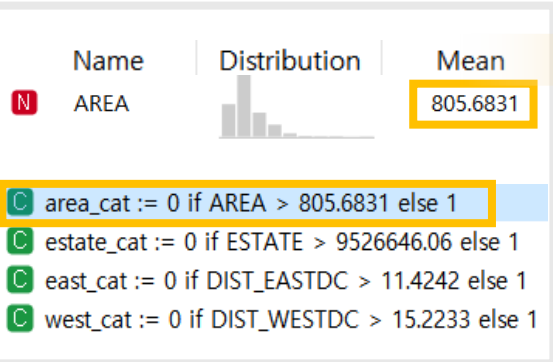
" Data when AREA is above 805.6831 on average "

- C area_cat := 0 if AREA > 805.6831 else 1
- C estate_cat := 0 if ESTATE > 9526646.06 else 1
- C east_cat := 0 if DIST_EASTDC > 11.4242 else 1
- C west_cat := 0 if DIST_WESTDC > 15.2233 else 1

GAS_STATION	area_cat	estate_cat	east_cat	west_cat	korea_cat	pop_cat	sch_cat	apart_cat	mkt_cat	SCORE_CAT
대성석유㈜관문...	High	Low	Far	Short	Far	High	High	High	High	적합
㈜타이거오일 ...	Low	Low	Far	Short	Far	High	High	High	High	적합
현대오일뱅크㈜...	Low	Low	Far	Short	Far	High	High	High	High	적합
우장산주유소	Low	Low	Far	Short	Far	High	High	High	High	부적합
주식회사 에스...	High	High	Far	Short	Far	High	High	High	High	부적합

The result of the change between "Minsup" and "Minconf"

	Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		Consequent
Minsup = 10%, Minconf = 75%	0.111	0.800	0.139	1.815	3.180	0.076	estate_cat=High, pop_cat=Low, apart_cat=Low	→	SCORE_CAT=매우부적합
	0.136	0.780	0.175	1.439	3.102	0.092	estate_cat=High, pop_cat=Low	→	SCORE_CAT=매우부적합

	Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		Consequent
Minsup = 10%, Minconf = 65%	0.100	0.746	0.134	1.857	2.991	0.067	area_cat=High, estate_cat=Low, pop_cat=High	→	SCORE_CAT=매우적합
	0.143	0.670	0.213	1.180	2.663	0.089	pop_cat=Low, sch_cat=Low, apart_cat=Low	→	SCORE_CAT=매우부적합

	Supp	Conf	Covr	Strg	Lift	Levr	Antecedent		Consequent
Minsup = 20%, Minconf = 40%	0.213	0.529	0.403	0.619	2.121	0.113	estate_cat=Low, pop_cat=High	→	SCORE_CAT=매우적합
	0.232	0.429	0.542	0.461	1.720	0.097	pop_cat=High	→	SCORE_CAT=매우적합

Result

The following is a graph comparing the accuracy of the algorithm.
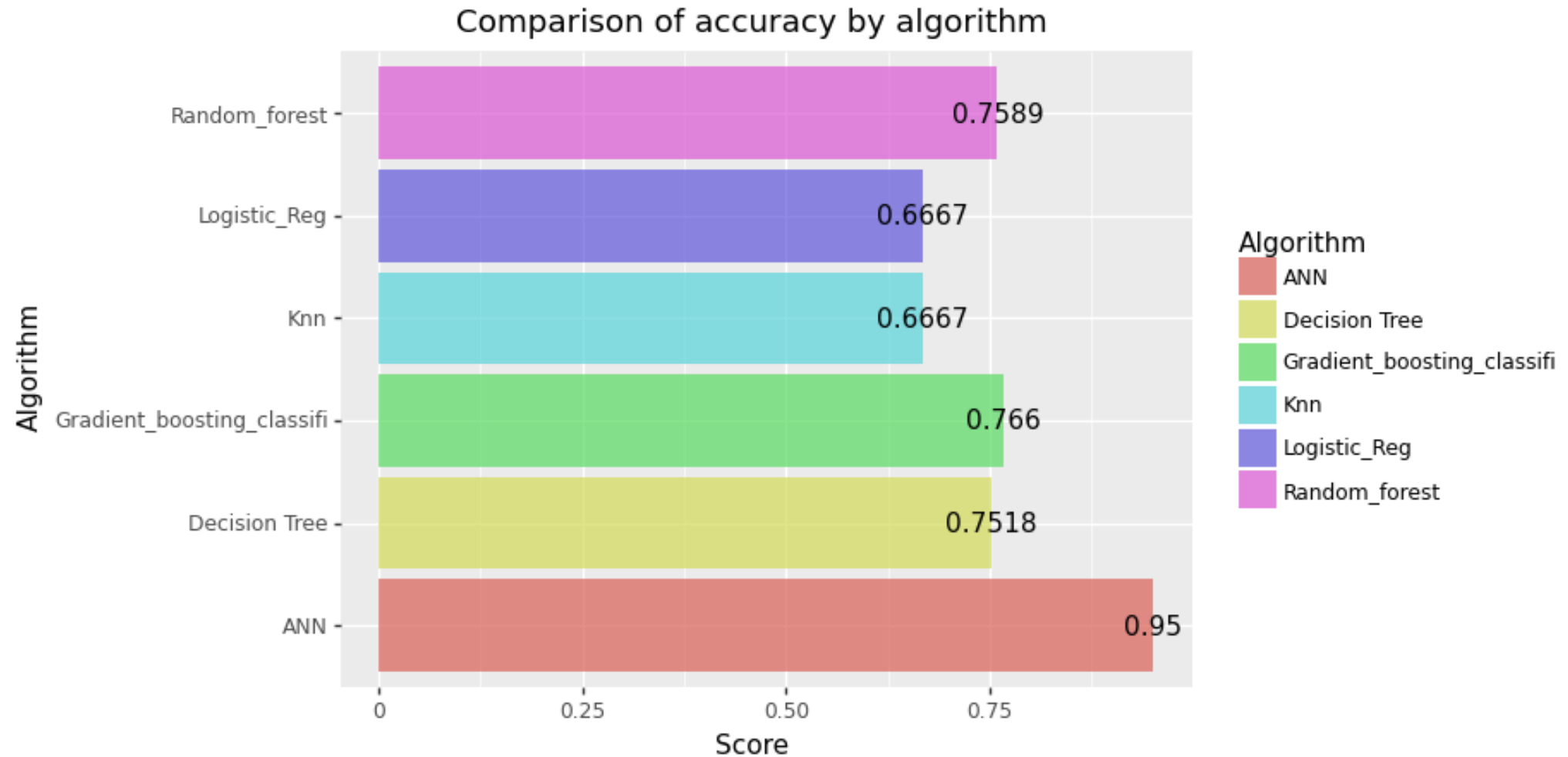
Comparison of accuracy by algorithm

Expectation effectiveness

SEOUL

There is a possibility that the introduction of MFC in Seoul on a trial basis will cause innovation in the logistics industry
→Recession caused by COVID-19, can revitalize the economy

CUSTOMER

As the logistics delivery process decreases, various products can be received faster than now

GAS STATION

Even those who have difficulty building their own fulfillment into the city at a low cost
Can increase the competitiveness in the market
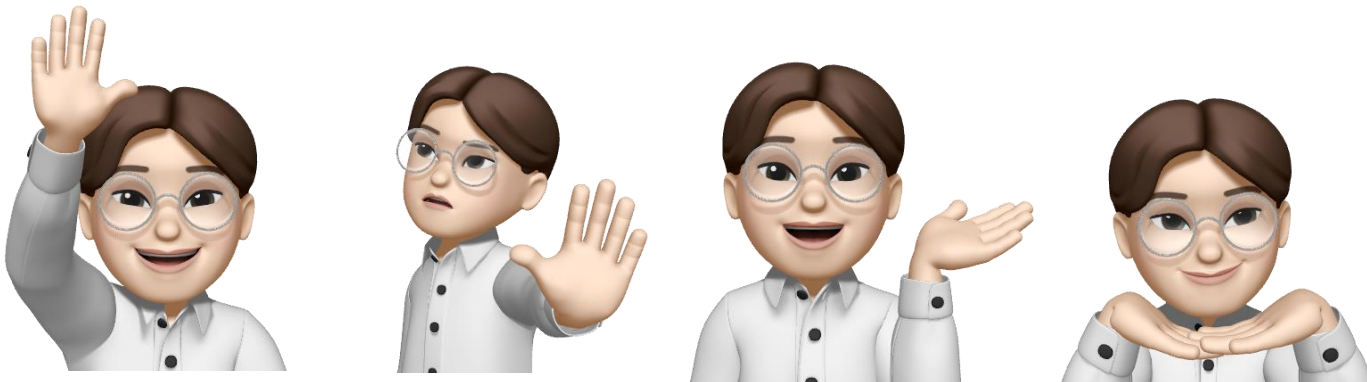
LOGISTICS COMPANY

Provides high delivery service at low cost while gaining advantage in the delivery market

Limitation

[1] Logistics data is only available by district, so logistics variables are not considered in the classification model
[2] Considering only the internal conditions of Seoul when analyzing the location
[3] There may be other meaningful variables that we did not think
[4] We don't use MCLP, so we can't find the best place in one place
[5] Our project can't consider coverage
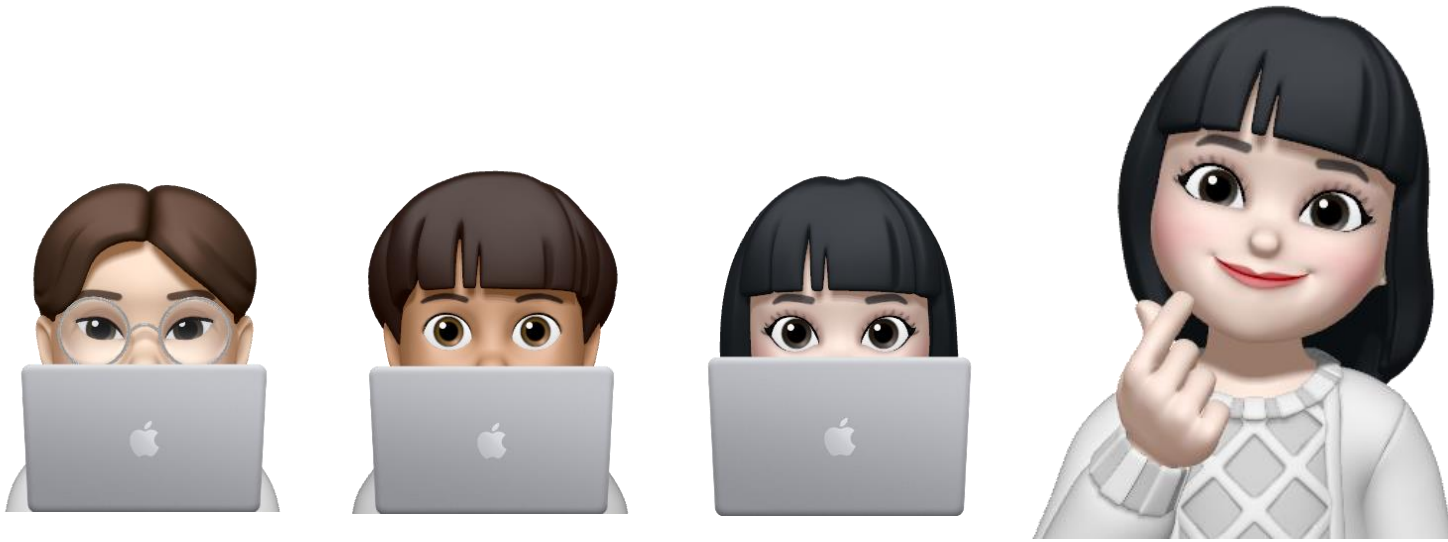
김나연 : Data-collection, Data-preprocessing using Qgis, EDA for classification, presentation material
강대경 : Data-collection, Data-preprocessing, Association, presentation material
신용 : Data-collection, Data-preprocessing, Clustering, Classification, EDA for clustering, Appendix
김찬 : Data-collection, Data-preprocessing, EDA for clustering, ANN, PT, Final report

Q & A

Thank you for watching!