#### Module import

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn import metrics # 모델평가시 이용
```

### 데이터 전처리

```
In [2]:
          X = pd.read_csv('./5조데이터(4차통합).csv',encoding='CP949') ; X
          X_{-} = X.copy(); X
Out[2]:
                                                                         방
                                                          네이버검
                                                                         학
                                                                             도마1동
                                                                                    도마2동
                                                                   진
                           기온 기온 기온
                                                                         여
                                                                               인구
                                                                                       인구
                                                                                                    가
                                                                                                    게
               2015-
                        64 13.9 13.4
                                     14.5 15.5 26.000000
                                                             NaN
                                                                         0 17755.0 20916.0 18026.0
               11-08
               2015-
                        31 13.1 11.5
                                     15.2
                                            1.7
                                                27.428571
                                                             NaN
                                                                         0 17753.0
                                                                                   20913.0 18025.0
                                                                                                   45 N
               11-09
               2015-
                        19 11.0
                                  8.0 14.5 NaN
                                               28.857143
                                                             NaN
                                                                         0 17751.0 20910.0 18024.0
               11-10
               2015-
                        28 11.9
                                  6.8 18.3
                                          NaN
                                                30.285714
                                                             NaN
                                                                         0 17749.0
                                                                                   20907.0 18023.0 45 N
               11-11
               2015-
                        24
                           13.6
                                  8.8 19.4
                                          NaN
                                               31.714286
                                                                         0 17747.0
                                                                                   20904.0
                                                                                            18022.0
                                                             NaN
               11-12
               2020-
                     화 60 19.1 14.9 24.5 NaN 61.428571 13.00523
                                                                               NaN
                                                                                       NaN
                                                                                               NaN 31 N
               2020-
         1693
                     수 54 19.0
                               14.4 23.6
                                          NaN
                                               67.142857 13.21658
                                                                               NaN
                                                                                                   31 N
                                                                                       NaN
                                                                                               NaN
               09-23
               2020-
         1694
                        57 20.8 15.7 26.4
                                               72.857143 13.80988
                                          NaN
                                                                               NaN
                                                                                       NaN
                                                                                               NaN
                                                                                                   31 N
               09-24
               2020-
         1695
                     금 77 20.0 14.8 25.9
                                                        17.88591
                                          NaN
                                               78.571429
                                                                               NaN
                                                                                       NaN
                                                                                               NaN 31 N
               09-25
               2020-
         1696
                       11 19.4 15.0 25.5 NaN 84.285714 19.52271
                                                                                               NaN 31 N
                                                                               NaN
                                                                                       NaN
               09-26
```

1697 rows × 25 columns

```
In [3]: # 월변수 만들기
X['월'] = X['날짜'].str[5:7]

# 월 , 요일 변수 one hot vector 로 바꾸기
X = pd.get_dummies(X, columns=['요일','월'],drop_first= False)
```

```
In [4]: # y 변수 추출
       y = np.array(X['주문수'])
In [5]:
       # 필요없는 변수 dropping
        X.drop(columns=['복날','날짜','주문수','최저기온',
                      '최고기온','확진자','사망자','완치자','전국확진자','전국완치
        자','전국사망자','유튜브조회수','코로나발발'],inplace=True)
      Imputation
In [6]:
       # 강수량 Imputation
        X['강수량mm'] = X['강수량mm'].fillna(0)
        # 강수량 변환
        X['강수량mm'] = np.log1p(X['강수량mm'])
In [7]:
       # 네이버검색량 , 지하철 승하차인원 Imputation
        from sklearn.impute import KNNImputer
        imputer = KNNImputer(n_neighbors=5)
        X[['네이버검색량']] = imputer.fit_transform(X[['네이버검색량']])
        X[['지하철승하차인원']] = imputer.fit_transform(X[['지하철승하차인원']])
In [8]:
       # 인구수 imputation
        # 현재, 팀 과제 프로젝트에서 대부분 등차수열로(linear 하게) imputation 해놓은 상태
        라, 맨 마지막 달의 인구만 na를 채우면 된다.
        # 계속 감소하는 추세였으므로, 제일 마지막 달의 인구는, 제일 작은 값을 가질것이다.
        # 그러므로 임시로 min 으로 채워넣자.
        min1 = np.min(X['도마1동인구'])
        min2 = np.min(X['도마2동인구'])
        min3 = np.min(X['변동인구'])
In [9]:
        print(min1, min2, min3)
       15111.0 18486.0 16392.0
In [10]:
       X['도마1동인구'].fillna(15111.0,inplace=True)
        X['도마2동인구'].fillna(18486.0,inplace=True)
        X['변동인구'].fillna(16392.0,inplace=True)
In [11]:
       X = X.astype(float)
In [12]:
       X.describe()
Out[12]:
                                             지하철승하차인
                             구글검색량 네이버검색량
              평균기온
                     강수량mm
                                                          공휴일
                                                                 방학여부
                                                                         도미
```

COL	unt	1697.000000	1697.000000	1697.000000	1697.000000	1697.000000	1697.000000	1697.000000	1697
mean	ean	13.840837	0.527349	52.084266	14.701071	201813.465625	0.050088	0.389511	16400
9	std	10.143406	1.058985	16.230386	4.738835	46265.105986	0.218192	0.487783	900
n	nin	-11.800000	0.000000	18.000000	6.817980	35976.000000	0.000000	0.000000	15111
2!	5%	5.100000	0.000000	39.285714	11.704160	175118.000000	0.000000	0.000000	15494
50	0%	14.400000	0.000000	50.428571	14.295300	201813.465625	0.000000	0.000000	16796
7	5%	22.600000	0.405465	64.714286	17.149520	240340.000000	0.000000	1.000000	17191
m	ıax	33.400000	5.193512	100.000000	100.000000	289768.000000	1.000000	1.000000	17755

8 rows × 30 columns

```
In [13]: # columns 의 명칭바꾸기. (한글로 하면 에러가 나온다.)
X.columns =
['temp','rain','google','naver','subway','holy','vacation','do1_pop','do2_po
'byun_pop','store','fri','thu','wed','mon','sun','sat','tue',
'mon1','mon2','mon3','mon4','mon5','mon6','mon7','mon8','mon9','mon10','mon1
```

#### Scaling

```
In [14]: # dataset train/test set 으로 나누기

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.20, random_state=0)
```

```
In [15]: X_train
```

Out[15]:		temp	rain	google	naver	subway	holy	vacation	do1_pop	do2_pop	byun_pop	
	801	1.1	0.000000	51.285714	10.495550	243130.000000	0.0	0.0	16898.0	19724.0	17134.0	
	1679	22.2	2.388763	67.714286	16.964600	140875.000000	0.0	0.0	15111.0	18486.0	16392.0	
	1223	23.4	0.000000	71.000000	12.348090	244722.000000	0.0	0.0	15616.0	18942.0	16711.0	
	1180	17.2	0.000000	66.000000	22.782000	201630.000000	0.0	0.0	15613.0	19033.0	16759.0	
	22	6.9	0.000000	45.428571	14.701071	201813.465625	0.0	0.0	17711.0	20850.0	18001.0	
	835	16.2	0.262364	34.571429	8.662820	243556.000000	0.0	0.0	16826.0	19661.0	17085.0	
	1216	17.9	2.734368	68.571429	15.084530	225629.000000	0.0	0.0	15625.0	18949.0	16718.0	
	1653	28.5	0.470004	82.285714	22.654320	183563.000000	0.0	1.0	15111.0	18493.0	16409.0	
	559	21.4	0.000000	40.000000	16.055380	164694.000000	0.0	0.0	17064.0	20262.0	17463.0	
	684	16.1	0.000000	45.428571	10.031040	244499.000000	0.0	0.0	17059.0	20078.0	17393.0	

```
['temp','rain','google','naver','subway','holy','do1_pop','do2_pop','byun_pd
In [17]:
         # standard transformation
         from sklearn.preprocessing import StandardScaler
         scaler = StandardScaler()
In [18]:
         # train set 에 scaling 을 fitting 한 이후, train 에서와 같은 변환을 test 에도
          해주어야한다.
         trans_col =
          ['temp','rain','google','naver','subway','holy','do1_pop','do2_pop','byun_pd
         scaler.fit(X_train.loc[:,trans_col])
         X_train.loc[:,trans_col] = scaler.transform(X_train.loc[:,trans_col])
         X_test.loc[:,trans_col] = scaler.transform(X_test.loc[:,trans_col])
         # 아래는 WARNING만 주는거라 걱정안해도 된다.(자세한건 SettingWithCopyWarning 검
         색)
         C:\Users\qoran\Anaconda3\envs\tensor\lib\site-packages\pandas\core\indexing.py:670: Se
         ttingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
         r_guide/indexing.html#returning-a-view-versus-a-copy
           iloc._setitem_with_indexer(indexer, value)
         C:\Users\goran\Anaconda3\envs\tensor\lib\site-packages\ipykernel_launcher.py:4: Settin
         gWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
         r_guide/indexing.html#returning-a-view-versus-a-copy
          after removing the cwd from sys.path.
         C:\Users\goran\Anaconda3\envs\tensor\lib\site-packages\pandas\core\indexing.py:670: Se
         ttingWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
         r_guide/indexing.html#returning-a-view-versus-a-copy
           iloc._setitem_with_indexer(indexer, value)
         C:\Users\goran\Anaconda3\envs\tensor\lib\site-packages\ipykernel_launcher.py:5: Settin
         gWithCopyWarning:
         A value is trying to be set on a copy of a slice from a DataFrame
         See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/use
         r_guide/indexing.html#returning-a-view-versus-a-copy
```

#### Correlation plot

In [16]:

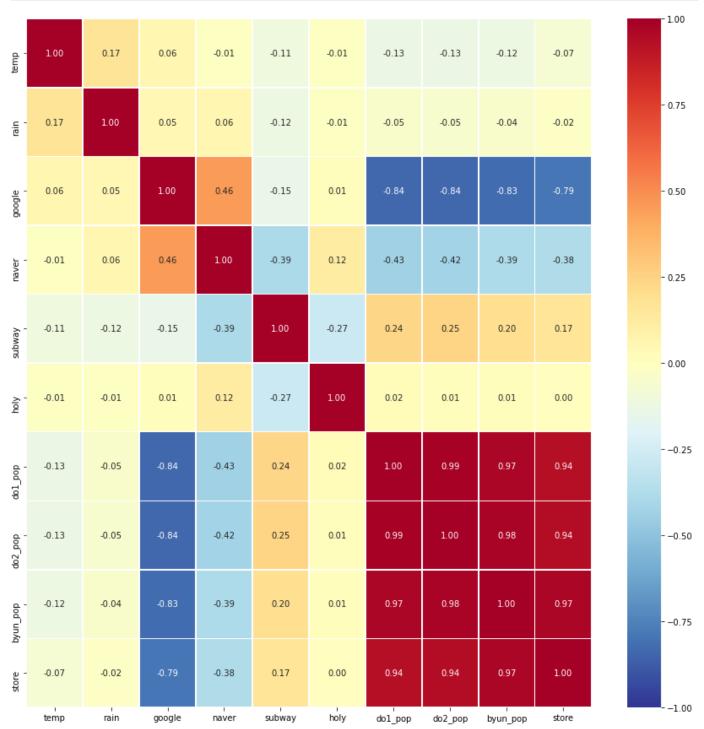
trans\_col =

```
In [19]: X_cor =
X[['temp','rain','google','naver','subway','holy','do1_pop','do2_pop','byun_
```

plt.figure(figsize=(15,15))

```
sns.heatmap(data = X_cor.corr(), annot=True,
fmt = '.2f', linewidths=.5, cmap='RdYlBu_r', vmin=-1, vmax=1)
```

#### Out[20]: <AxesSubplot:>



In [21]: X\_train

_				-
$\cap$	1.1	+	171	
v				

	temp	rain	google	naver	subway	holy	vacation	do1_pop	do2_pop	byun_po
801	-1.232665	-0.502136	-0.049334	-0.874331	0.903906	-0.22248	0.0	0.548946	0.105571	-0.06621
1679	0.846370	1.724104	0.963010	0.478670	-1.326573	-0.22248	0.0	-1.438669	-1.509246	-1.46963
1223	0.964609	-0.502136	1.165479	-0.486873	0.938632	-0.22248	0.0	-0.876976	-0.914451	-0.86628
1180	0.353708	-0.502136	0.857374	1.695379	-0.001330	-0.22248	0.0	-0.880313	-0.795753	-0.77549
22	-0.661177	-0.502136	-0.410257	0.005253	0.002672	-0.22248	0.0	1.453216	1.574298	1.57362

```
835
      0.255175 -0.257622 -1.079285
                                   -1.257647
                                               0.913198 -0.22248
                                                                            0.468863
                                                                                      0.023395
                                                                                               -0.15889
1216
      0.422680
                2.046195
                          1.015828
                                     0.085454
                                               0.522158 -0.22248
                                                                           -0.866965
                                                                                     -0.905320
                                                                                               -0.85304
1653
      1.467124 -0.064109
                           1.860915
                                     1.668674 -0.395424 -0.22248
                                                                           -1.438669
                                                                                     -1.500116 -1.43748
559
      0.767544 -0.502136 -0.744771
                                     0.288507 -0.807011 -0.22248
                                                                            0.733581
                                                                                      0.807325
                                                                                                0.55605
      0.245322 -0.502136 -0.410257 -0.971483 0.933767 -0.22248
                                                                       0.0
                                                                            0.728020
                                                                                     0.567320 0.42365
684
```

1357 rows × 30 columns

```
In [22]:
            X test
                    temp
                               rain
                                       google
                                                 naver
                                                         subway
                                                                     holy vacation
                                                                                    do1_pop
                                                                                              do2_pop byun_po
Out[22]:
           1018 -0.542938 -0.502136
                                    0.012287
                                             -0.202550
                                                        0.985420 -0.22248
                                                                               0.0 -0.645625
                                                                                             -0.271394 -0.52772
             6 -0.010863 0.940136
                                   -1.079285
                                              0.005253
                                                        0.002672 -0.22248
                                                                               0.0
                                                                                    1.488808
                                                                                             1.636908
                                                                                                      1.60956
            107 -1.508556 -0.502136
                                    -1.035270
                                              -0.173313
                                                        0.002672
                                                                                    1.260794
                                                                                             1.263856
                                                                                                       1.59064
            34 -0.621764 -0.502136
                                   -0.832801
                                              0.005253
                                                        0.002672 -0.22248
                                                                                    1.420960
                                                                               0.0
                                                                                             1.511688
                                                                                                       1.55092
           1686 0.787250
                         1.136124
                                    0.575678
                                             0.088216 -1.213844 -0.22248
                                                                               0.0 -1.438669
                                                                                            -1.509246 -1.46963
            315
                0.540919 -0.502136 -1.237739
                                             -1.241071
                                                        0.002672 -0.22248
                                                                               0.0
                                                                                    1.053913
                                                                                             1.119071
                                                                                                       1.25776
                 1.151821 -0.502136
                                    0.117923
                                              0.838502 -1.359423
                                                                                    0.713561
                                                                                             0.747324
                                                                                                       0.48796
            170 -0.030569
                           2.104829
                                    -1.008861
                                             -0.465232
                                                        0.002672
                                                                 -0.22248
                                                                                    1.210742
                                                                                             1.142550
                                                                                                       1.42988
           1635
                1.023728 -0.188556
                                    2.028172
                                              1.255890
                                                       -2.658534 -0.22248
                                                                               1.0 -1.438669
                                                                                             -1.480550
                                                                                                      -1.40154
           1014 -0.326166 -0.332219 -0.163773 1.501994
                                                        0.359019 -0.22248
                                                                               0.0 -0.627829 -0.266176 -0.52772
          340 rows × 30 columns
In [23]:
            # na 값은 없다.
            X_test.isnull().sum().sum()
Out[23]:
In [24]:
            # 예측값 저장 dictionary
            Data = { 'y_test' : y_test }
In [25]:
            # 평가값 저장 dictionary
            score = {}
```

## **Multi Linear Regression**

```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(X_train, y_train)
```

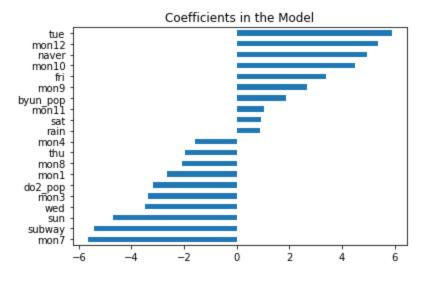
Out[26]: LinearRegression()

```
In [27]: from sklearn import metrics
y_pred = model.predict(X_test)
print ("MSE :", metrics.mean_squared_error(y_test,y_pred))
print("R squared :", metrics.r2_score(y_test,y_pred))
score['linear'] = [metrics.mean_squared_error(y_test,y_pred),
model.score(X_test, y_test)]
Data['linear'] = y_pred
```

MSE : 115.87375882979677 R squared : 0.5077488263894528

```
coef = pd.Series(model.coef_, index = X_train.columns).sort_values()
imp_coef = pd.concat([coef.head(10), coef.tail(10)])
imp_coef.plot(kind = "barh")
plt.title("Coefficients in the Model")
```

Out[28]: Text(0.5, 1.0, 'Coefficients in the Model')



# Ridge regression

```
w = rg \min_{w} \left( \sum_{i=1}^{N} e_i^2 + \lambda \sum_{j=1}^{M} w_j^2 
ight)
```

```
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import Ridge

para_range = np.logspace(-3, 3, num=50) # 10^-3 ~ 10^3
model = RidgeCV(alphas = para_range , cv=5)
# cross validaaion 을 5 fold cross validation 으로 지정 ,
# para_range 의 범위만큼 ,cv 를 해서 최적의 alpha를 구하려하였다.
model.fit(X_train, y_train);
```

```
In [30]:

from sklearn import metrics

predicted = model.predict(X_test)

# 우리가 fitting 한 coefficient 로 X_test 를 이용해 Y_test 를 predict

#ridgecv.alpha_ # Estimated regularization parametor (최적값)
```

```
print('best_alpha :', model.alpha_)
print ("MSE :", metrics.mean_squared_error(y_test, predicted))
print('R_squared :', model.score(X_test, y_test)) # C-V 로 찾은 최적의 ridge
로 계산한 R^2
```

best\_alpha : 59.636233165946365 MSE : 115.78052629560398 R\_squared : 0.5081448938411224

```
# 데이터 저장

score['Ridge'] = [metrics.mean_squared_error(y_test,
predicted), model.score(X_test, y_test)]

Data['Ridge'] = y_pred
```

```
In [32]: # 변수의 계수 시각화

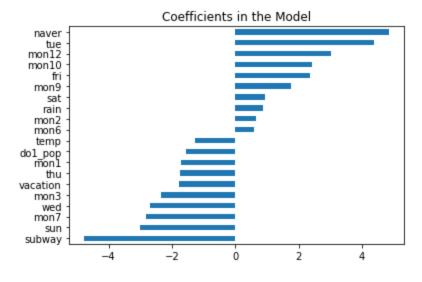
coef = pd.Series(model.coef_, index = X_train.columns).sort_values()

imp_coef = pd.concat([coef.head(10), coef.tail(10)])

imp_coef.plot(kind = "barh")

plt.title("Coefficients in the Model")
```

Out[32]: Text(0.5, 1.0, 'Coefficients in the Model')



# lasso regression

```
w = rg \min_{w} \left( \sum_{i=1}^{N} e_i^2 + \lambda \sum_{j=1}^{M} |w_j| 
ight)
```

```
from sklearn.linear_model import LassoCV

from sklearn.linear_model import Lasso
alphas = np.logspace(-3, 3, num=50) # 10^-3 ~ 10^3
lassocv = LassoCV(alphas = alphas, cv=5)
# 위 ridge 때와 동일
lassocv.fit(X_train, y_train);
```

```
from sklearn import metrics
predicted = lassocv.predict(X_test)
```

```
#lassocv.alpha_ # Estimated regularization parametor (최적값)
print('best_alpha :',lassocv.alpha_)
print ("MSE :", metrics.mean_squared_error(y_test, predicted))
print('R_squared :',lassocv.score(X_test, y_test)) # C-V 로 찾은 최적의
ridge 로 계산한 R^2
```

```
best_alpha : 0.0517947467923121
MSE : 114.83521939143081
R_squared : 0.5121607162128201
```

```
score['lasso'] = [metrics.mean_squared_error(y_test, predicted),
model.score(X_test, y_test)]
Data['lasso'] = y_pred
```

```
In [37]: # 계수 시각화

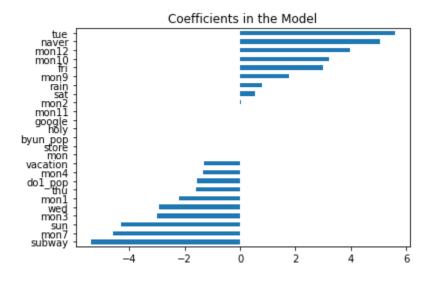
coef = pd.Series(lassocv.coef_, index = X_train.columns).sort_values()

imp_coef = pd.concat([coef.head(10), coef.tail(15)])

imp_coef.plot(kind = "barh")

plt.title("Coefficients in the Model")
```

```
Out[37]: Text(0.5, 1.0, 'Coefficients in the Model')
```



# K-Neighbors Regression

```
from sklearn.neighbors import KNeighborsRegressor
from sklearn.model_selection import GridSearchCV
model = KNeighborsRegressor()
param_grid ={'n_neighbors' : np.arange(1,10)}
model = GridSearchCV(model,param_grid,cv=5)
model.fit(X_train,y_train)
```

```
print ("MSE :", metrics.mean_squared_error(y_test, y_pred))
          print("R squared :", metrics.r2_score(y_test, y_pred))
        best N : {'n_neighbors': 9}
        MSE: 110.66125635439359
        R squared: 0.5298924116746597
In [40]:
         score['K-NN'] = [metrics.mean_squared_error(y_test, y_pred),
         model.score(X_test, y_test)]
         Data['K-NN'] = y_pred
        RandomForest Regressoion
In [41]:
         from sklearn.ensemble import RandomForestRegressor
                   RandomForestRegressor(random_state=42)
         model.fit(X_train,y_train)
Out[41]: RandomForestRegressor(random_state=42)
In [42]:
         y_pred = model.predict(X_test)
          print ("MSE :", metrics.mean_squared_error(y_test, y_pred))
         print('R_squared :', model.score(X_test, y_test))
        MSE: 91.9599994117647
        R_squared : 0.6093384896388988
In [43]:
         score['random_forest'] = [metrics.mean_squared_error(y_test, y_pred),
         model.score(X_test, y_test)]
         Data['random_forest'] = y_pred
In [44]:
         feat_importances = pd.Series(model.feature_importances_, index= X.columns)
         feat_importances.nlargest(15).plot(kind='barh')
Out[44]: <AxesSubplot:>
           mon6
            store
            mon
            wed
         vacation
          mon10
            tue
         byun_pop
           temp
          google
          subway
          dol pop
          do2_pop
           naver
                             0.10
                                    0.15
                                            0.20
              0.00
                      0.05
```

# Gradient Boosting resgressoion

```
In [45]:
         from sklearn.ensemble import GradientBoostingRegressor
         model = GradientBoostingRegressor(random_state=42)
         model.fit(X_train, y_train)
         GradientBoostingRegressor(random_state=42)
Out[45]:
In [46]:
         y_pred = model.predict(X_test)
         print ("MSE :", metrics.mean_squared_error(y_test, y_pred))
          print('R_squared :', model.score(X_test, y_test))
         MSE: 87.64051494326498
         R_squared : 0.627688384563208
In [47]:
         score['Gradient_boosting'] = [metrics.mean_squared_error(y_test, y_pred),
         model.score(X_test, y_test)]
         Data['Gradient_boosting'] = y_pred
In [48]:
         feat_importances = pd.Series(model.feature_importances_, index= X.columns)
         feat_importances.nlargest(10).plot(kind='barh')
Out[48]: <AxesSubplot:>
            rain
         vacation
            temp
          subway
             tue
           google
         byun_pop
         dol_pop
          do2_pop
           naver
              0.00
                     0.05
                           0.10
                                 0.15
                                        0.20
                                              0.25
                                                     0.30
        xgboost Regression
In [49]:
         import xqboost as xqb
         from xgboost.sklearn import XGBRegressor
```

```
import xgboost as xgb
from xgboost.sklearn import XGBRegressor
model = XGBRegressor(n_estimators = 150,
learning_rate=0.08, max_depth=3, random_state=42)
model.fit(X_train, y_train)
```

```
Out[49]: XGBRegressor(base_score=0.5, booster='gbtree', colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=-1, importance_type='gain', interaction_constraints='', learning_rate=0.08, max_delta_step=0, max_depth=3, min_child_weight=1, missing=nan, monotone_constraints='()', n_estimators=150, n_jobs=0, num_parallel_tree=1, random_state=42, reg_alpha=0, reg_lambda=1, scale_pos_weight=1, subsample=1, tree_method='exact', validate_parameters=1, verbosity=None)
```

In [50]:

```
from sklearn import metrics
          y_pred = model.predict(X_test)
          print ("MSE :", metrics.mean_squared_error(y_test, y_pred))
          print('R_squared :', model.score(X_test, y_test))
         MSE: 86.19491623165206
         R_squared: 0.6338295304926034
In [51]:
          score['xgb'] = [metrics.mean_squared_error(y_test, y_pred),
          model.score(X_test, y_test)]
          Data['xgb'] = y_pred
In [52]:
          feat_importances = pd.Series(model.feature_importances_, index= X.columns)
          feat_importances.nlargest(20).plot(kind='barh')
Out[52]: <AxesSubplot:>
              sat
             mon
            mon5
            mon7
              fri
             thu
           google
         byun pop
           subway
            store
            mon3
           mon12
             holy
           mon10
             tue
             wed
          do2_pop
vacation
            naver
          dol_pop
               0.000 0.025 0.050 0.075 0.100 0.125 0.150 0.175 0.200
        비교
In [53]:
          # 각 모델들의 MSE , R squre
          score
         {'linear': [115.87375882979677, 0.5077488263894528],
Out[53]:
          'Ridge': [115.78052629560398, 0.5081448938411224],
          'lasso': [114.83521939143081, 0.5081448938411224],
          'K-NN': [110.66125635439359, 0.5298924116746597],
          'random_forest': [91.9599994117647, 0.6093384896388988],
          'Gradient_boosting': [87.64051494326498, 0.627688384563208],
          'xgb': [86.19491623165206, 0.6338295304926034]}
In [54]:
          # 시각화 하기위해 파일저장.
          pred_DATA = pd.DataFrame(Data)
          pred_DATA.to_csv('예측.csv')
In [55]:
          pred_DATA.head(10)
                                                K-NN random_forest Gradient_boosting
                     linear
                              Ridge
                                       lasso
                                                                                     xgb
Out[55]:
           y_test
```

49.41

45.424855 47.355961

0

39 39.591610 39.591610 39.591610 47.555556

1	53	43.442307	43.442307	43.442307	45.666667	44.20	47.707230	48.964478
2	35	38.667962	38.667962	38.667962	34.000000	37.63	31.881639	31.860603
3	60	47.198234	47.198234	47.198234	52.888889	49.79	47.914982	48.031036
4	73	54.452415	54.452415	54.452415	67.555556	68.10	63.964419	63.798450
5	24	24.652574	24.652574	24.652574	27.888889	22.72	24.367213	24.255486
6	42	37.779270	37.779270	37.779270	40.000000	38.45	40.595756	39.900398
7	41	37.048577	37.048577	37.048577	36.111111	39.32	39.082240	39.168682
8	50	48.935753	48.935753	48.935753	49.222222	44.32	48.479283	46.267185
9	27	36.003448	36.003448	36.003448	36.888889	39.09	42.556822	40.453506

In [56]:

# 시각화는 따로 tableau 프로그램을 사용하였습니다.

In [ ]: