Stats 131 Final Project

December 2, 2019

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score as acc
#run pip install mlxtend in your terminal to install mlxtend
from mlxtend.feature_selection import SequentialFeatureSelector as sfs
import statsmodels.api as sm
import statsmodels.formula.api as smf
from mlxtend.plotting import plot_sequential_feature_selection as plot_sfs
```

1 Introduction

This study aims to investigate the relationship between the concentration of PM2.5 and atmospheric pollutants and the influence of meteorological conditions on PM2.5 concentration. Mathematical statistics methods were employed to analyze the data of PM2.5, atomspheric pollutants and meteorology in Changping ,Dongsi and Huairou District of Beijing, from March 2013 to February 2017. the bivariate correlation analysis showed that the PM2.5 concentration had a strong correlation with the concentrations of atmospheric pollutants such as PM10,SO2,NO2,O3,CO and the meteorological conditions such as PRES, WAPM. The fitting models we used OLS regression and feature Sequential Feature Selection forward method and gbm method for each season. After compared the value of R squared, we decided the model of PM2.5 concentration for each season use gbm method. –Mary

2 Data Preparation

2.1 Imputation of Missing Data (Do not run these, it will take forever)

[ ]:
```
# Import the three data sets and concatenate them
changping = pd.read_csv('/Users/Rocco/UCLA/Stats 131/Final Project/
 ↪PRSA_Data_20130301-20170228/PRSA_Data_Changping_20130301-20170228.csv')
changping = changping.iloc[:,1:]
dongsi = pd.read_csv('/Users/Rocco/UCLA/Stats 131/Final Project/
 ↪PRSA_Data_20130301-20170228/PRSA_Data_Dongsi_20130301-20170228.csv')
dongsi = dongsi.iloc[:,1:]
huairou = pd.read_csv('/Users/Rocco/UCLA/Stats 131/Final Project/
 ↪PRSA_Data_20130301-20170228/PRSA_Data_Huairou_20130301-20170228.csv')
huairou = huairou.iloc[:,1:]
data = pd.concat([changping, dongsi, huairou], axis = 0)
```

[ ]:
```
# Create a "date" column of the form of YYYY-MM-DD HH:MM:SS"
date = pd.to_datetime({"year":data.year,"month":data.month,"day":data.
 ↪day,"hour":data.hour})
data['date'] = date
```

[ ]:
```
# Reindex
data = data.reset_index(drop=True)
```

[ ]:
```
data.head()
```

[ ]:
```
data.tail()
```

[ ]:
```
# to see if has na values
data.info()
```

[ ]:
```
# export the merged csv file (before removing na) for future use
data.to_csv("data(hasna).csv",index = False)
```

[ ]:
```
# create a list that contains the column name where has na
nanlistname = ['PM2.
 ↪5','PM10','SO2','NO2','CO','O3','TEMP','PRES','DEWP','RAIN','WSPM']
```

[ ]:
```
# define a function that cleans na
# input a column and replace na with the mean of the its two nearest neighbour
def fillna(columns):
    for c in columns:
        a = c.notnull()
        for i in range(0, data.shape[0]):
            #print(a[i])
            if a[i]==False:
```

```
                for k in range(i,data.shape[0]):
                    if a[k]==True:
                        c[i] = (c[i-1] + c[k])/2
                        break
```

[ ]:
```
# fill na for 'wd' using previous non-na value
data['wd'].fillna(method = 'ffill',inplace = True )
```

[ ]:
```
# fill na for the other columns that contain na
fillna([data['SO2'],data['PM2.
 ↪5'],data['PM10'],data['CO'],data['NO2'],data['O3'],data['DEWP'],data['TEMP'],data['PRES'],d
```

[ ]:
```
# check if na's have been filled up
data.info()
```

[ ]:
```
# export the non na csv file
data.to_csv("data(nona).csv",index = False)
```

Now we have done the imputation of Missing Data. Starting from here, we will import `data(nona).csv` file everytime we launch the notebook (to save time)!

[2]:
```
# Import the no-na data file
data = pd.read_csv('/Users/Rocco/UCLA/Stats 131/Final Project/data(nona).csv')
wd = data.wd
```

[3]:
```
data.head()
```

[3]:

	year	month	day	hour	PM2.5	PM10	SO2	NO2	CO	O3	TEMP	PRES	\
0	2013	3	1	0	3.0	6.0	13.0	7.0	300.0	85.0	-2.3	1020.8	
1	2013	3	1	1	3.0	3.0	6.0	6.0	300.0	85.0	-2.5	1021.3	
2	2013	3	1	2	3.0	3.0	22.0	13.0	400.0	74.0	-3.0	1021.3	
3	2013	3	1	3	3.0	6.0	12.0	8.0	300.0	81.0	-3.6	1021.8	
4	2013	3	1	4	3.0	3.0	14.0	8.0	300.0	81.0	-3.5	1022.3	

	DEWP	RAIN	wd	WSPM	station	date
0	-19.7	0.0	E	0.5	Changping	2013-03-01 00:00:00
1	-19.0	0.0	ENE	0.7	Changping	2013-03-01 01:00:00
2	-19.9	0.0	ENE	0.2	Changping	2013-03-01 02:00:00
3	-19.1	0.0	NNE	1.0	Changping	2013-03-01 03:00:00
4	-19.4	0.0	N	2.1	Changping	2013-03-01 04:00:00

2.2 One-Hot Encoding for wd variable

2.2.1 Note wd is a categorical variables with multiple (16) levels, we need to convert it to dummy variables using One-Hot Encoding for future model fitting purpose.

[4]:
```
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
```

[5]:
```
wd_num = {
    'E':1,
    'ENE':2,
    'ESE':3,
    'N':4,
    'NE':5,
    'NNE':6,
    'NNW':7,
    'NW':8,
    'S':9,
    'SE' :10,
    'SSE':11,
    'SSW':12,
    'SW':13,
    'W':14,
    'WNW':15,
    'WSW':16,
}
```

[6]:
```
wd_encoded=np.array([[wd_num.get(value)] for value in data.wd])
label_encoder = LabelEncoder()
onehot_encoder = OneHotEncoder(sparse=False)
wd_encoded = wd_encoded.reshape(len(wd_encoded), 1)
onehot_encoded = onehot_encoder.fit_transform(wd_encoded)
```

```
/Users/Rocco/opt/anaconda3/lib/python3.7/site-
packages/sklearn/preprocessing/_encoders.py:415: FutureWarning: The handling of
integer data will change in version 0.22. Currently, the categories are
determined based on the range [0, max(values)], while in the future they will be
determined based on the unique values.
If you want the future behaviour and silence this warning, you can specify
"categories='auto'".
In case you used a LabelEncoder before this OneHotEncoder to convert the
categories to integers, then you can now use the OneHotEncoder directly.
  warnings.warn(msg, FutureWarning)
```

[7]:
```
encoded_wd = pd.DataFrame.from_records(onehot_encoded, columns=wd_num.keys())
encoded_wd
```

[7]:
```
            E  ENE  ESE    N   NE  NNE  NNW   NW    S   SE  SSE  SSW   SW    W  \
0         1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
1         0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
2         0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
3         0.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
4         0.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
…       …  …  …  …  …  …  …  …  …  …  …  …  …  …  …
105187    0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
105188    0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0
105189    0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0
105190    0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0
105191    0.0  0.0  0.0  0.0  1.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0  0.0

          WNW  WSW
0         0.0  0.0
1         0.0  0.0
2         0.0  0.0
3         0.0  0.0
4         0.0  0.0
…       …  …
105187    1.0  0.0
105188    0.0  0.0
105189    0.0  0.0
105190    0.0  0.0
105191    0.0  0.0

[105192 rows x 16 columns]
```

[8]:
```
data=pd.concat([data.drop(['wd'], axis=1), encoded_wd, wd], axis=1)
```

[9]:
```
# Set a multi index
data = data.set_index(['station','date'])
```

[10]:
```
data.head()
```

[10]:
```
                                year  month  day  hour  PM2.5  PM10   SO2  \
station   date
Changping 2013-03-01 00:00:00  2013      3    1     0    3.0   6.0  13.0
          2013-03-01 01:00:00  2013      3    1     1    3.0   3.0   6.0
          2013-03-01 02:00:00  2013      3    1     2    3.0   3.0  22.0
          2013-03-01 03:00:00  2013      3    1     3    3.0   6.0  12.0
          2013-03-01 04:00:00  2013      3    1     4    3.0   3.0  14.0

                                NO2     CO    O3  …   NW    S   SE  SSE  \
station   date                                    …
Changping 2013-03-01 00:00:00   7.0  300.0  85.0  …  0.0  0.0  0.0  0.0
          2013-03-01 01:00:00   6.0  300.0  85.0  …  0.0  0.0  0.0  0.0
```

```
                           2013-03-01 02:00:00  13.0  400.0  74.0  …  0.0  0.0  0.0  0.0
                           2013-03-01 03:00:00   8.0  300.0  81.0  …  0.0  0.0  0.0  0.0
                           2013-03-01 04:00:00   8.0  300.0  81.0  …  0.0  0.0  0.0  0.0

                                                SSW   SW    W  WNW  WSW   wd
station   date
Changping 2013-03-01 00:00:00  0.0  0.0  0.0  0.0  0.0    E
          2013-03-01 01:00:00  0.0  0.0  0.0  0.0  0.0  ENE
          2013-03-01 02:00:00  0.0  0.0  0.0  0.0  0.0  ENE
          2013-03-01 03:00:00  0.0  0.0  0.0  0.0  0.0  NNE
          2013-03-01 04:00:00  0.0  0.0  0.0  0.0  0.0    N

[5 rows x 32 columns]
```

[11]:
```
data.tail()
```

[11]:
```
                              year  month  day  hour  PM2.5  PM10  SO2   NO2  \
station date
Huairou 2017-02-28 19:00:00  2017      2   28    19   16.0  28.0  2.0  19.0
        2017-02-28 20:00:00  2017      2   28    20   21.0  34.0  4.0  24.0
        2017-02-28 21:00:00  2017      2   28    21   17.0  33.0  2.0  39.0
        2017-02-28 22:00:00  2017      2   28    22   11.0  29.0  3.0  32.0
        2017-02-28 23:00:00  2017      2   28    23   11.0  20.0  2.0  27.0

                                    CO    O3  …   NW    S   SE  SSE  SSW   SW  \
station date                                  …
Huairou 2017-02-28 19:00:00   300.0  95.0  …  0.0  0.0  0.0  0.0  0.0  0.0
        2017-02-28 20:00:00   500.0  80.0  …  0.0  0.0  0.0  0.0  1.0  0.0
        2017-02-28 21:00:00   900.0  60.0  …  0.0  0.0  1.0  0.0  0.0  0.0
        2017-02-28 22:00:00  1400.0  69.0  …  0.0  0.0  0.0  0.0  0.0  0.0
        2017-02-28 23:00:00   400.0  77.0  …  0.0  0.0  0.0  0.0  0.0  0.0

                                   W  WNW  WSW   wd
station date
Huairou 2017-02-28 19:00:00  0.0  1.0  0.0  WNW
        2017-02-28 20:00:00  0.0  0.0  0.0  SSW
        2017-02-28 21:00:00  0.0  0.0  0.0   SE
        2017-02-28 22:00:00  0.0  0.0  0.0  ENE
        2017-02-28 23:00:00  0.0  0.0  0.0   NE

[5 rows x 32 columns]
```

[12]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
MultiIndex: 105192 entries, (Changping, 2013-03-01 00:00:00) to (Huairou,
2017-02-28 23:00:00)
```

```
Data columns (total 32 columns):
year     105192 non-null int64
month    105192 non-null int64
day      105192 non-null int64
hour     105192 non-null int64
PM2.5    105192 non-null float64
PM10     105192 non-null float64
SO2      105192 non-null float64
NO2      105192 non-null float64
CO       105192 non-null float64
O3       105192 non-null float64
TEMP     105192 non-null float64
PRES     105192 non-null float64
DEWP     105192 non-null float64
RAIN     105192 non-null float64
WSPM     105192 non-null float64
E        105192 non-null float64
ENE      105192 non-null float64
ESE      105192 non-null float64
N        105192 non-null float64
NE       105192 non-null float64
NNE      105192 non-null float64
NNW      105192 non-null float64
NW       105192 non-null float64
S        105192 non-null float64
SE       105192 non-null float64
SSE      105192 non-null float64
SSW      105192 non-null float64
SW       105192 non-null float64
W        105192 non-null float64
WNW      105192 non-null float64
WSW      105192 non-null float64
wd       105192 non-null object
dtypes: float64(27), int64(4), object(1)
memory usage: 26.5+ MB
```

[13]:
```
# check the dimension of the data sets for each station
print(data.loc['Changping'].shape)
print(data.loc['Dongsi'].shape)
print(data.loc['Huairou'].shape)
```

```
(35064, 32)
(35064, 32)
(35064, 32)
```

[14]:
```
# select via the ounner then inner index
```

```
# data.loc[('Huairou', '2017-01-01 00:00:00'):('Huairou', '2017-01-31 23:00:
↪00')]
```

2.3 A new column for season

[15]:
```
# define a dictionary for season
s = {
1: 'Winter',
2: 'Winter',
3: 'Spring',
4: 'Spring',
5: 'Spring',
6: 'Summer',
7: 'Summer',
8: 'Summer',
9: 'Fall',
10: 'Fall',
11: 'Fall',
12: 'Winter'}
```

[16]:
```
# add a 'season' column that indicates season
data["season"]=[s.get(value) for value in data.month]
```

[17]:
```
data.head()
```

[17]:

		year	month	day	hour	PM2.5	PM10	SO2	\
station	date								
Changping	2013-03-01 00:00:00	2013	3	1	0	3.0	6.0	13.0	
	2013-03-01 01:00:00	2013	3	1	1	3.0	3.0	6.0	
	2013-03-01 02:00:00	2013	3	1	2	3.0	3.0	22.0	
	2013-03-01 03:00:00	2013	3	1	3	3.0	6.0	12.0	
	2013-03-01 04:00:00	2013	3	1	4	3.0	3.0	14.0	

		NO2	CO	O3	…	S	SE	SSE	SSW	\
station	date				…					
Changping	2013-03-01 00:00:00	7.0	300.0	85.0	…	0.0	0.0	0.0	0.0	
	2013-03-01 01:00:00	6.0	300.0	85.0	…	0.0	0.0	0.0	0.0	
	2013-03-01 02:00:00	13.0	400.0	74.0	…	0.0	0.0	0.0	0.0	
	2013-03-01 03:00:00	8.0	300.0	81.0	…	0.0	0.0	0.0	0.0	
	2013-03-01 04:00:00	8.0	300.0	81.0	…	0.0	0.0	0.0	0.0	

		SW	W	WNW	WSW	wd	season
station	date						
Changping	2013-03-01 00:00:00	0.0	0.0	0.0	0.0	E	Spring
	2013-03-01 01:00:00	0.0	0.0	0.0	0.0	ENE	Spring
	2013-03-01 02:00:00	0.0	0.0	0.0	0.0	ENE	Spring

```
                     2013-03-01 03:00:00  0.0  0.0  0.0  0.0  NNE  Spring
                     2013-03-01 04:00:00  0.0  0.0  0.0  0.0    N  Spring

[5 rows x 33 columns]
```

[18]:
```
data.tail()
```

[18]:
```
                                year  month  day  hour  PM2.5  PM10  SO2   NO2  \
station date
Huairou 2017-02-28 19:00:00  2017      2   28    19   16.0  28.0  2.0  19.0
        2017-02-28 20:00:00  2017      2   28    20   21.0  34.0  4.0  24.0
        2017-02-28 21:00:00  2017      2   28    21   17.0  33.0  2.0  39.0
        2017-02-28 22:00:00  2017      2   28    22   11.0  29.0  3.0  32.0
        2017-02-28 23:00:00  2017      2   28    23   11.0  20.0  2.0  27.0

                                    CO    O3  …    S   SE  SSE  SSW   SW    W  \
station date                                  …
Huairou 2017-02-28 19:00:00   300.0  95.0  …  0.0  0.0  0.0  0.0  0.0  0.0
        2017-02-28 20:00:00   500.0  80.0  …  0.0  0.0  0.0  1.0  0.0  0.0
        2017-02-28 21:00:00   900.0  60.0  …  0.0  1.0  0.0  0.0  0.0  0.0
        2017-02-28 22:00:00  1400.0  69.0  …  0.0  0.0  0.0  0.0  0.0  0.0
        2017-02-28 23:00:00   400.0  77.0  …  0.0  0.0  0.0  0.0  0.0  0.0

                                WNW  WSW   wd  season
station date
Huairou 2017-02-28 19:00:00  1.0  0.0  WNW  Winter
        2017-02-28 20:00:00  0.0  0.0  SSW  Winter
        2017-02-28 21:00:00  0.0  0.0   SE  Winter
        2017-02-28 22:00:00  0.0  0.0  ENE  Winter
        2017-02-28 23:00:00  0.0  0.0   NE  Winter

[5 rows x 33 columns]
```

2.4 Another column for seasonal year

Since Winter spans two years, we need to define a "seasonal year" column that indicates correct corresponding year for each season.

Note our data is from 2013-03-01 to 2017-02-28, and we have Spring (2013, 2014, 2015, 2016), Summer (2013, 2014, 2015, 2016), Fall (2013, 2014, 2015, 2016), and Winter (2013, 2014, 2015, 2016). Thus, we will consider the date from 2013-12 to 2014-02 as 2013 winter, etc.

[19]:
```
# concatenate year and month columns
yearmonth = data[['year', 'month']].astype(str).apply(lambda x: ''.join(x),␣
 ↪axis=1).astype(int)
yearmonth
```

[19]:
```
station    date
Changping  2013-03-01 00:00:00    20133
           2013-03-01 01:00:00    20133
           2013-03-01 02:00:00    20133
           2013-03-01 03:00:00    20133
           2013-03-01 04:00:00    20133
                                  …
Huairou    2017-02-28 19:00:00    20172
           2017-02-28 20:00:00    20172
           2017-02-28 21:00:00    20172
           2017-02-28 22:00:00    20172
           2017-02-28 23:00:00    20172
Length: 105192, dtype: int64
```

[20]:
```
# define a dictionary for seasonal year
seasonal_year = {
    20133: 2013, 20143: 2014, 20153: 2015, 20163: 2016,
    20134: 2013, 20144: 2014, 20154: 2015, 20164: 2016,
    20135: 2013, 20145: 2014, 20155: 2015, 20165: 2016,
    20136: 2013, 20146: 2014, 20156: 2015, 20166: 2016,
    20137: 2013, 20147: 2014, 20157: 2015, 20167: 2016,
    20138: 2013, 20148: 2014, 20158: 2015, 20167: 2016,
    20139: 2013, 20149: 2014, 20159: 2015, 20169: 2016,
    201310: 2013, 201410: 2014, 201510: 2015, 201610: 2016,
    201311: 2013, 201411: 2014, 201511: 2015, 201611: 2016,
    201312: 2013, 201412: 2014, 201512: 2015, 201612: 2016,
    20141: 2013, 20151: 2014, 20161: 2015, 20171: 2016,
    20142: 2013, 20152: 2014, 20162: 2015, 20172: 2016
}
```

[21]:
```
data["seasonal year"]=[seasonal_year.get(value) for value in yearmonth]
```

[22]:
```
data.head()
```

[22]:

		year	month	day	hour	PM2.5	PM10	SO2	\
station	date								
Changping	2013-03-01 00:00:00	2013	3	1	0	3.0	6.0	13.0	
	2013-03-01 01:00:00	2013	3	1	1	3.0	3.0	6.0	
	2013-03-01 02:00:00	2013	3	1	2	3.0	3.0	22.0	
	2013-03-01 03:00:00	2013	3	1	3	3.0	6.0	12.0	
	2013-03-01 04:00:00	2013	3	1	4	3.0	3.0	14.0	

		NO2	CO	O3	…	SE	SSE	SSW	SW	\
station	date				…					
Changping	2013-03-01 00:00:00	7.0	300.0	85.0	…	0.0	0.0	0.0	0.0	
	2013-03-01 01:00:00	6.0	300.0	85.0	…	0.0	0.0	0.0	0.0	
	2013-03-01 02:00:00	13.0	400.0	74.0	…	0.0	0.0	0.0	0.0	

```
                                2013-03-01 03:00:00   8.0  300.0  81.0  …  0.0  0.0  0.0  0.0
                                2013-03-01 04:00:00   8.0  300.0  81.0  …  0.0  0.0  0.0  0.0

                                                     W  WNW  WSW   wd  season  seasonal year
station   date
Changping 2013-03-01 00:00:00  0.0  0.0  0.0    E  Spring         2013.0
          2013-03-01 01:00:00  0.0  0.0  0.0  ENE  Spring         2013.0
          2013-03-01 02:00:00  0.0  0.0  0.0  ENE  Spring         2013.0
          2013-03-01 03:00:00  0.0  0.0  0.0  NNE  Spring         2013.0
          2013-03-01 04:00:00  0.0  0.0  0.0    N  Spring         2013.0

[5 rows x 34 columns]
```

[23]:
```
data.tail()
```

[23]:
```
                                year  month  day  hour  PM2.5  PM10  SO2   NO2  \
station date
Huairou 2017-02-28 19:00:00  2017      2   28    19   16.0  28.0  2.0  19.0
        2017-02-28 20:00:00  2017      2   28    20   21.0  34.0  4.0  24.0
        2017-02-28 21:00:00  2017      2   28    21   17.0  33.0  2.0  39.0
        2017-02-28 22:00:00  2017      2   28    22   11.0  29.0  3.0  32.0
        2017-02-28 23:00:00  2017      2   28    23   11.0  20.0  2.0  27.0

                                   CO    O3  …   SE  SSE  SSW   SW    W  WNW  \
station date                                 …
Huairou 2017-02-28 19:00:00   300.0  95.0  …  0.0  0.0  0.0  0.0  0.0  1.0
        2017-02-28 20:00:00   500.0  80.0  …  0.0  0.0  1.0  0.0  0.0  0.0
        2017-02-28 21:00:00   900.0  60.0  …  1.0  0.0  0.0  0.0  0.0  0.0
        2017-02-28 22:00:00  1400.0  69.0  …  0.0  0.0  0.0  0.0  0.0  0.0
        2017-02-28 23:00:00   400.0  77.0  …  0.0  0.0  0.0  0.0  0.0  0.0

                                WSW   wd  season  seasonal year
station date
Huairou 2017-02-28 19:00:00  0.0  WNW  Winter         2016.0
        2017-02-28 20:00:00  0.0  SSW  Winter         2016.0
        2017-02-28 21:00:00  0.0   SE  Winter         2016.0
        2017-02-28 22:00:00  0.0  ENE  Winter         2016.0
        2017-02-28 23:00:00  0.0   NE  Winter         2016.0

[5 rows x 34 columns]
```

So far, we have done data cleaning and manuplication.

3 Data Exploration

3.1 We start to explore the seasonal change in each pollutant for each station in each seasonal year.

[24]:
```
# Find seasonal mean of each variable for each station in each year
seasonmean = data.iloc[:,4:].groupby(["station","seasonal year","season"],␣
↪sort=False).mean().unstack()
seasonmean
```

[24]:

		PM2.5				\
season		Spring	Summer	Fall	Winter	
station	seasonal year					
Changping	2013.0	80.655344	65.964624	72.303571	98.583527	
	2014.0	80.520652	59.997652	85.599124	77.857936	
	2015.0	64.533047	51.061821	57.959657	71.895375	
	2016.0	60.327729	53.886228	70.250344	90.147454	
Dongsi	2013.0	88.608582	81.326285	90.847985	113.620515	
	2014.0	84.381692	75.524434	89.077953	87.091223	
	2015.0	77.574649	61.578663	86.430503	92.311126	
	2016.0	79.700449	71.000683	87.081638	118.470209	
Huairou	2013.0	72.830389	64.213315	68.394918	97.323942	
	2014.0	75.157484	64.433316	74.853911	68.070584	
	2015.0	69.569497	47.971213	67.677470	75.843907	
	2016.0	62.889832	52.605277	68.694598	79.862963	

		PM10				\
season		Spring	Summer	Fall	Winter	
station	seasonal year					
Changping	2013.0	110.808650	77.973053	88.198947	112.591462	
	2014.0	123.715127	80.222763	112.249542	106.426397	
	2015.0	110.631459	66.254734	68.917518	96.192508	
	2016.0	103.874490	67.644168	91.379923	104.987384	
Dongsi	2013.0	120.952899	92.131708	102.716461	118.380176	
	2014.0	133.648007	85.953284	129.537592	114.761779	
	2015.0	128.750181	77.945867	102.821300	107.937729	
	2016.0	115.161618	78.721995	109.692659	151.137182	
Huairou	2013.0	124.012455	91.786458	87.448260	105.916650	
	2014.0	113.197124	84.182694	95.504609	91.079928	
	2015.0	107.627451	63.544554	76.798063	83.412717	
	2016.0	101.728884	67.916987	88.613668	98.275694	

		SO2		…	W		\
season		Spring	Summer	…	Fall	Winter	
station	seasonal year			…			
Changping	2013.0	25.097358	9.153538	…	0.016941	0.051389	

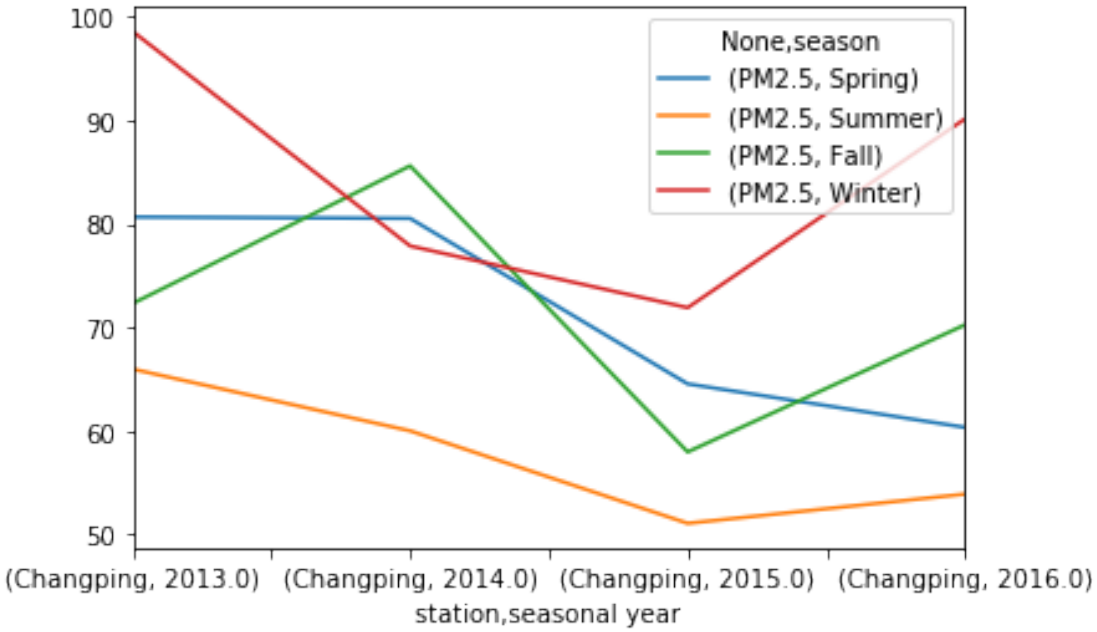
```
          2014.0         21.126902   5.153616  …  0.036630  0.073148
          2015.0         11.038901   3.880898  …  0.090201  0.054029
          2016.0          8.745138   3.498196  …  0.031593  0.022222
Dongsi    2013.0         31.407160  12.892948  …  0.028388  0.026389
          2014.0         25.479303   8.374615  …  0.038462  0.038426
          2015.0         15.793014   5.860168  …  0.031593  0.026099
          2016.0         13.683018   5.363900  …  0.020604  0.019907
Huairou   2013.0         32.893011   6.448759  …  0.098901  0.087500
          2014.0         17.776834   4.431046  …  0.051740  0.057870
          2015.0          9.320148   4.061424  …  0.040751  0.054487
          2016.0          8.823483   3.901895  …  0.048993  0.031481
```

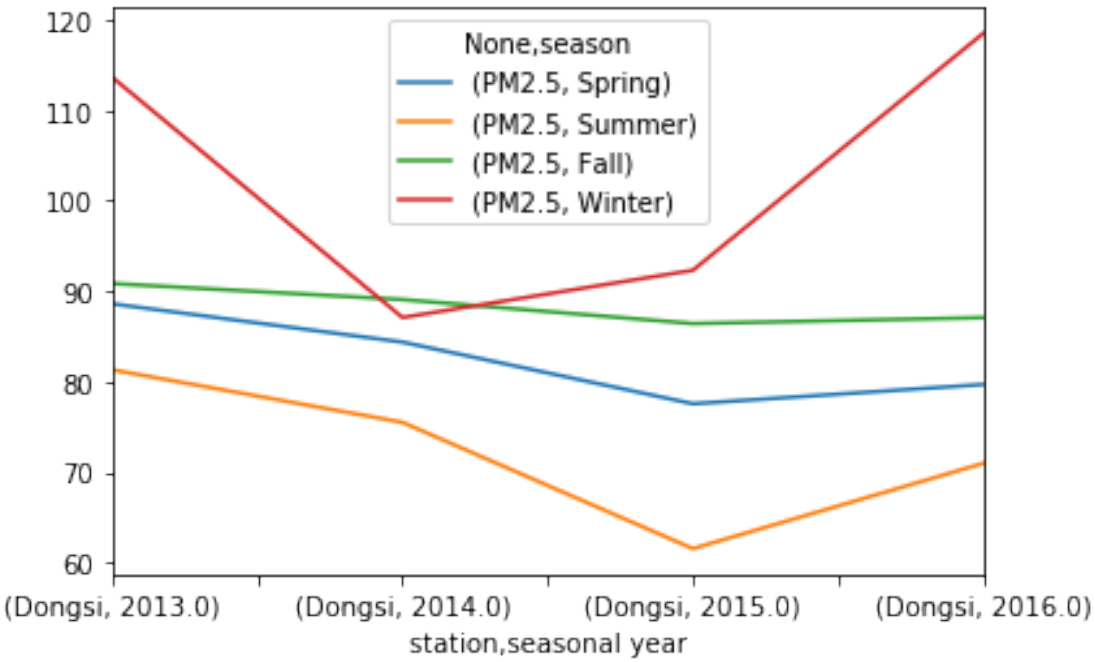
```
                                WNW                                      WSW  \
season                        Spring    Summer      Fall    Winter    Spring
station   seasonal year
Changping 2013.0          0.027174  0.037138  0.072344  0.114352  0.018116
          2014.0          0.071558  0.042120  0.074634  0.161111  0.020380
          2015.0          0.071558  0.062500  0.100733  0.184524  0.014040
          2016.0          0.096920  0.038934  0.074634  0.091667  0.010870
Dongsi    2013.0          0.038043  0.033062  0.062729  0.046296  0.052989
          2014.0          0.037591  0.019475  0.035714  0.053704  0.062953
          2015.0          0.033062  0.033514  0.048535  0.058608  0.083786
          2016.0          0.053895  0.019126  0.024725  0.017593  0.049366
Huairou   2013.0          0.163496  0.129076  0.227106  0.215741  0.038043
          2014.0          0.167572  0.125906  0.177198  0.157870  0.048460
          2015.0          0.105978  0.105978  0.115842  0.154762  0.032156
          2016.0          0.115036  0.086066  0.119048  0.060648  0.042572
```

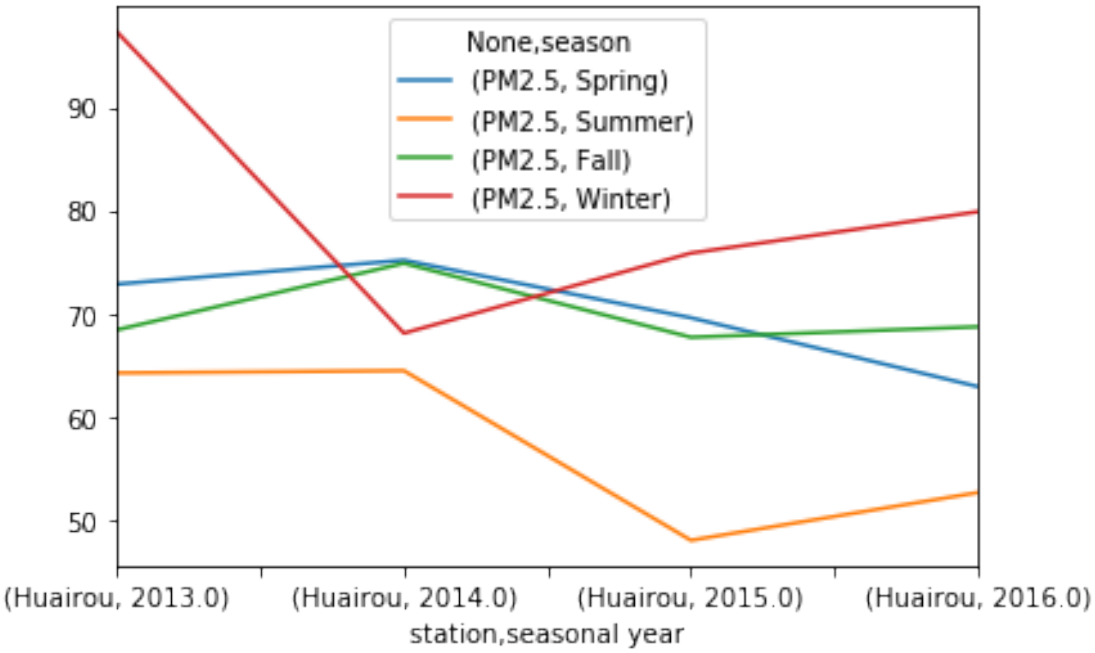
```
season                        Summer      Fall    Winter
station   seasonal year
Changping 2013.0          0.018569  0.012363  0.015278
          2014.0          0.023551  0.021062  0.011574
          2015.0          0.021286  0.045330  0.037546
          2016.0          0.023224  0.014652  0.011111
Dongsi    2013.0          0.056612  0.049451  0.037037
          2014.0          0.061141  0.052656  0.056944
          2015.0          0.046196  0.052198  0.035714
          2016.0          0.034153  0.025641  0.043519
Huairou   2013.0          0.068841  0.039377  0.046296
          2014.0          0.045743  0.031136  0.036574
          2015.0          0.052083  0.038462  0.028846
          2016.0          0.056694  0.039377  0.024074

[12 rows x 108 columns]
```

[25]:
```
# plot the chage in PM2.5
seasonmean[["PM2.5"]].groupby("station").plot()
```

[25]:
```
station
Changping    AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi       AxesSubplot(0.125,0.125;0.775x0.755)
Huairou      AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```





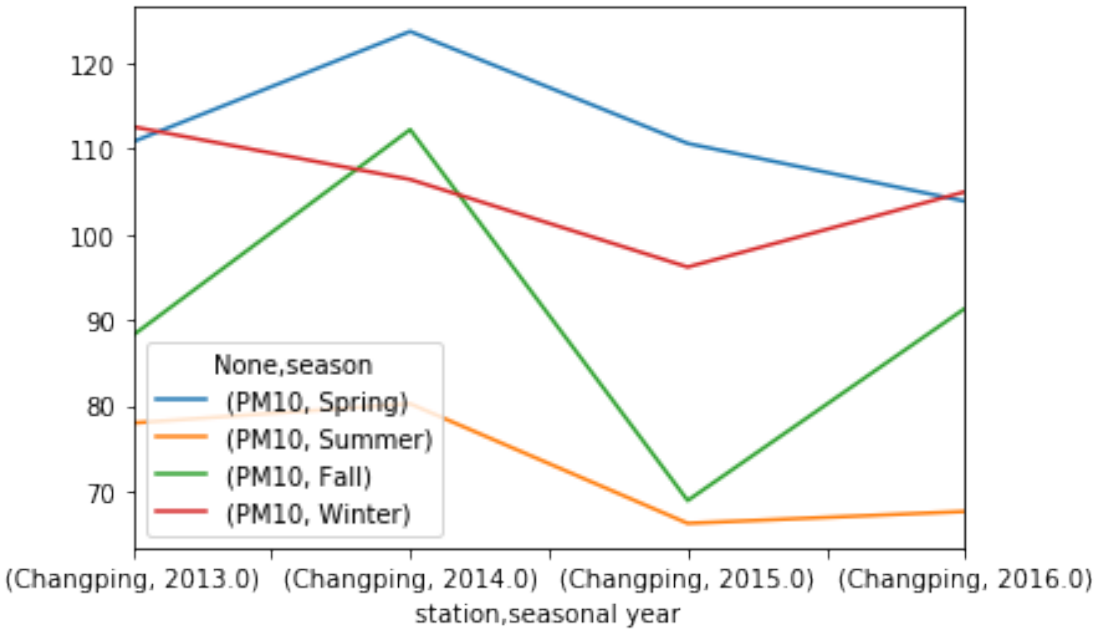


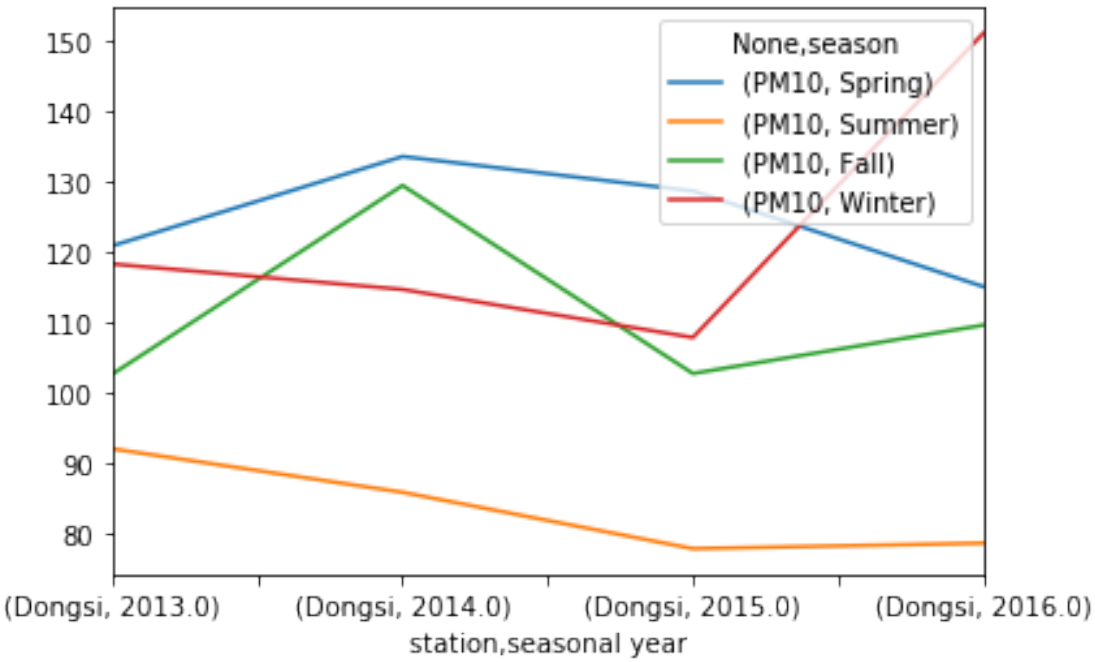
As we can see from above graphs, in each station, overall, Winter PM2.5 level is higher than other seasons except for year 2014, and Summer PM2.5 level is always lower than other seasons. Furthermore, the level of PM 2.5 in each station has an overall dereasing trend in the first 3 years but rebounds up a little bit in 2016.

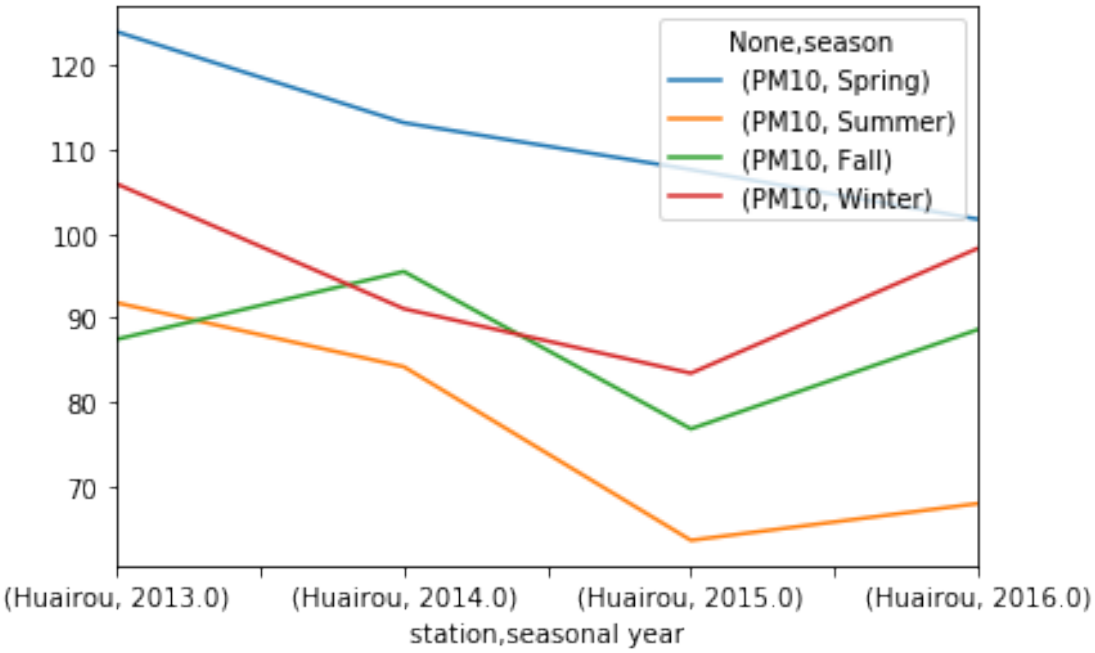
Let's look at changes in other pollutants.

[26]:
```
seasonmean[['PM10']].groupby("station").plot()
```

[26]:
```
station
Changping     AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi        AxesSubplot(0.125,0.125;0.775x0.755)
Huairou       AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```



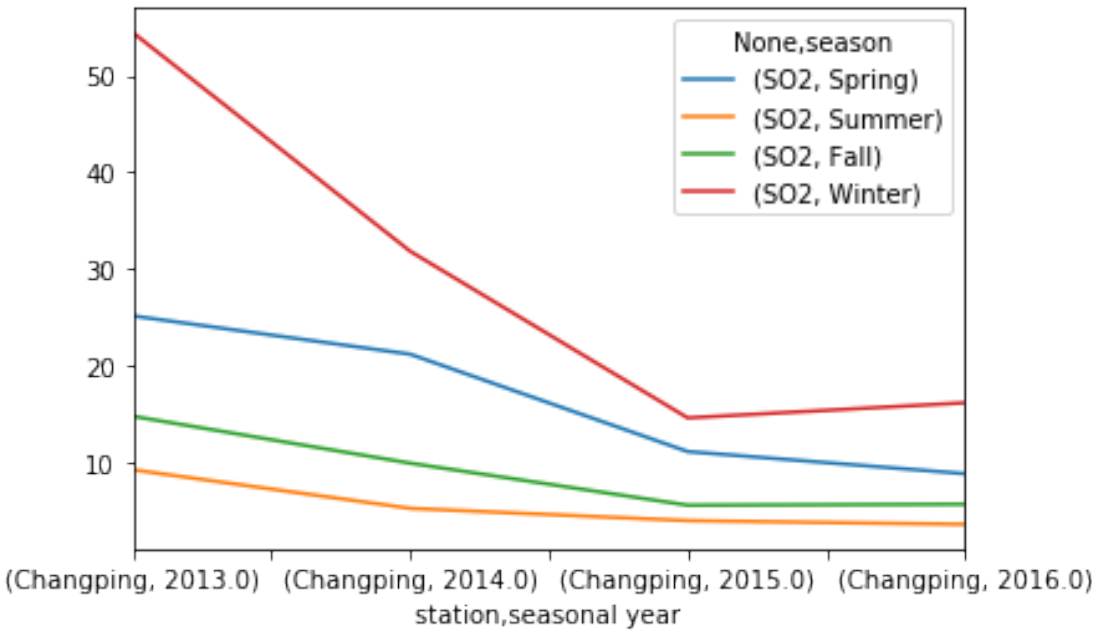


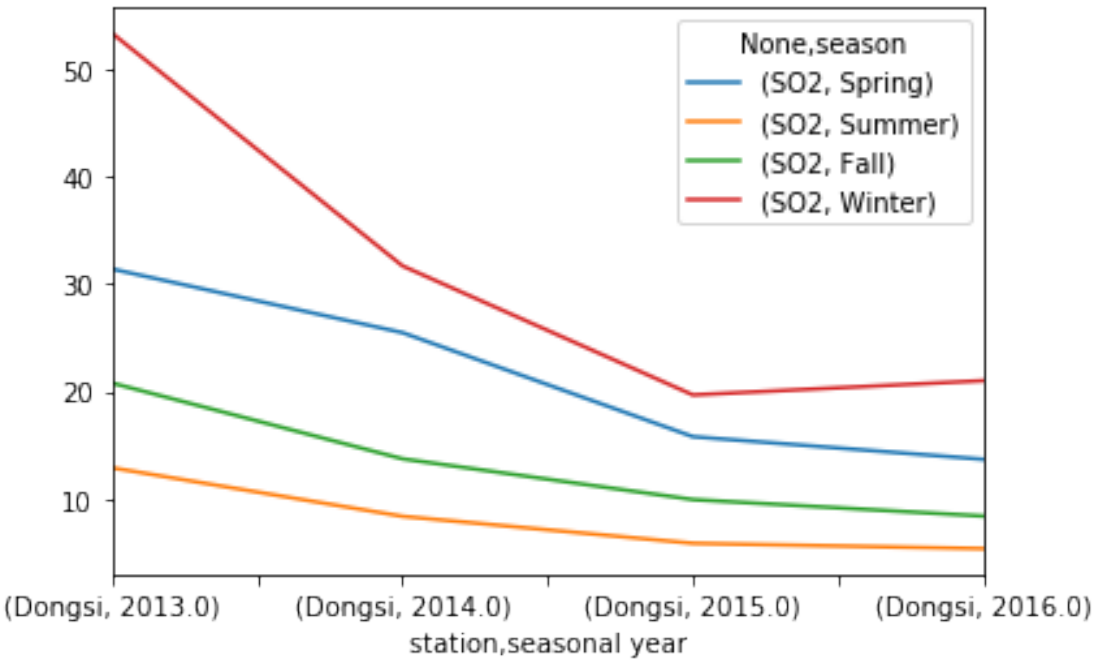


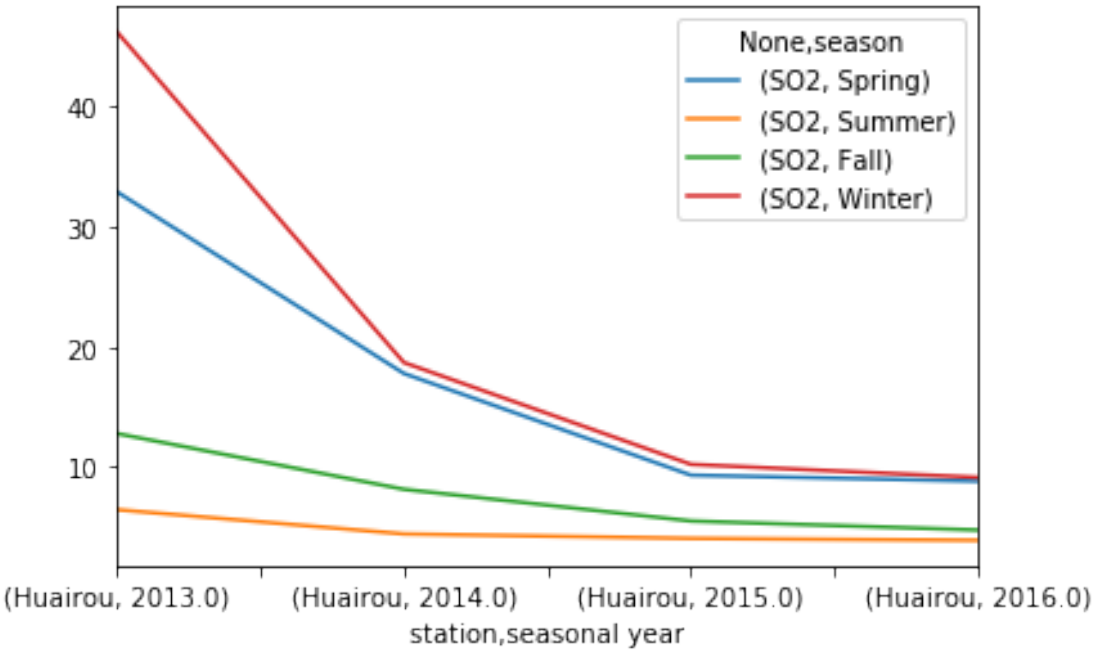
Surprisingly, for PM10, Spring is the worst. This might be due to pollination in spring. Since we are more concerned about the air pollution from fine inhalable particles (PM2.5) and PM10 is confounded with PM2.5, thus we will disregard PM10 from now on.

[27]:
```
seasonmean[['SO2']].groupby("station").plot()
```

[27]:
```
station
Changping    AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi       AxesSubplot(0.125,0.125;0.775x0.755)
Huairou      AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```

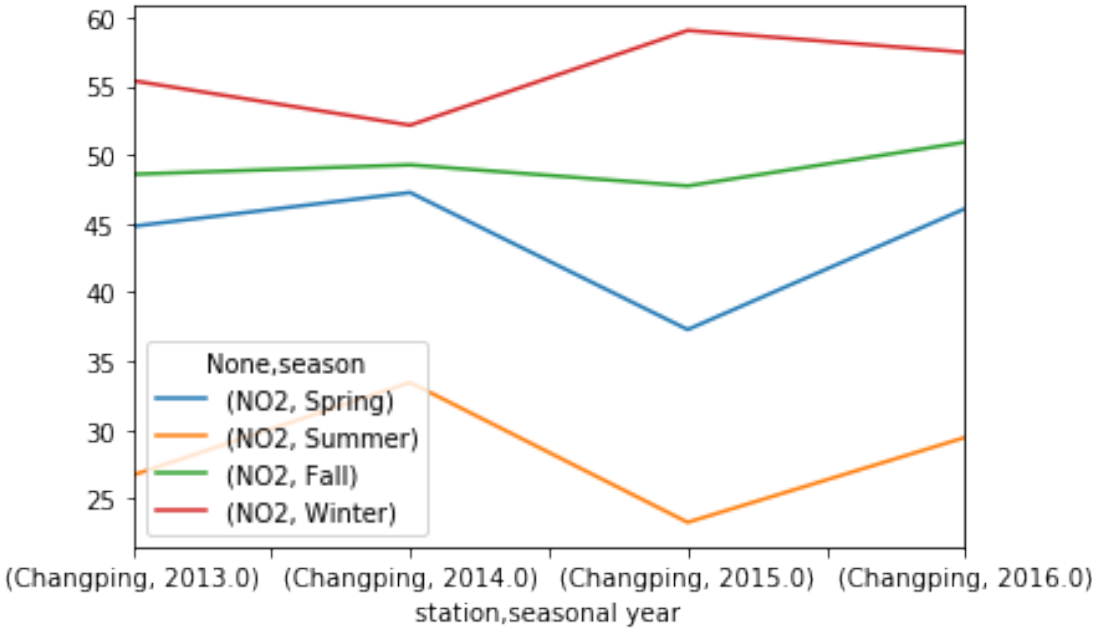


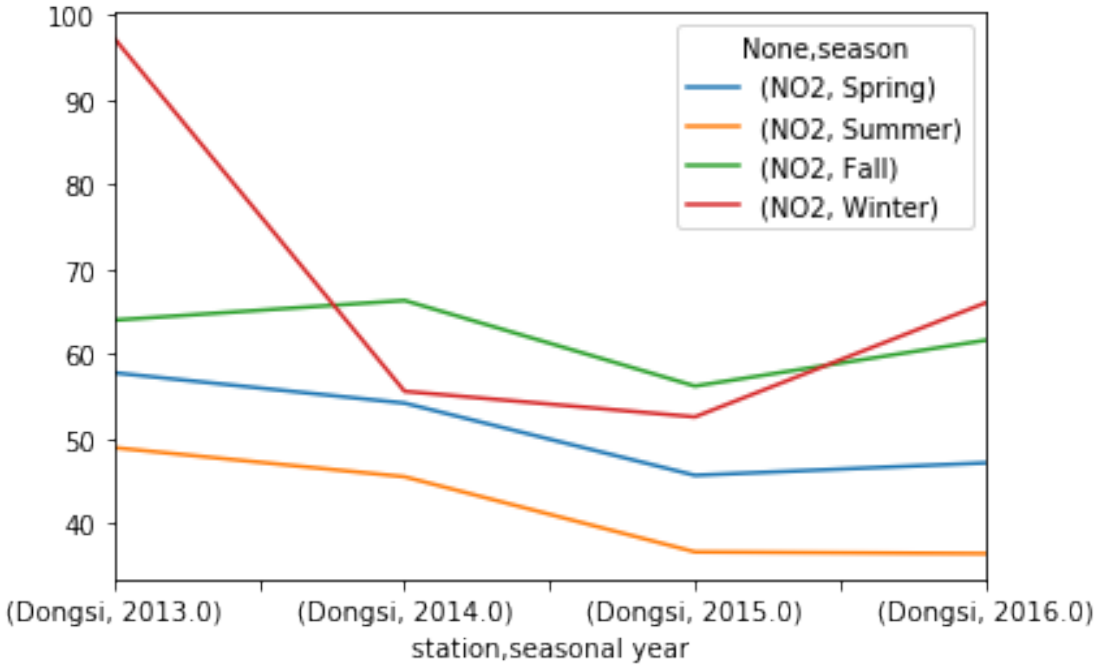


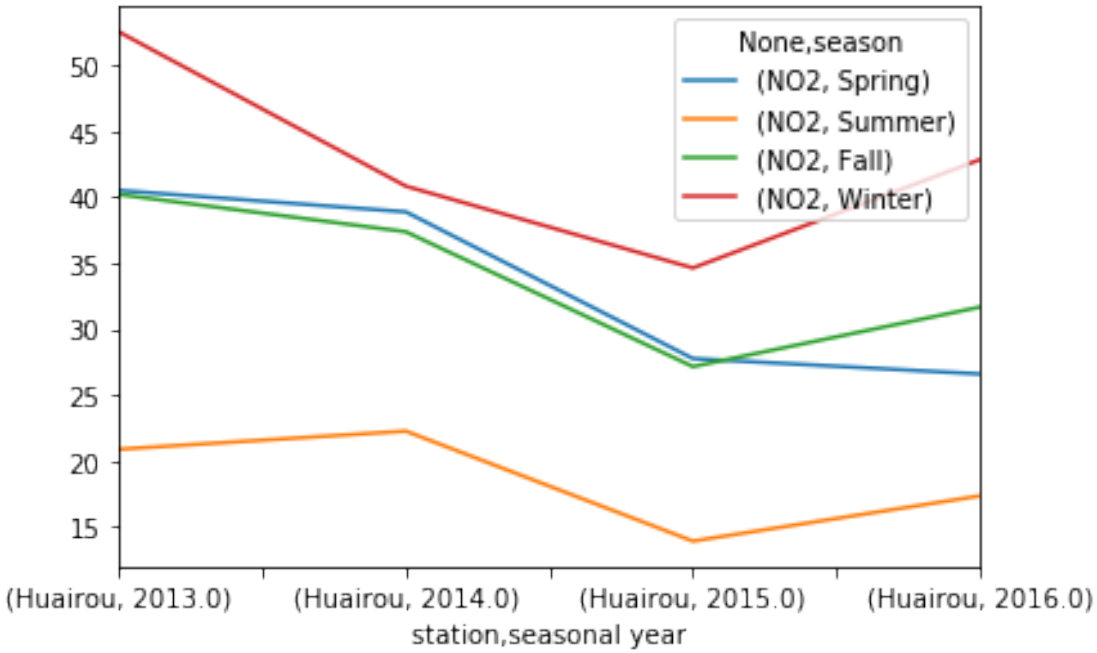


[28]:
```
seasonmean[['NO2']].groupby("station").plot()
```

[28]:
```
station
Changping     AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi        AxesSubplot(0.125,0.125;0.775x0.755)
Huairou       AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```

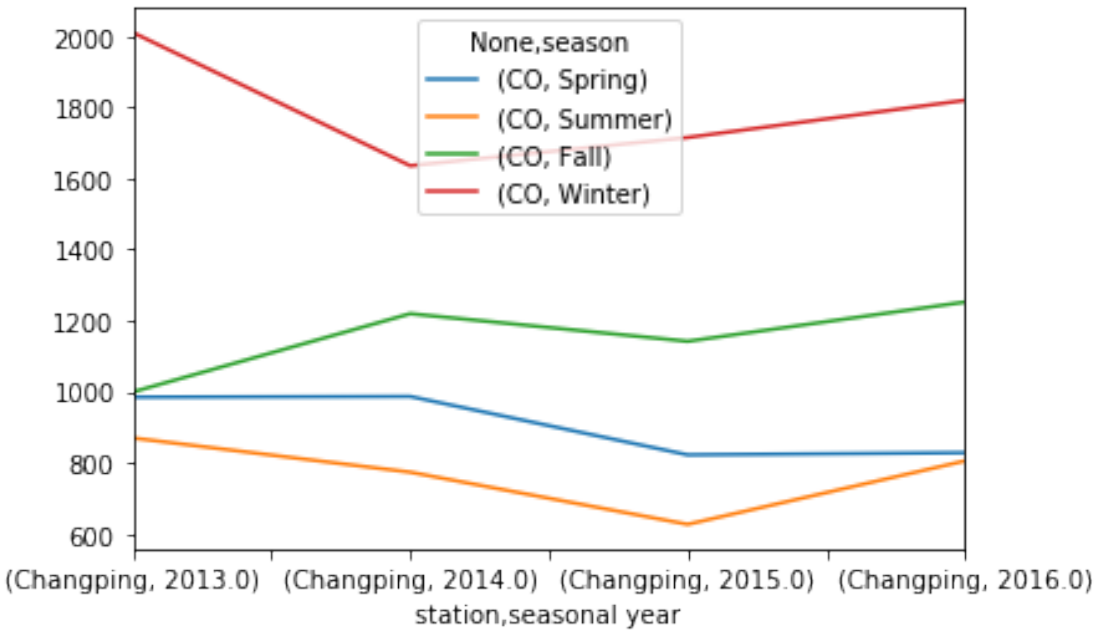


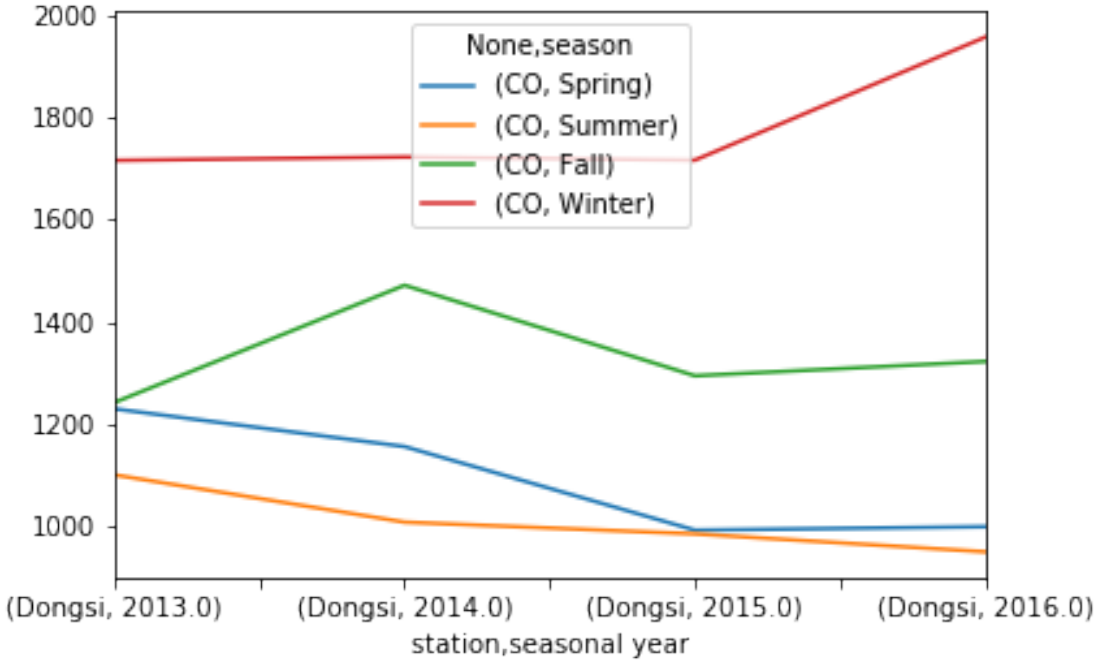


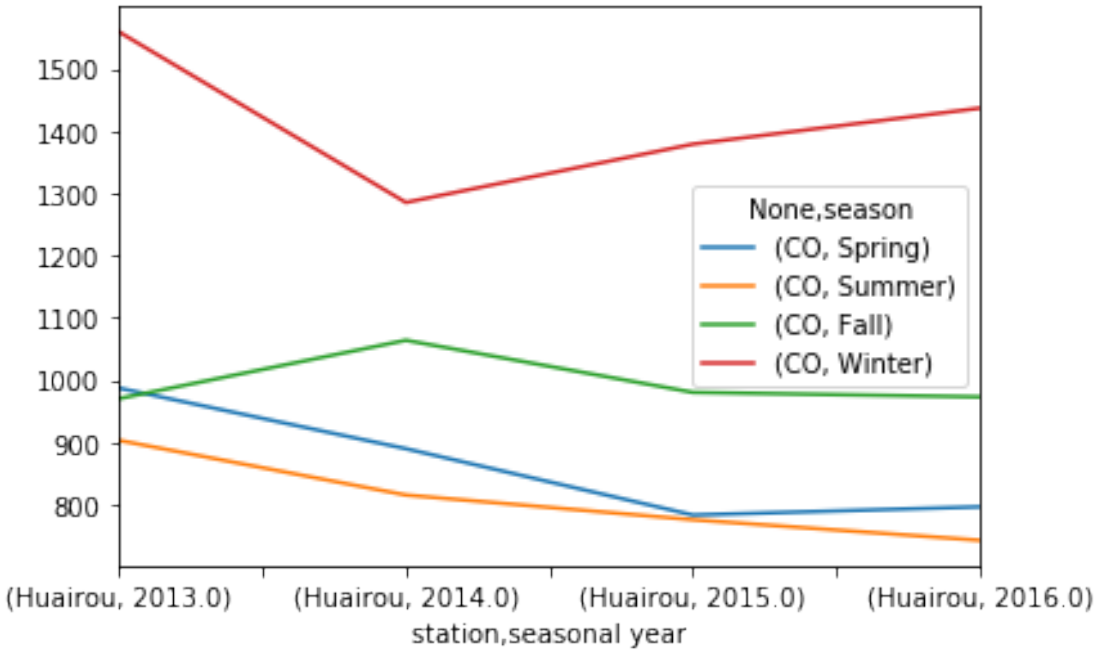


[29]:
```
seasonmean[['CO']].groupby("station").plot()
```

[29]:
```
station
Changping    AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi       AxesSubplot(0.125,0.125;0.775x0.755)
Huairou      AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```


None,season
(CO, Spring)
(CO, Summer)
(CO, Fall)
(CO, Winter)
2000
1800
1600
1400
1200
1000
800
600
(Changping, 2013.0)
(Changping, 2014.0)
(Changping, 2015.0)
(Changping, 2016.0)
station,seasonal year

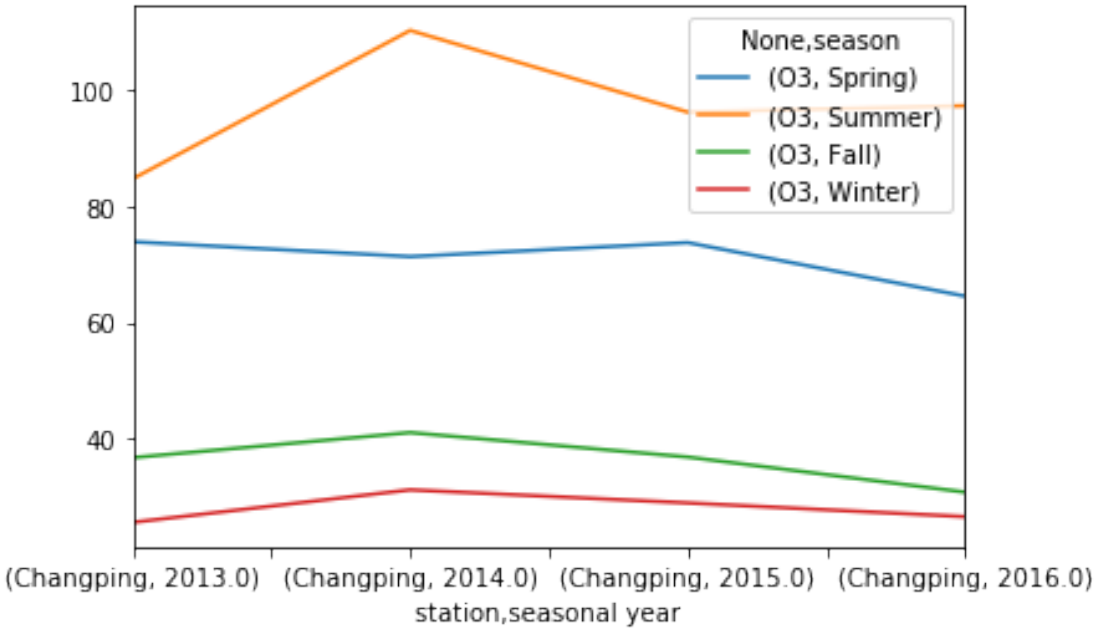

None,season
(CO, Spring)
(CO, Summer)
(CO, Fall)
(CO, Winter)
2000
1800
1600
1400
1200
1000
(Dongsi, 2013.0)
(Dongsi, 2014.0)
(Dongsi, 2015.0)
(Dongsi, 2016.0)
station,seasonal year

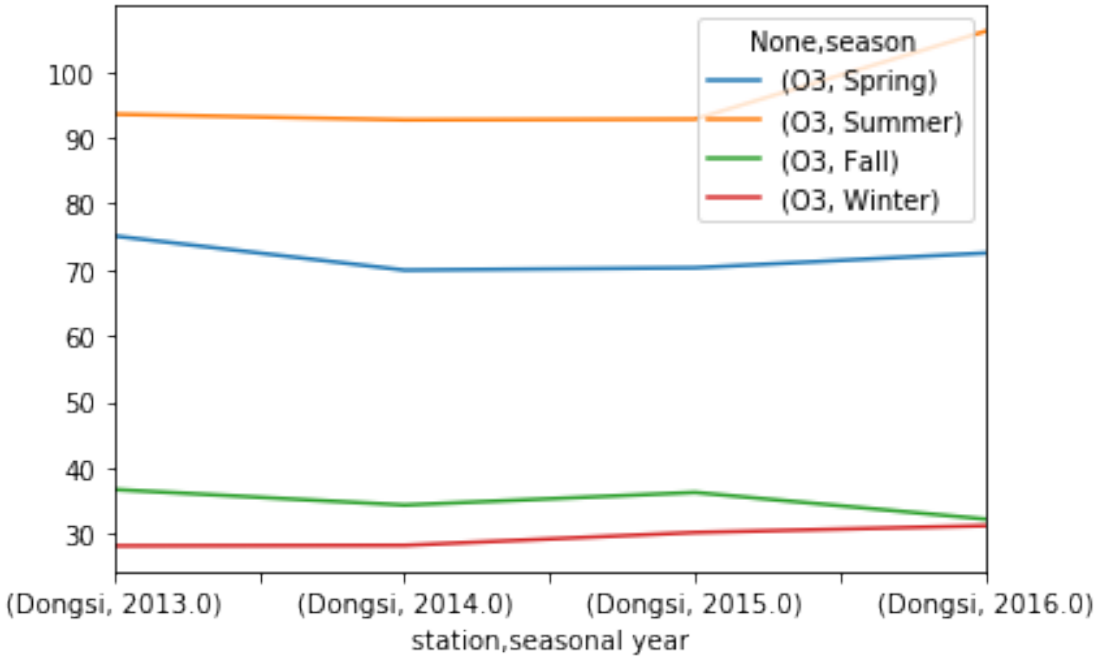


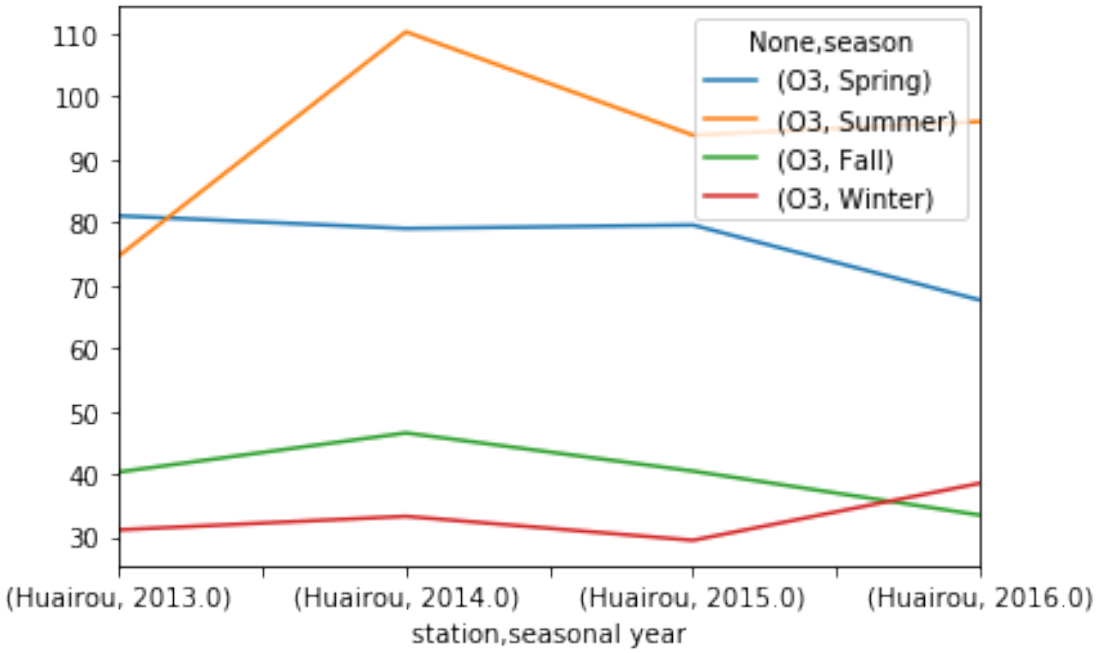
For SO2, NO2 and CO, the seasonal trends match that of PM2.5, that is, overall, Winter has high level of pollutants than any other seasons and Summer has low level of pollutants than other seasons. Also notice that, overall, SO2 is decreasing over year

[30]:
```
seasonmean[['O3']].groupby("station").plot()
```

[30]:
```
station
Changping    AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi       AxesSubplot(0.125,0.125;0.775x0.755)
Huairou      AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```


None,season
(O3, Spring)
(O3, Summer)
(O3, Fall)
(O3, Winter)
100
80
60
40
(Changping, 2013.0)
(Changping, 2014.0)
(Changping, 2015.0)
(Changping, 2016.0)
station,seasonal year


None,season
(O3, Spring)
(O3, Summer)
(O3, Fall)
(O3, Winter)
100
90
80
70
60
50
40
30
(Dongsi, 2013.0)
(Dongsi, 2014.0)
(Dongsi, 2015.0)
(Dongsi, 2016.0)
station,seasonal year

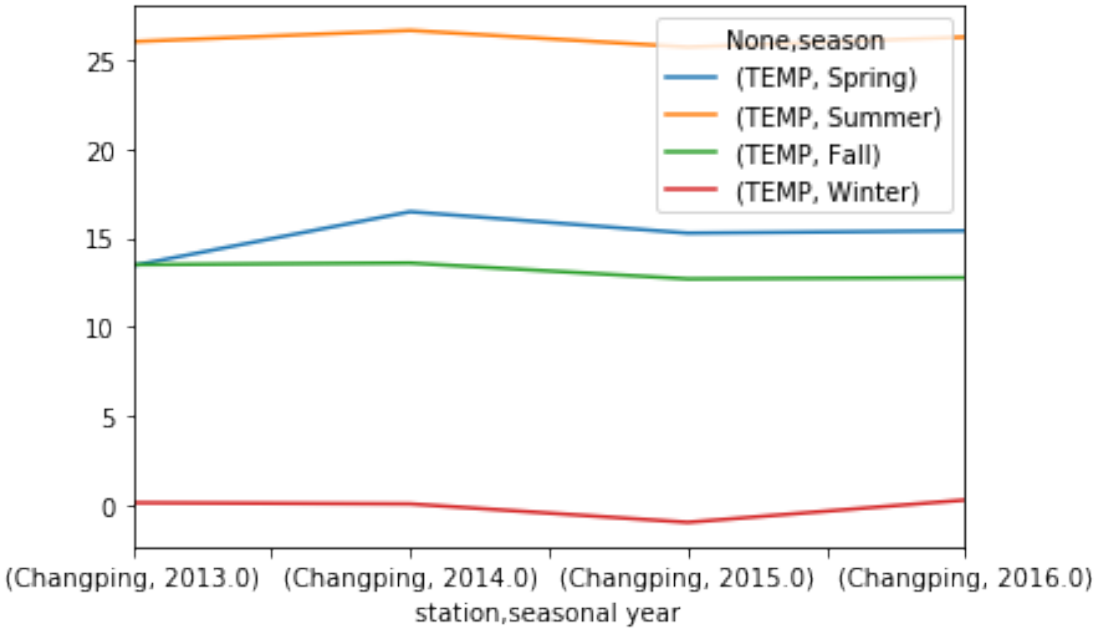


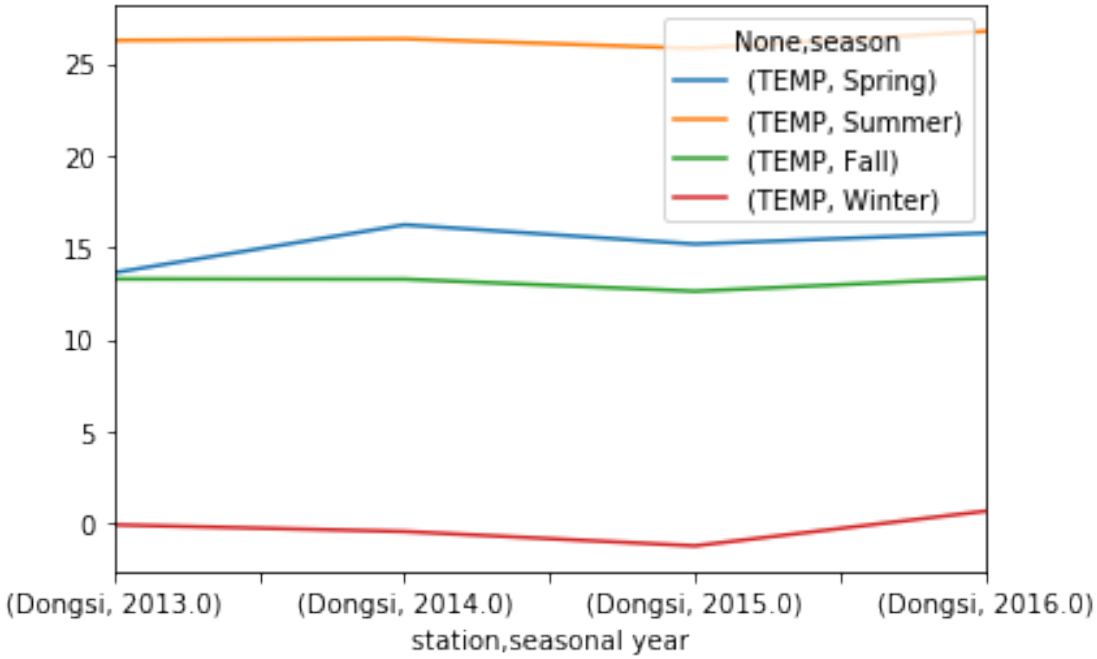
For O3, the results are just reversed, which makes sense since ozone has the highest concentration in summer and lowest in winter.

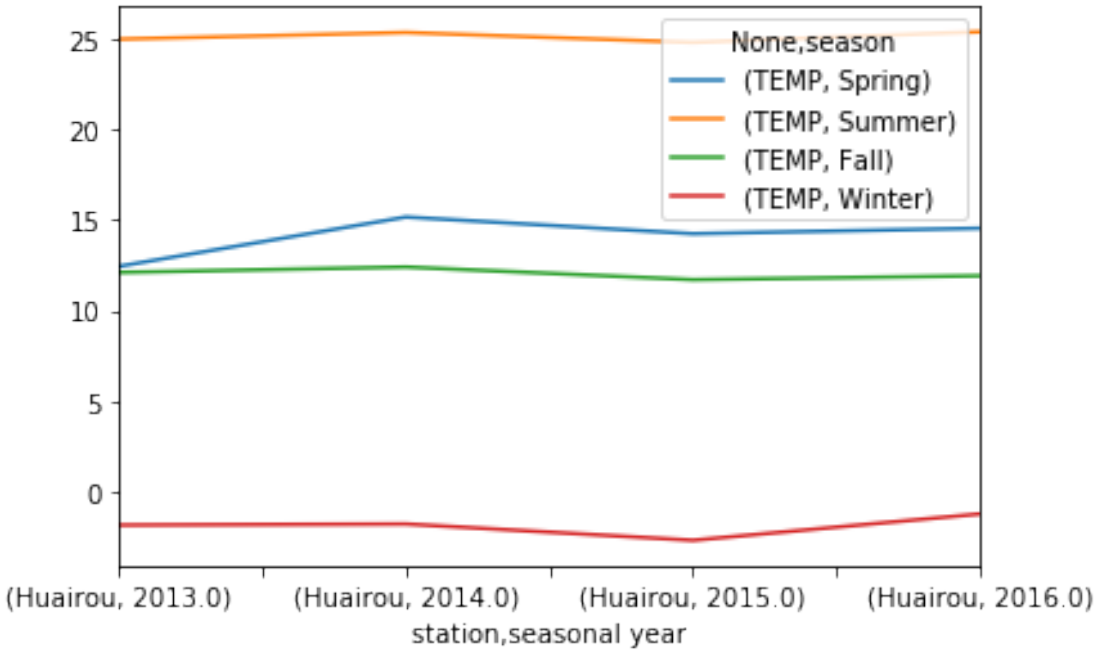
3.2 Next, let's find the seasonal change in each meteorological condition for each station in each seasonal year.

[31]:
```
seasonmean[['TEMP']].groupby("station").plot()
```

[31]:
```
station
Changping    AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi       AxesSubplot(0.125,0.125;0.775x0.755)
Huairou      AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```


None,season
(TEMP, Spring)
(TEMP, Summer)
(TEMP, Fall)
(TEMP, Winter)
25
20
15
10
5
0
(Changping, 2013.0)
(Changping, 2014.0)
(Changping, 2015.0)
(Changping, 2016.0)
station,seasonal year


None,season
(TEMP, Spring)
(TEMP, Summer)
(TEMP, Fall)
(TEMP, Winter)
25
20
15
10
5
0
(Dongsi, 2013.0)
(Dongsi, 2014.0)
(Dongsi, 2015.0)
(Dongsi, 2016.0)
station,seasonal year

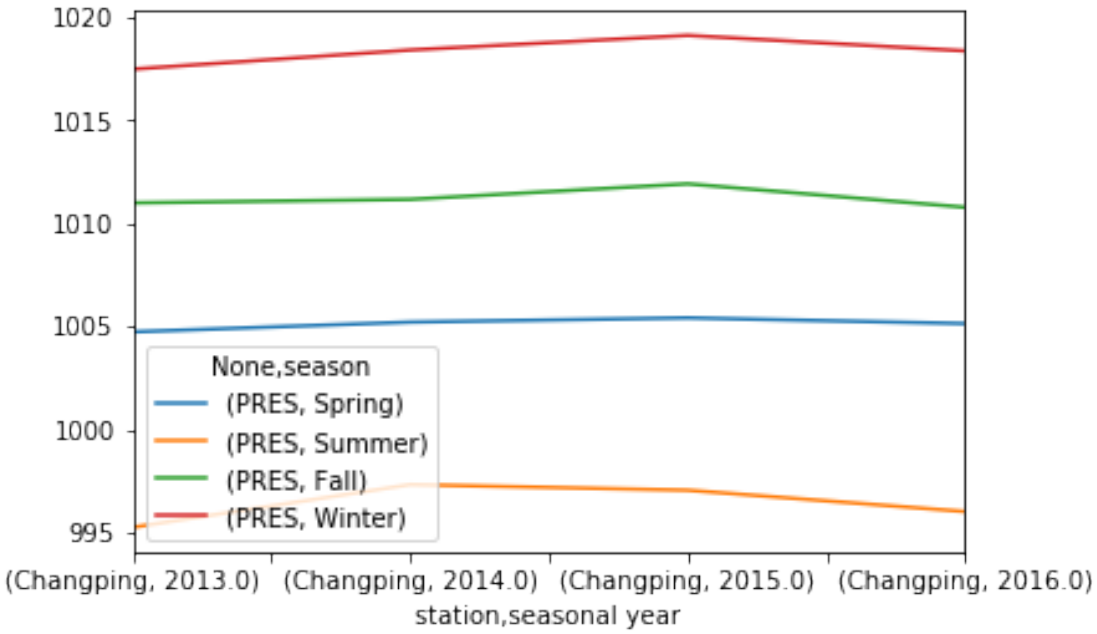


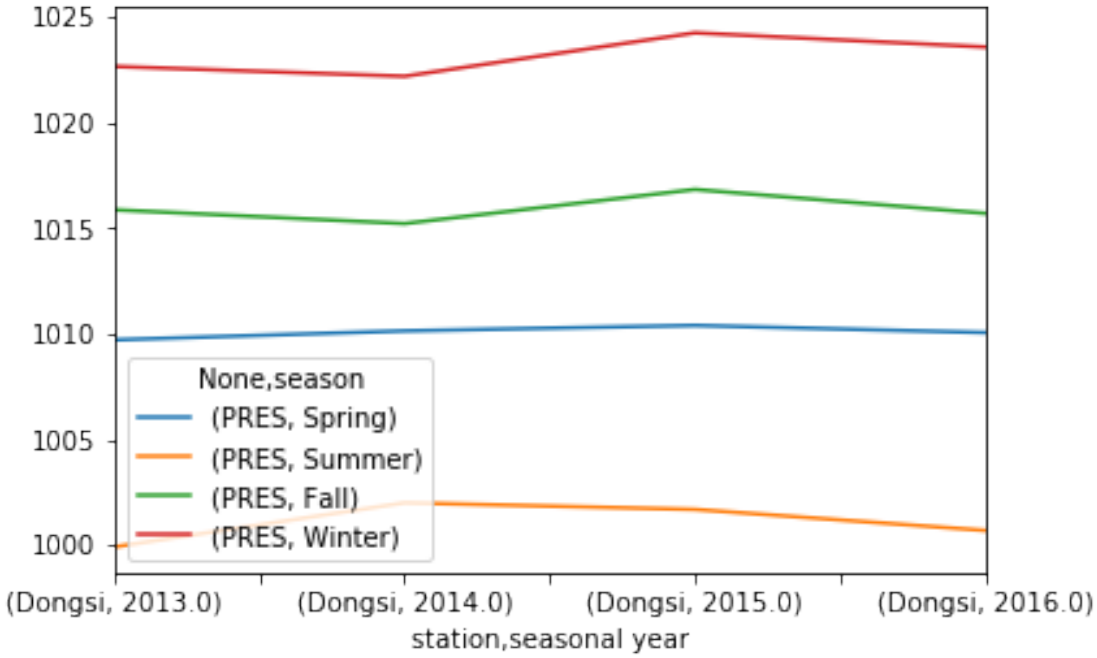
We can see from above plots, the temp trends to seasonal, summer has high temp and winter has low temp in Beijing. *`temp` has negative relationship with `PM2.5` How can you tell?*

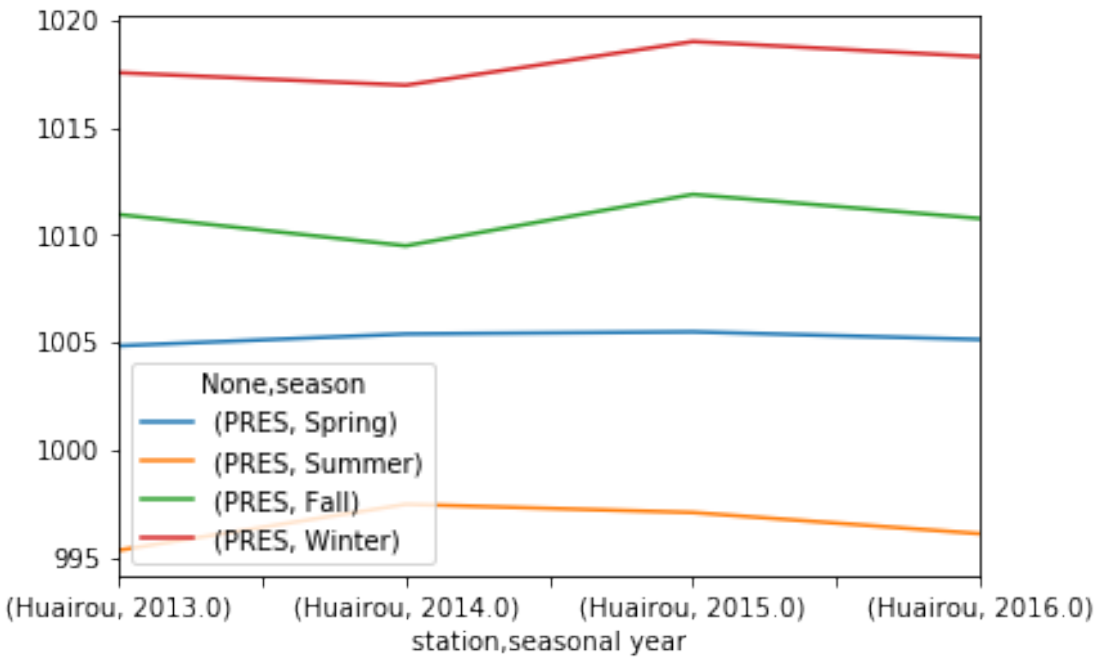
.

[32]:
```
seasonmean[['PRES']].groupby("station").plot()
```

[32]:
```
station
Changping     AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi        AxesSubplot(0.125,0.125;0.775x0.755)
Huairou       AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```


1020
1015
1010
1005
1000
995
None,season
(PRES, Spring)
(PRES, Summer)
(PRES, Fall)
(PRES, Winter)
(Changping, 2013.0)
(Changping, 2014.0)
(Changping, 2015.0)
(Changping, 2016.0)
station,seasonal year

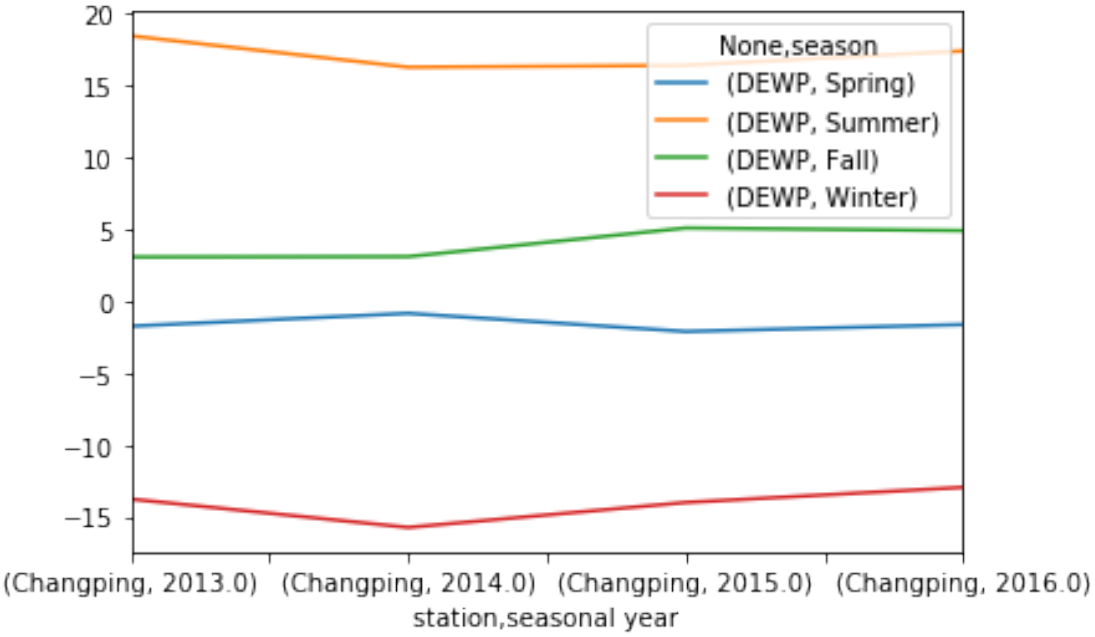

1025
1020
1015
1010
1005
1000
None,season
(PRES, Spring)
(PRES, Summer)
(PRES, Fall)
(PRES, Winter)
(Dongsi, 2013.0)
(Dongsi, 2014.0)
(Dongsi, 2015.0)
(Dongsi, 2016.0)
station,seasonal year

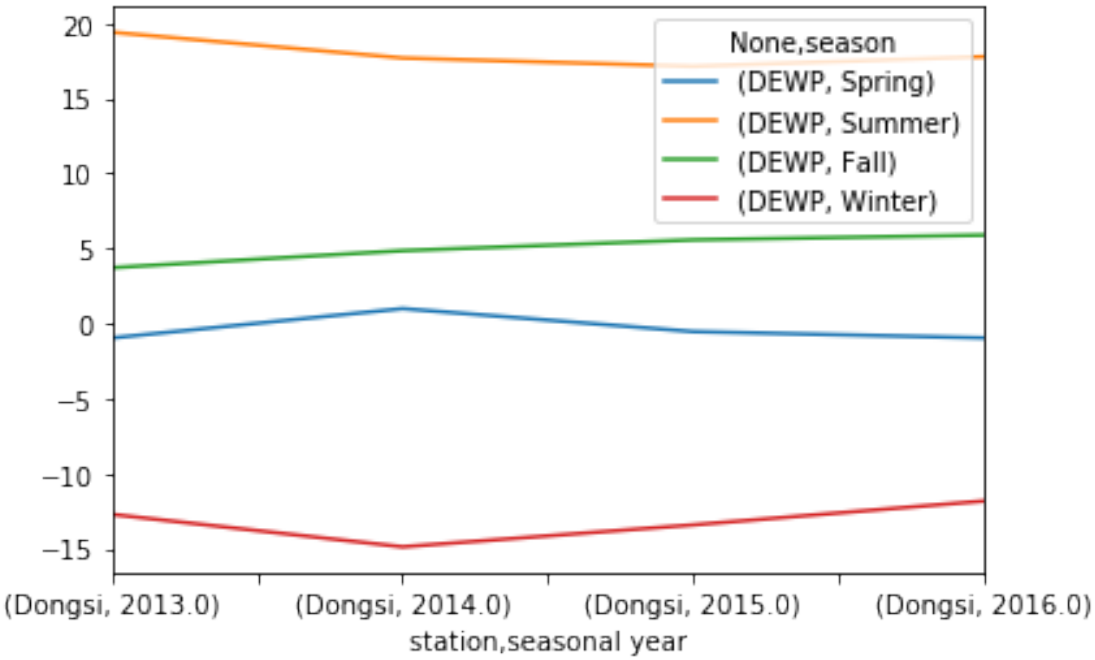


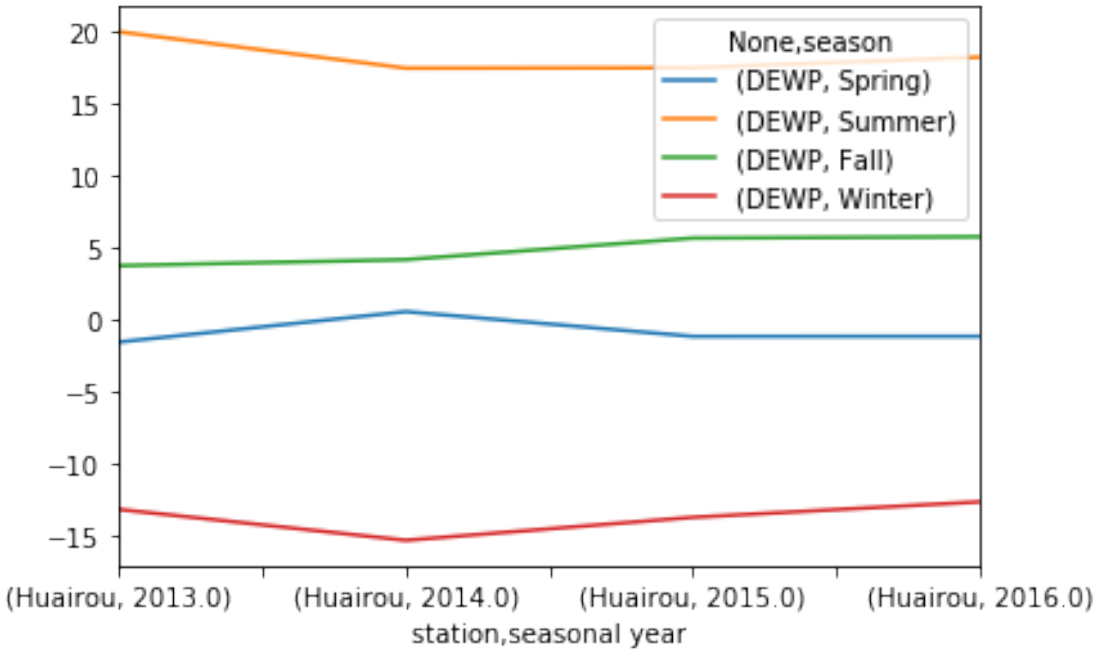
pressure plots show that summer is low and winter is high in Beijing. And Dongsi has overall high pressure than the other two regions.

[33]:
```
seasonmean[['DEWP']].groupby("station").plot()
```

[33]:
```
station
Changping     AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi        AxesSubplot(0.125,0.125;0.775x0.755)
Huairou       AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```


None,season
(DEWP, Spring)
(DEWP, Summer)
(DEWP, Fall)
(DEWP, Winter)
20
15
10
5
0
−5
−10
−15
(Changping, 2013.0)
(Changping, 2014.0)
(Changping, 2015.0)
(Changping, 2016.0)
station,seasonal year

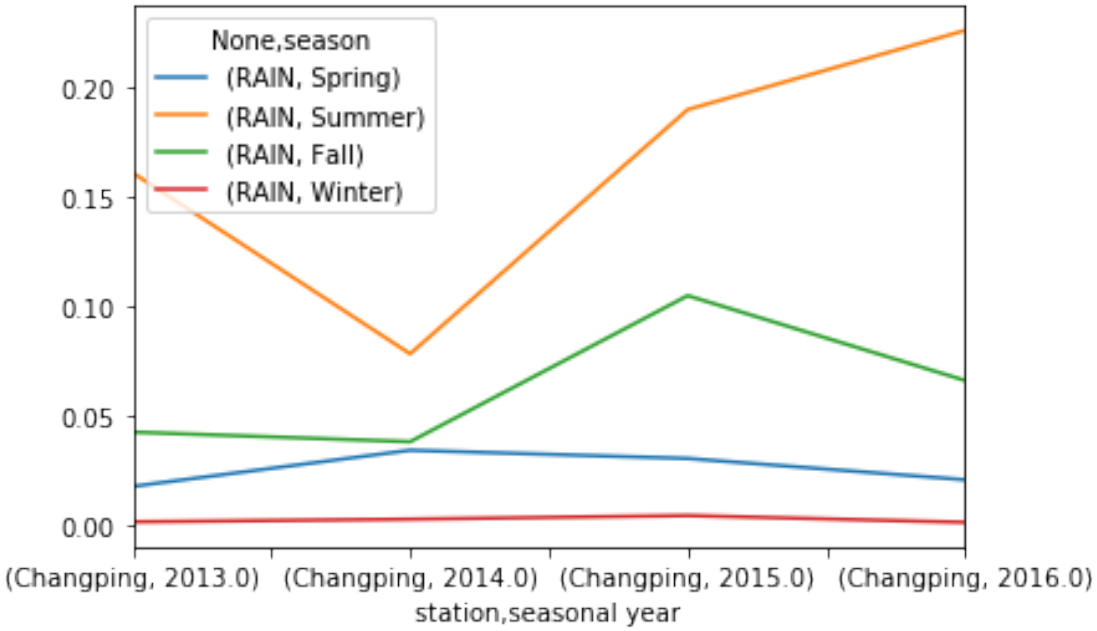

None,season
(DEWP, Spring)
(DEWP, Summer)
(DEWP, Fall)
(DEWP, Winter)
20
15
10
5
0
−5
−10
−15
(Dongsi, 2013.0)
(Dongsi, 2014.0)
(Dongsi, 2015.0)
(Dongsi, 2016.0)
station,seasonal year

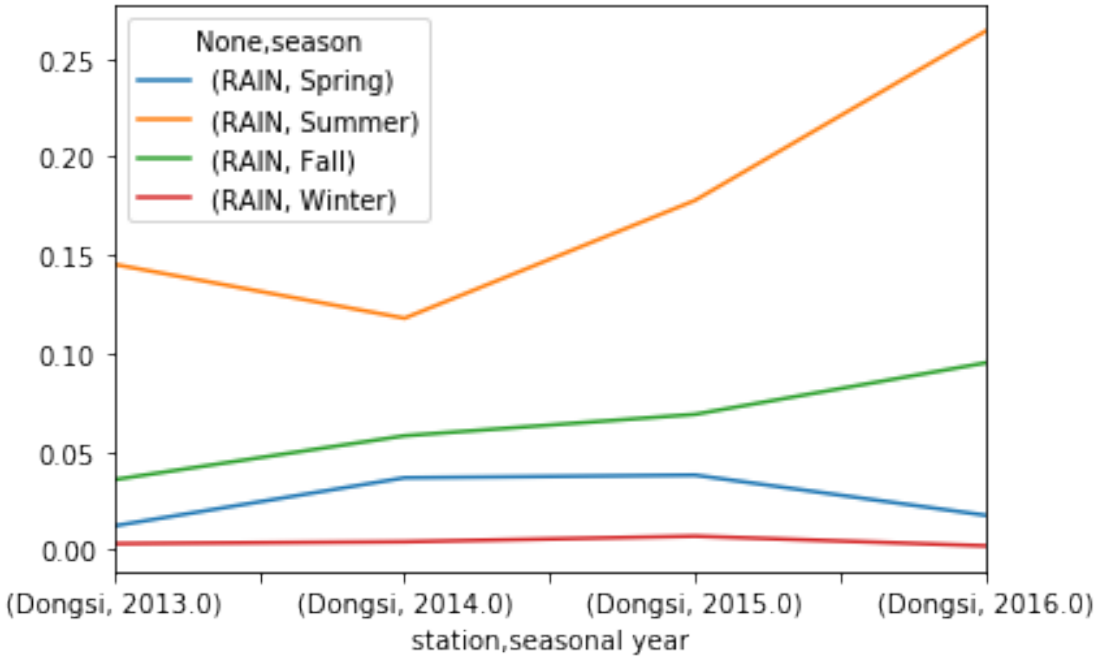


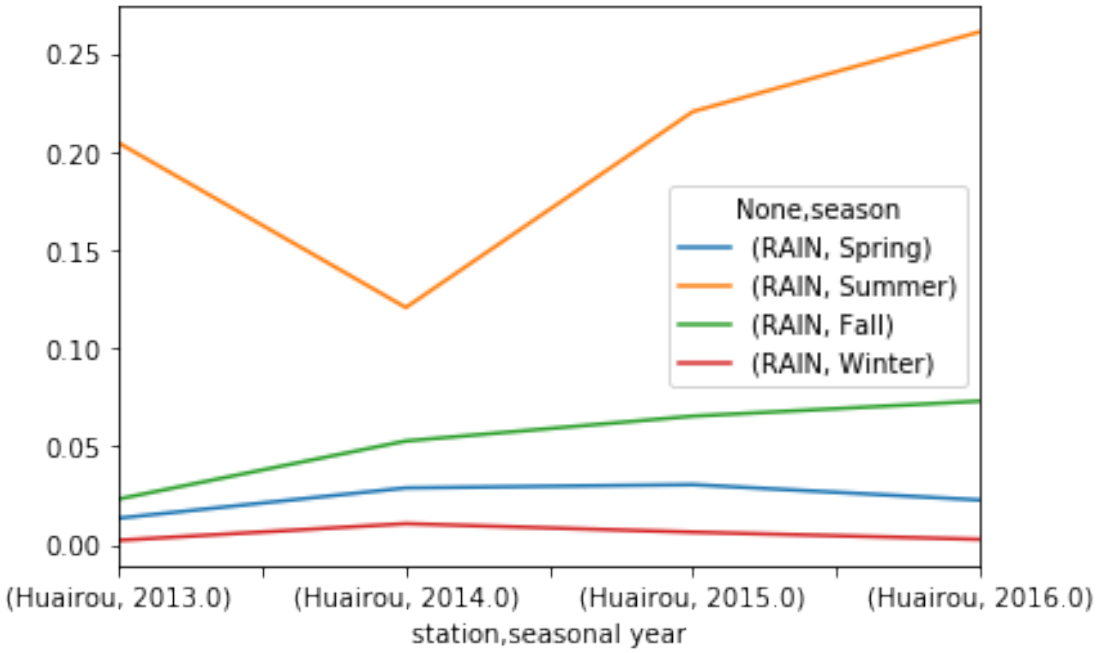
DEWP is high in summer and low in winter in Beijing. For each station, DEWP has similar trend in each season which indicates that DEWP is consistent in Beijing.

[34]:
```
seasonmean[['RAIN']].groupby("station").plot()
```

[34]:
```
station
Changping     AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi        AxesSubplot(0.125,0.125;0.775x0.755)
Huairou       AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```


None,season
(RAIN, Spring)
(RAIN, Summer)
(RAIN, Fall)
(RAIN, Winter)
0.20
0.15
0.10
0.05
0.00
(Changping, 2013.0)
(Changping, 2014.0)
(Changping, 2015.0)
(Changping, 2016.0)
station,seasonal year

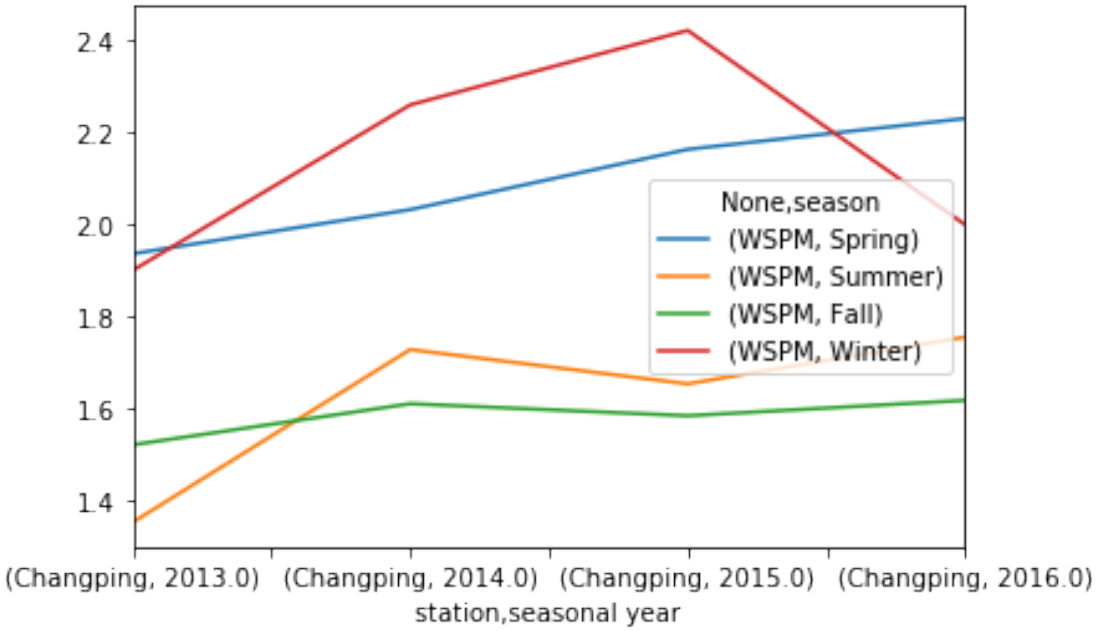

None,season
(RAIN, Spring)
(RAIN, Summer)
(RAIN, Fall)
(RAIN, Winter)
0.25
0.20
0.15
0.10
0.05
0.00
(Dongsi, 2013.0)
(Dongsi, 2014.0)
(Dongsi, 2015.0)
(Dongsi, 2016.0)
station,seasonal year

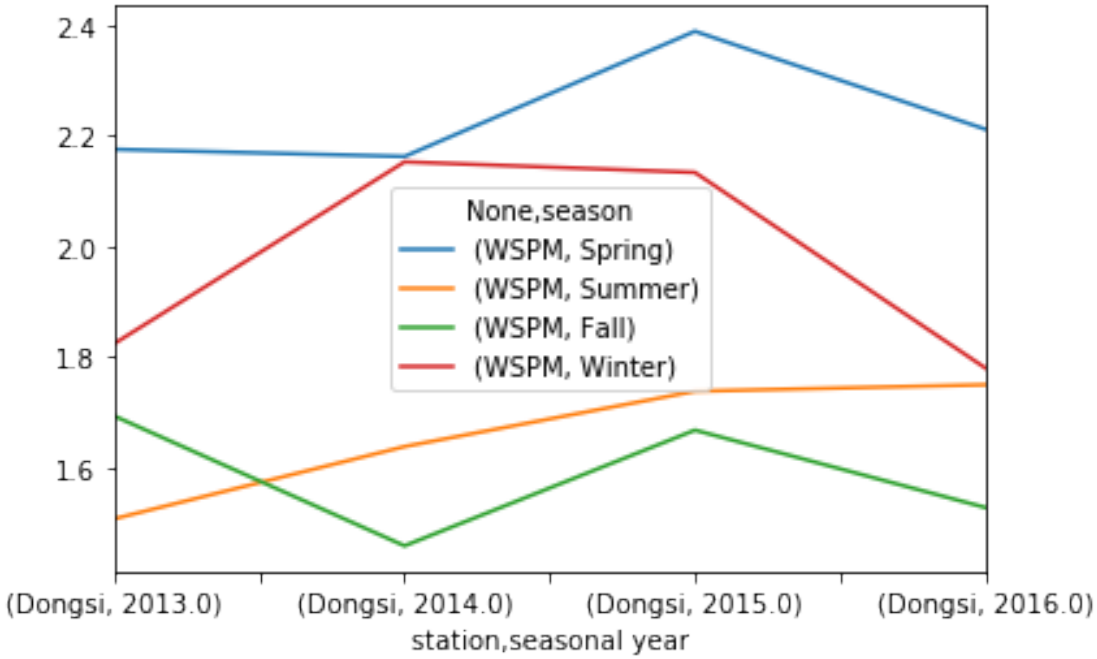


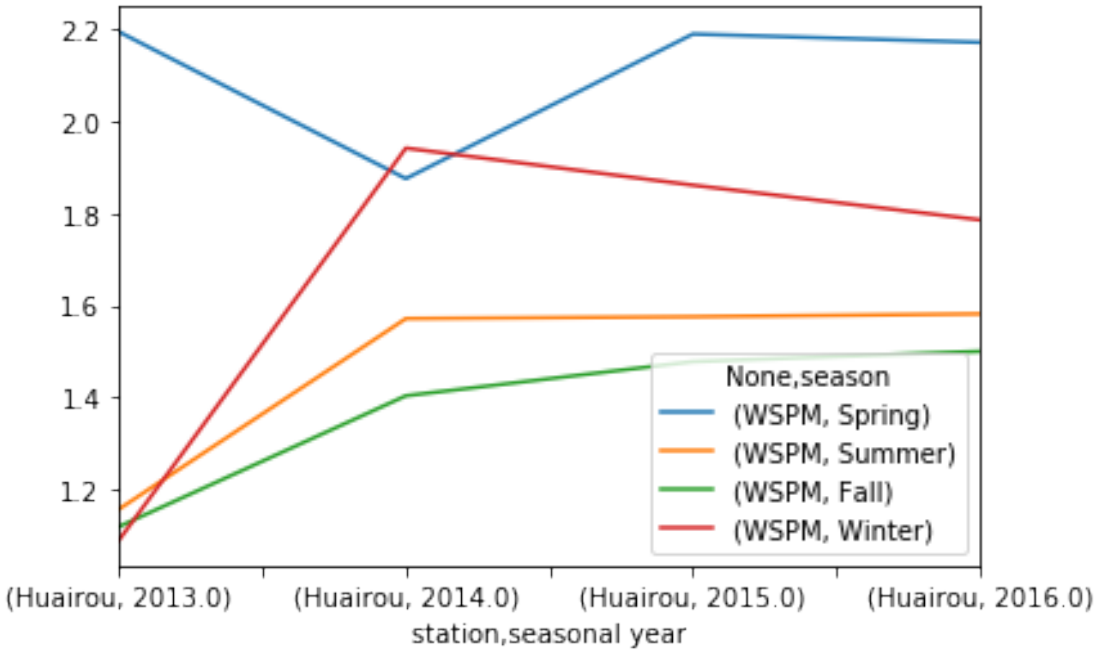
We can see that `RAIN` is high in summer and low in winter in Beijing, but we can see that the rain in summer in 2014 is much lower than any others in summer.

[35]:
```
seasonmean[['WSPM']].groupby("station").plot()
```

[35]:
```
station
Changping     AxesSubplot(0.125,0.125;0.775x0.755)
Dongsi        AxesSubplot(0.125,0.125;0.775x0.755)
Huairou       AxesSubplot(0.125,0.125;0.775x0.755)
dtype: object
```


2.4
2.2
2.0
1.8
1.6
1.4
None,season
(WSPM, Spring)
(WSPM, Summer)
(WSPM, Fall)
(WSPM, Winter)
(Changping, 2013.0)
(Changping, 2014.0)
(Changping, 2015.0)
(Changping, 2016.0)
station,seasonal year


2.4
2.2
2.0
1.8
1.6
None,season
(WSPM, Spring)
(WSPM, Summer)
(WSPM, Fall)
(WSPM, Winter)
(Dongsi, 2013.0)
(Dongsi, 2014.0)
(Dongsi, 2015.0)
(Dongsi, 2016.0)
station,seasonal year



WSPM varies over year but we can see that overall, Spring and Fall have stronger wind compared to Summer and Winter.

3.3 Now, we will look at the change in pollutants by station.

Since we are only interested in seasonal change, we use the seaonal mean of each pollutant to analyze the data.

[36]:
```
stationmean = data.iloc[:,4:].groupby(["seasonal year","season","station"],␣
↪sort=False).mean().unstack()
stationmean
```

[36]:

		PM2.5			PM10	\
station		Changping	Dongsi	Huairou	Changping	
seasonal year	season					
2013.0	Spring	80.655344	88.608582	72.830389	110.808650	
	Summer	65.964624	81.326285	64.213315	77.973053	
	Fall	72.303571	90.847985	68.394918	88.198947	
	Winter	98.583527	113.620515	97.323942	112.591462	
2014.0	Spring	80.520652	84.381692	75.157484	123.715127	
	Summer	59.997652	75.524434	64.433316	80.222763	
	Fall	85.599124	89.077953	74.853911	112.249542	
	Winter	77.857936	87.091223	68.070584	106.426397	
2015.0	Spring	64.533047	77.574649	69.569497	110.631459	
	Summer	51.061821	61.578663	47.971213	66.254734	

```
              Fall    57.959657   86.430503  67.677470   68.917518
              Winter  71.895375   92.311126  75.843907   96.192508
2016.0        Spring  60.327729   79.700449  62.889832  103.874490
              Summer  53.886228   71.000683  52.605277   67.644168
              Fall    70.250344   87.081638  68.694598   91.379923
              Winter  90.147454  118.470209  79.862963  104.987384

                                                    SO2                    \
station                      Dongsi     Huairou  Changping     Dongsi    Huairou
seasonal year season
2013.0        Spring  120.952899  124.012455  25.097358  31.407160  32.893011
              Summer   92.131708   91.786458   9.153538  12.892948   6.448759
              Fall    102.716461   87.448260  14.701292  20.784370  12.782472
              Winter  118.380176  105.916650  54.466967  53.356790  46.197343
2014.0        Spring  133.648007  113.197124  21.126902  25.479303  17.776834
              Summer   85.953284   84.182694   5.153616   8.374615   4.431046
              Fall    129.537592   95.504609   9.835053  13.727679   8.143315
              Winter  114.761779   91.079928  31.794868  31.696115  18.688812
2015.0        Spring  128.750181  107.627451  11.038901  15.793014   9.320148
              Summer   77.945867   63.544554   3.880898   5.860168   4.061424
              Fall    102.821300   76.798063   5.479904   9.934195   5.506296
              Winter  107.937729   83.412717  14.529376  19.679144  10.217822
2016.0        Spring  115.161618  101.728884   8.745138  13.683018   8.823483
              Summer   78.721995   67.916987   3.498196   5.363900   3.901895
              Fall    109.692659   88.613668   5.574523   8.398008   4.757212
              Winter  151.137182   98.275694  16.092361  21.006163   9.130208

                                NO2  …        SW         W                    \
station                  Changping  …   Huairou Changping    Dongsi   Huairou
seasonal year season                …
2013.0        Spring     44.784511  …  0.070652  0.014946  0.028080  0.094203
              Summer     26.687710  …  0.059783  0.031703  0.025815  0.095562
              Fall       48.568468  …  0.036172  0.016941  0.028388  0.098901
              Winter     55.375159  …  0.054630  0.051389  0.026389  0.087500
2014.0        Spring     47.241395  …  0.063406  0.049819  0.034420  0.072464
              Summer     33.432177  …  0.059783  0.033062  0.033514  0.057518
              Fall       49.254861  …  0.038919  0.036630  0.038462  0.051740
              Winter     52.135688  …  0.022685  0.073148  0.038426  0.057870
2015.0        Spring     37.277018  …  0.057065  0.046196  0.032156  0.041667
              Summer     23.262239  …  0.061141  0.033967  0.023551  0.049819
              Fall       47.721712  …  0.049908  0.090201  0.031593  0.040751
              Winter     59.028274  …  0.023810  0.054029  0.026099  0.054487
2016.0        Spring     46.074474  …  0.063406  0.030797  0.024004  0.046649
              Summer     29.438482  …  0.083333  0.029372  0.013661  0.058060
              Fall       50.905048  …  0.050366  0.031593  0.020604  0.048993
              Winter     57.434375  …  0.047222  0.022222  0.019907  0.031481
```

		WNW			WSW		\
station		Changping	Dongsi	Huairou	Changping	Dongsi	
seasonal year	season						
2013.0	Spring	0.027174	0.038043	0.163496	0.018116	0.052989	
	Summer	0.037138	0.033062	0.129076	0.018569	0.056612	
	Fall	0.072344	0.062729	0.227106	0.012363	0.049451	
	Winter	0.114352	0.046296	0.215741	0.015278	0.037037	
2014.0	Spring	0.071558	0.037591	0.167572	0.020380	0.062953	
	Summer	0.042120	0.019475	0.125906	0.023551	0.061141	
	Fall	0.074634	0.035714	0.177198	0.021062	0.052656	
	Winter	0.161111	0.053704	0.157870	0.011574	0.056944	
2015.0	Spring	0.071558	0.033062	0.105978	0.014040	0.083786	
	Summer	0.062500	0.033514	0.105978	0.021286	0.046196	
	Fall	0.100733	0.048535	0.115842	0.045330	0.052198	
	Winter	0.184524	0.058608	0.154762	0.037546	0.035714	
2016.0	Spring	0.096920	0.053895	0.115036	0.010870	0.049366	
	Summer	0.038934	0.019126	0.086066	0.023224	0.034153	
	Fall	0.074634	0.024725	0.119048	0.014652	0.025641	
	Winter	0.091667	0.017593	0.060648	0.011111	0.043519	

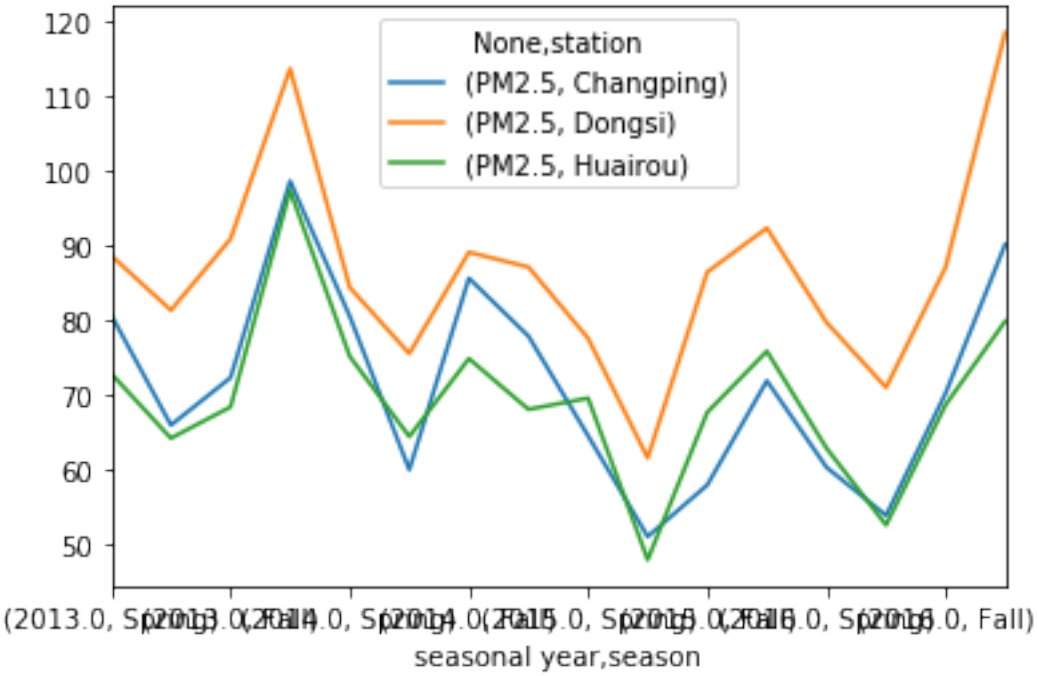
station		Huairou
seasonal year	season	
2013.0	Spring	0.038043
	Summer	0.068841
	Fall	0.039377
	Winter	0.046296
2014.0	Spring	0.048460
	Summer	0.045743
	Fall	0.031136
	Winter	0.036574
2015.0	Spring	0.032156
	Summer	0.052083
	Fall	0.038462
	Winter	0.028846
2016.0	Spring	0.042572
	Summer	0.056694
	Fall	0.039377
	Winter	0.024074

[16 rows x 81 columns]

3.3.1 PM2.5 level in each stations

[37]:
```
stationmean[['PM2.5']].plot()
```

[37]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff660e528d0>

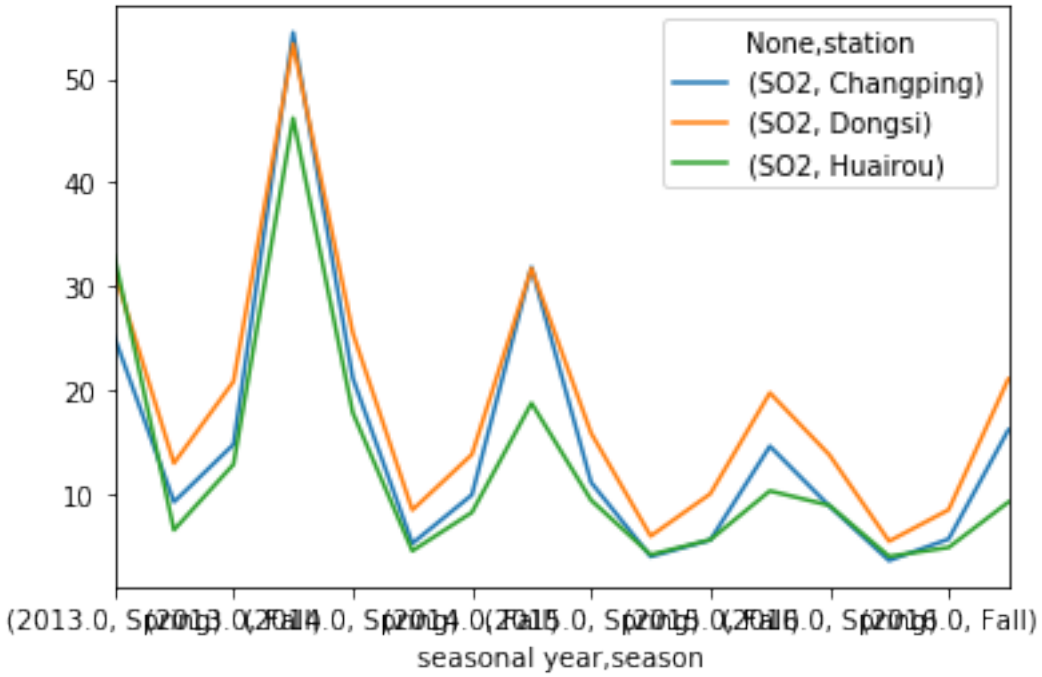


As we can see, Dongsi has much higer level of PM2.5 than the other two stations. This might be due to the fact that Dongsi is located at the center of Beijing, where has more cars and more pollutants.

3.3.2 What about SO2, NO2, and CO level in each stations?

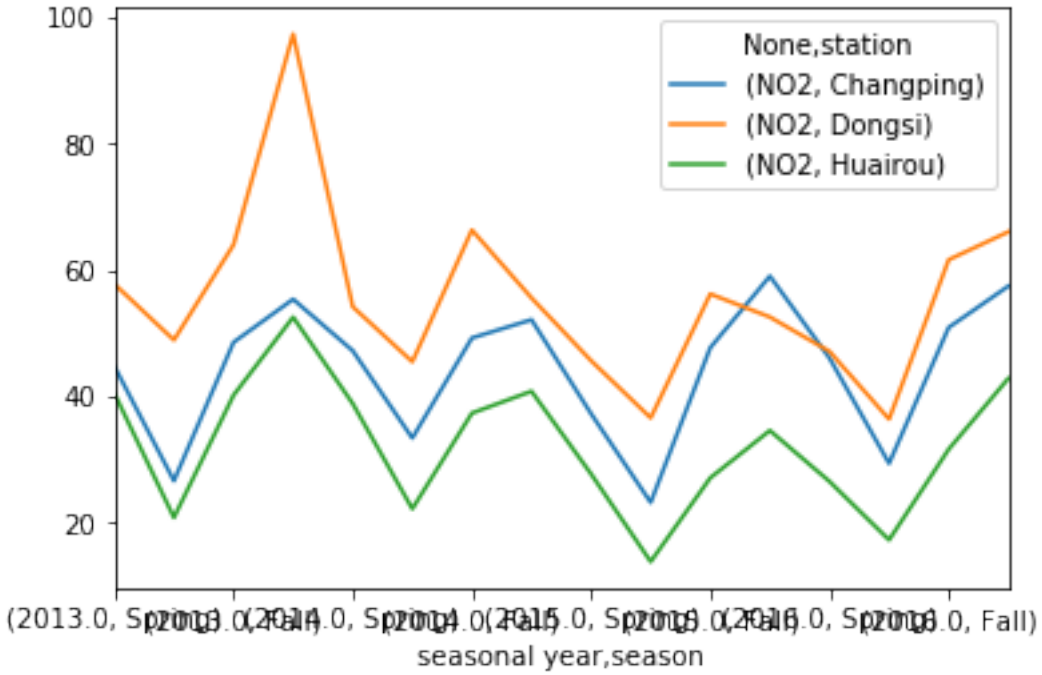
[38]:
```
stationmean[['SO2']].plot()
```

[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff6408f9710>



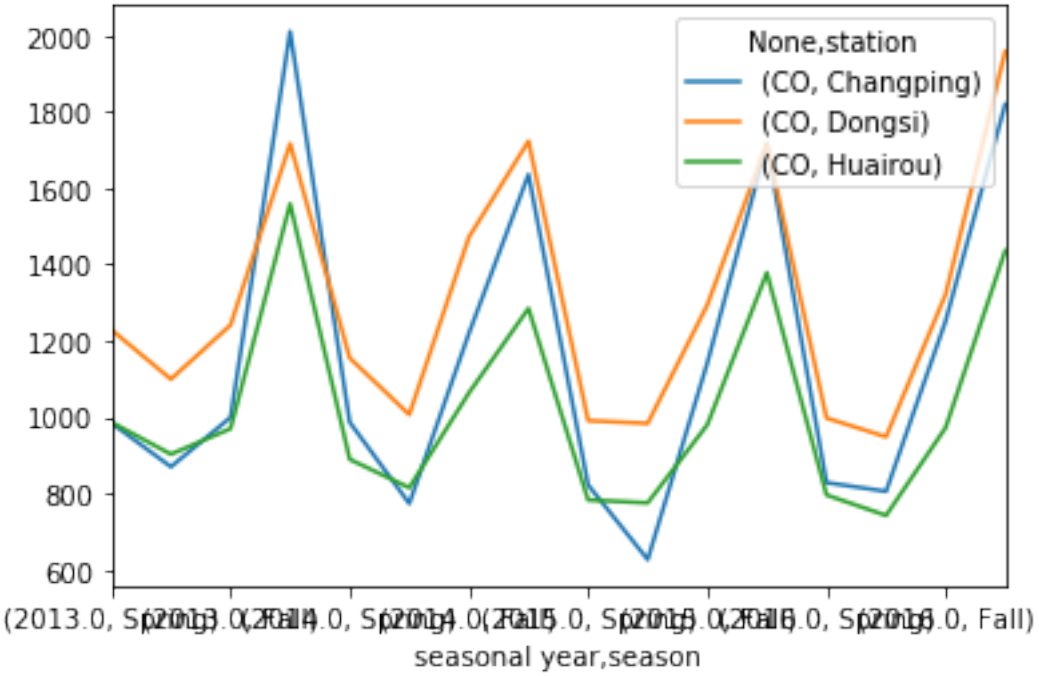
[39]:
```
stationmean[['NO2']].plot()
```

[39]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff670f28790>



[40]:
```
stationmean[['CO']].plot()
```

[40]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff6915f0c50>
```

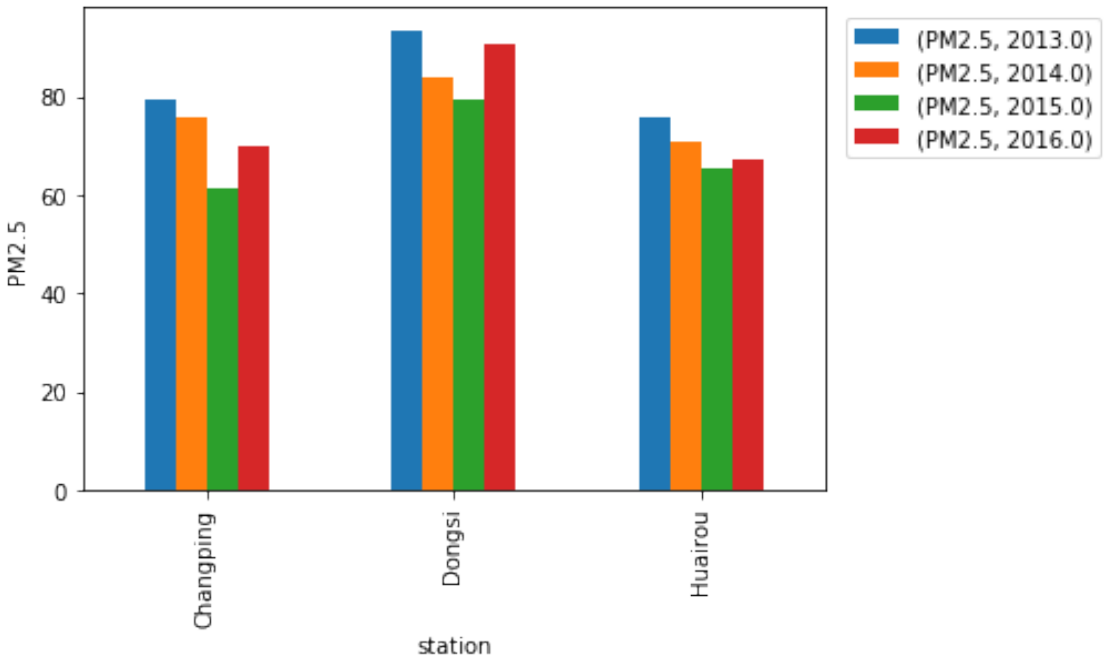


These graphs verifies our guess that Dongsi has more pollutants than the other two due to its geographical location.

3.4 Let's briefly look at the trend in each pollutant over year and see if it's decreasing or not.

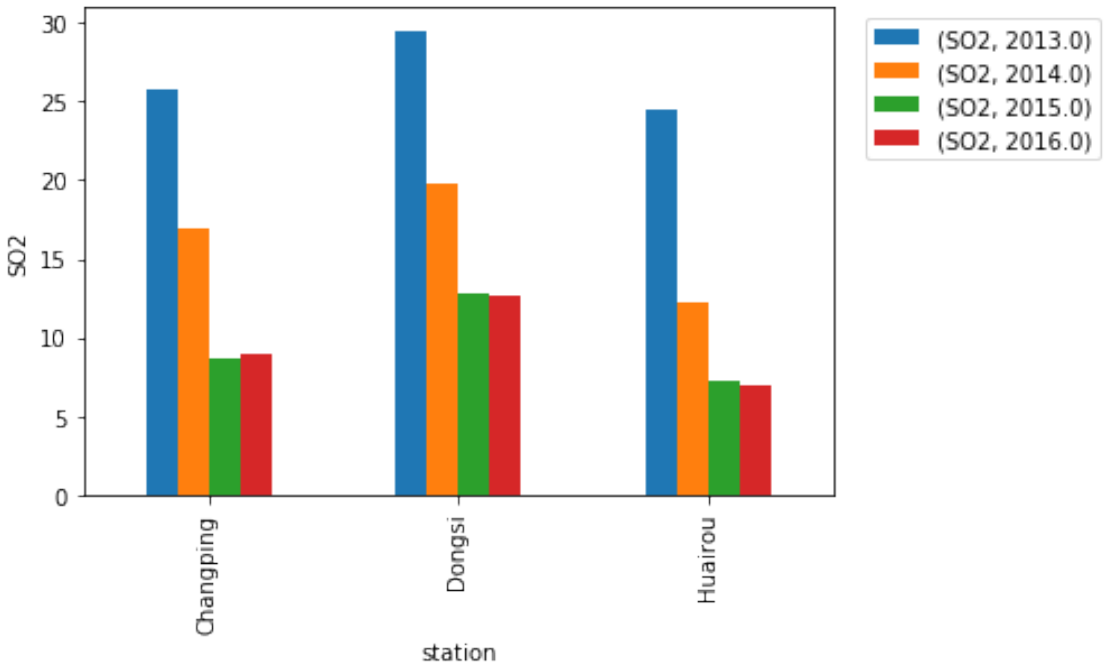
[41]:
```
yearmean=data.groupby(["station","seasonal year"]).mean()[["PM2.5"]].unstack()
yearmean.plot(kind='bar')
plt.legend(loc='upper center', bbox_to_anchor=(1.2, 1))
plt.ylabel('PM2.5')
```

[41]:
```
Text(0, 0.5, 'PM2.5')
```



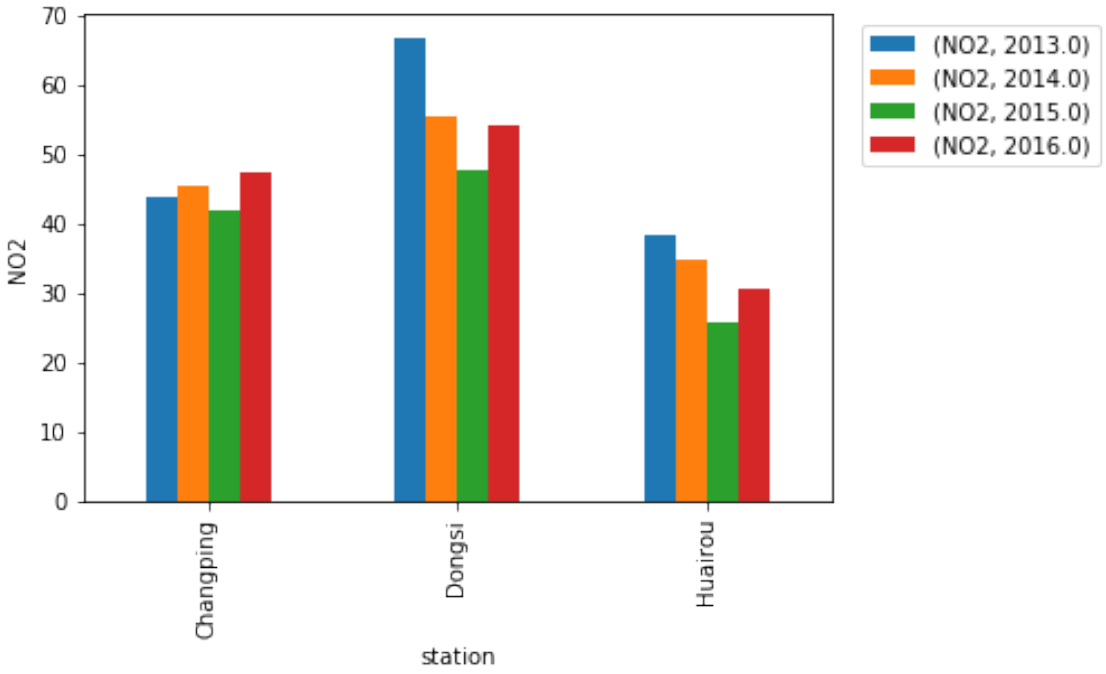
[42]:
```
yearmean=data.groupby(["station","seasonal year"]).mean()[["SO2"]].unstack()
yearmean.plot(kind='bar')
plt.legend(loc='upper center', bbox_to_anchor=(1.2, 1))
plt.ylabel('SO2')
```

[42]: `Text(0, 0.5, 'SO2')`



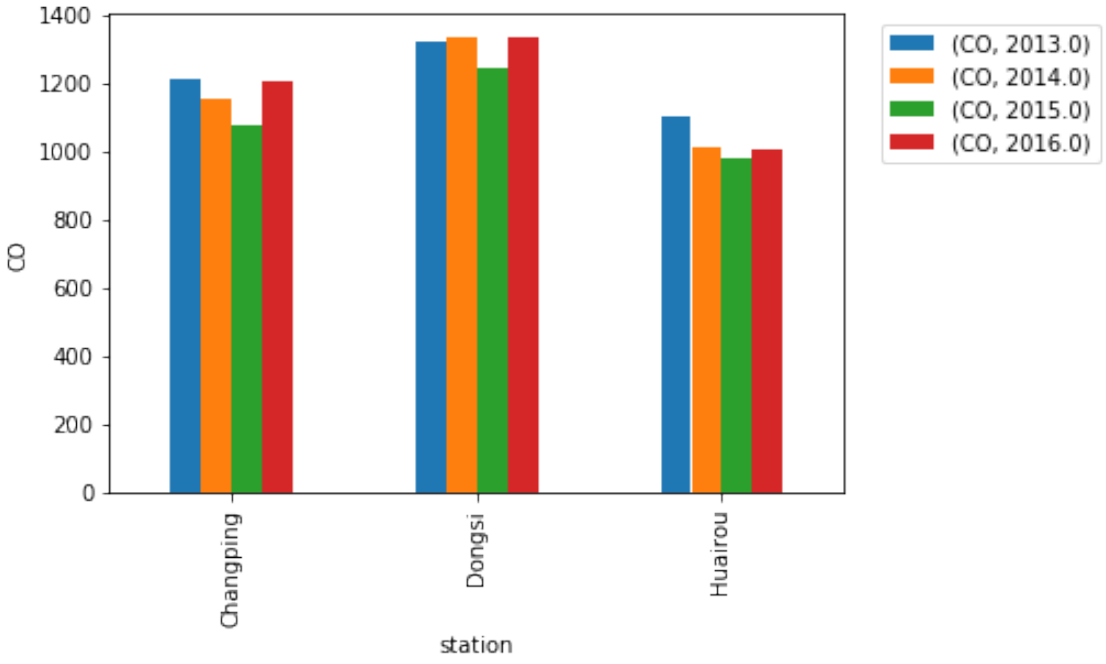
[43]:
```
yearmean=data.groupby(["station","seasonal year"]).mean()[["NO2"]].unstack()
yearmean.plot(kind='bar')
plt.legend(loc='upper center', bbox_to_anchor=(1.2, 1))
plt.ylabel('NO2')
```

[43]: Text(0, 0.5, 'NO2')



[44]:
```
yearmean=data.groupby(["station","seasonal year"]).mean()[["CO"]].unstack()
yearmean.plot(kind='bar')
plt.legend(loc='upper center', bbox_to_anchor=(1.2, 1))
plt.ylabel('CO')
```

[44]: Text(0, 0.5, 'CO')



As the bar plots show, PM2.5 level as well as other pollutant, overall, do decreae in year 2013 to 2015 but rebound up in 2016. (notes these are seasonal year)

4 Variable Relationships Exploration

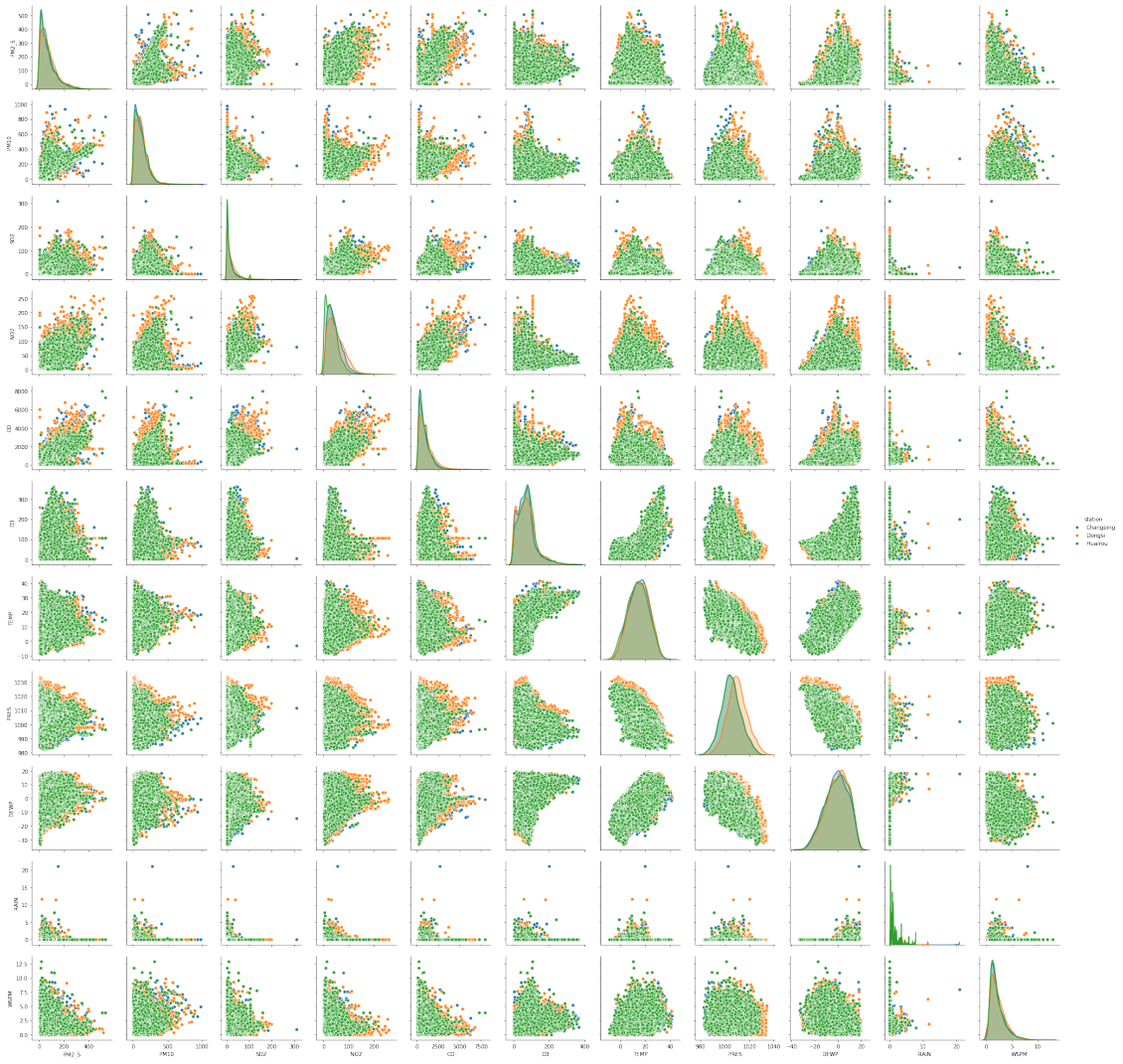
First, let's seperate data into four seasons and begin by looking at the correlation plots for each season.

[45]:
```
spring = data.loc[data.season=="Spring"].rename(columns={'PM2.5':'PM2_5'})
summer = data.loc[data.season=="Summer"].rename(columns={'PM2.5':'PM2_5'})
fall = data.loc[data.season=="Fall"].rename(columns={'PM2.5':'PM2_5'})
winter = data.loc[data.season=="Winter"].rename(columns={'PM2.5':'PM2_5'})
```

4.0.1 Pairplots (Do not run `sns.pairplot` below if your computer is slow)

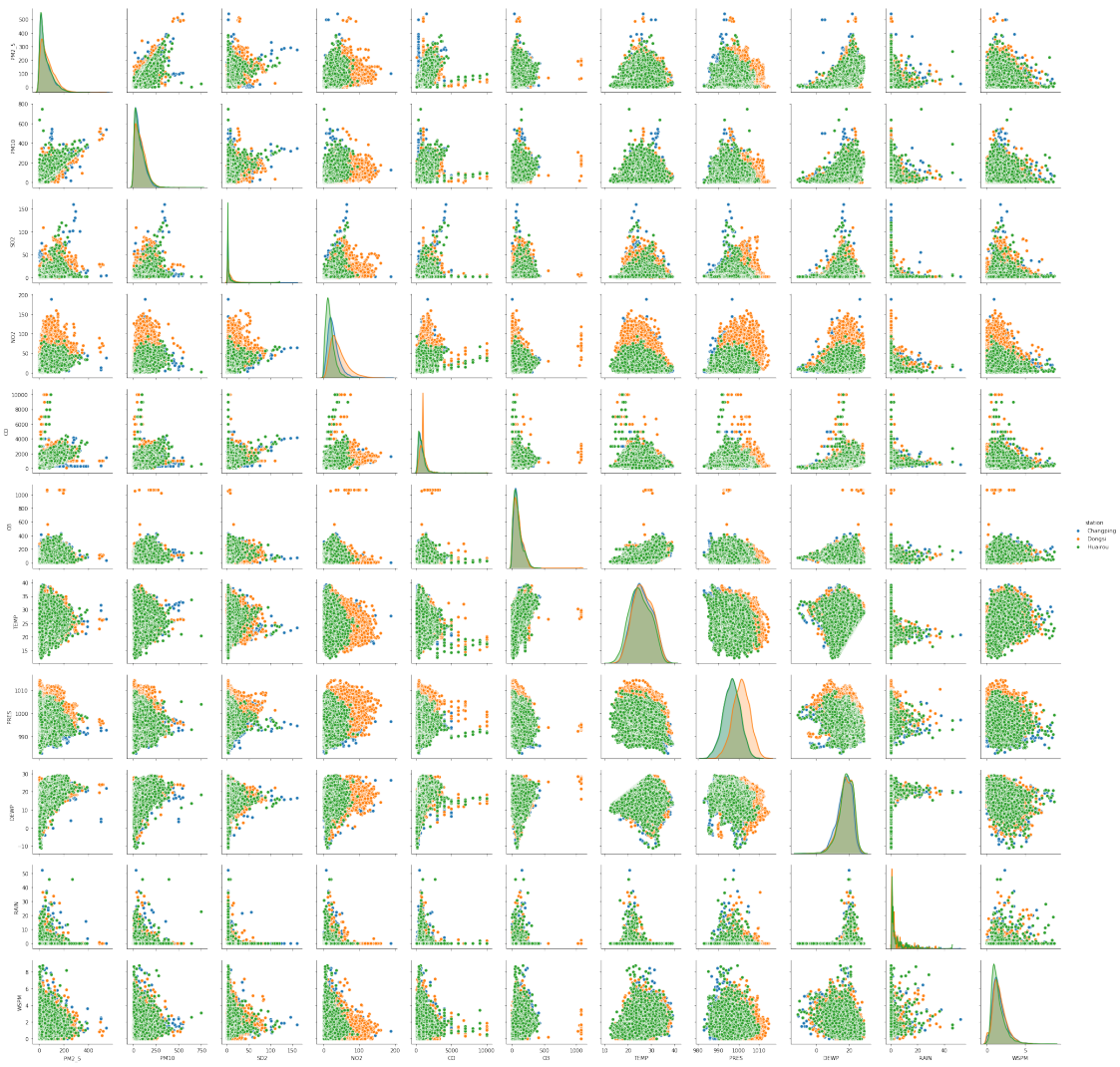
[46]:
```
# pairplot for spring
sns.pairplot(spring.iloc[:,4:15].reset_index(level='station'), hue="station")
```

[46]: `<seaborn.axisgrid.PairGrid at 0x7ff681989690>`



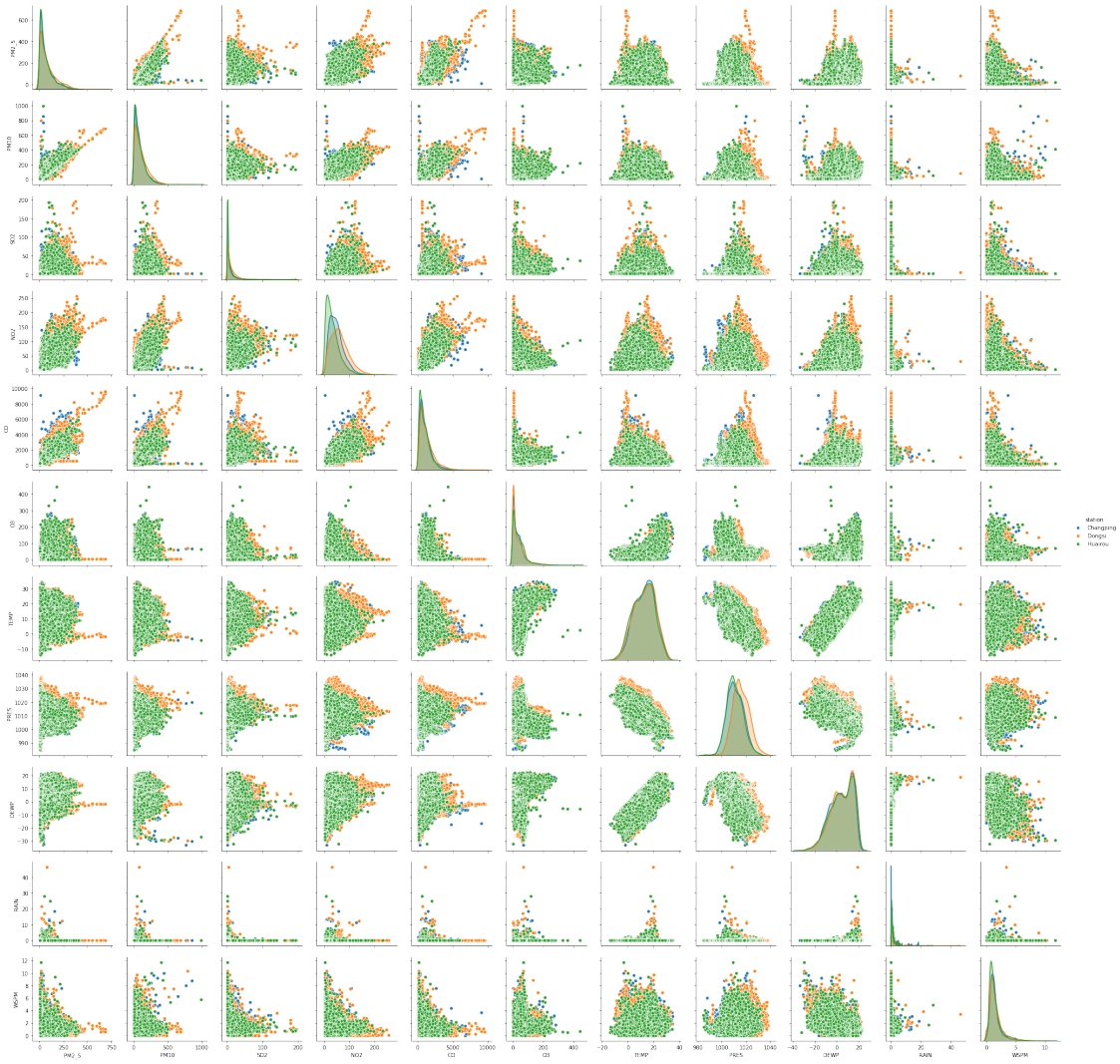
[47]:
```
# pairplot for summer
sns.pairplot(summer.iloc[:,4:15].reset_index(level='station'), hue="station")
```

[47]: <seaborn.axisgrid.PairGrid at 0x7ff630332c90>



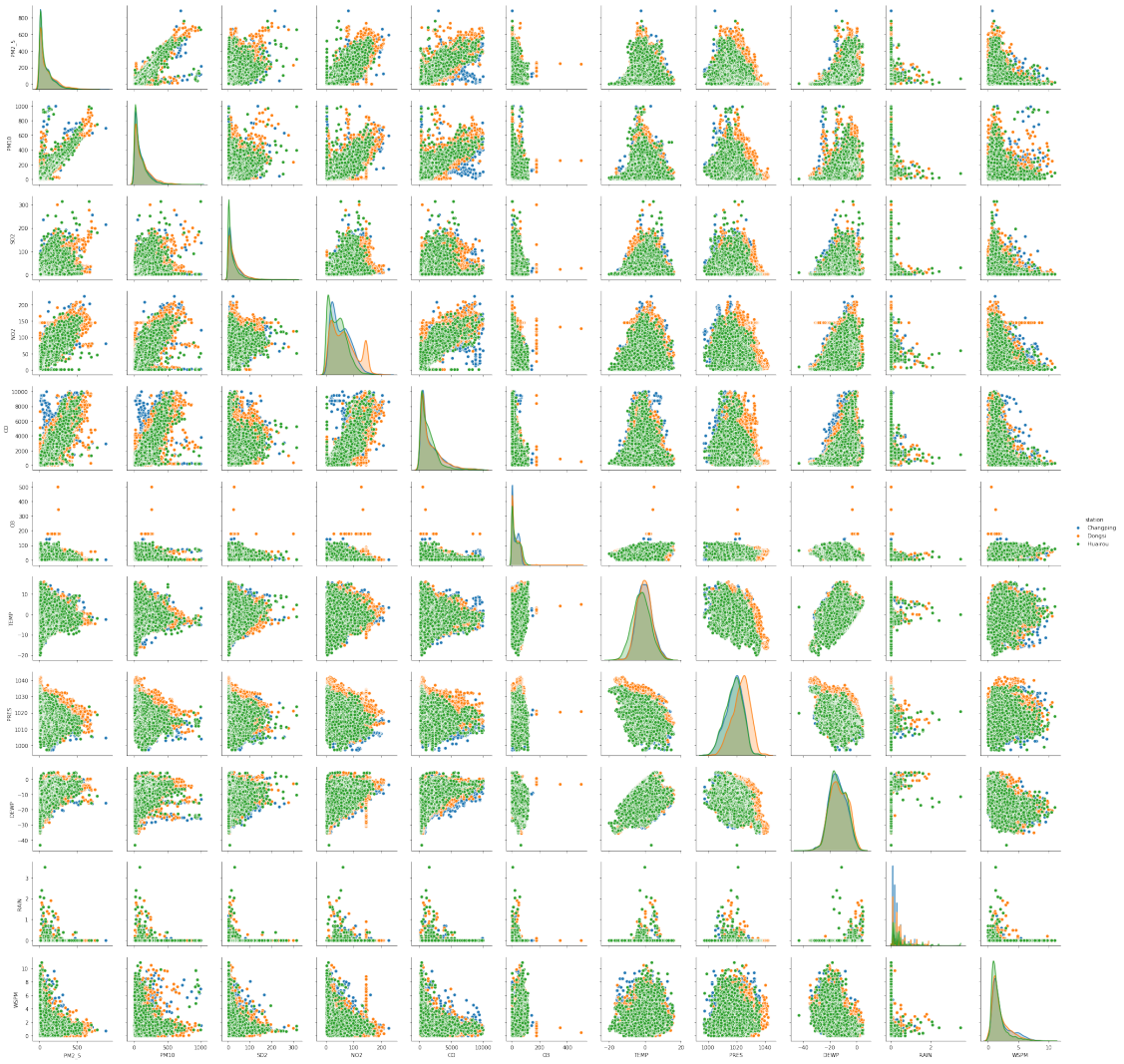
[48]:
```
# pairplot for fall
sns.pairplot(fall.iloc[:,4:15].reset_index(level='station'), hue="station")
```

[48]: <seaborn.axisgrid.PairGrid at 0x7ff6843eb8d0>



[49]:
```
# pairplot for winter
sns.pairplot(winter.iloc[:,4:15].reset_index(level='station'), hue="station")
```

[49]: <seaborn.axisgrid.PairGrid at 0x7ff6a66723d0>



Need some brief explaination here

Note that there're a lot of scattered dots in "vertical" or "horizontal" pattern, this is due to missiing data we filled in.

4.0.2 Let's look at the correlation between PM2.5 and the other variables for each station during each season.

[50]:
```
corr_by_sta_seas = data.drop(['year','month','day','hour','seasonal year'],␣
↪axis=1).groupby(["station","season"]).corr()
```

[51]:
```
corr_by_sta_seas.loc['Changping'][['PM2.5']].unstack(0).iloc[1:11,:]
```

[51]:

	PM2.5			
season	Fall	Spring	Summer	Winter
PM10	0.921551	0.735264	0.841275	0.918406
SO2	0.282360	0.586615	0.267836	0.510883
NO2	0.666793	0.626607	0.233472	0.816709
CO	0.707398	0.761008	0.605365	0.824717
O3	-0.069126	0.047388	0.172680	-0.578375
TEMP	-0.036949	0.012142	0.053590	-0.002240
PRES	-0.096560	-0.135232	-0.037387	-0.267922
DEWP	0.239069	0.382357	0.448877	0.634112
RAIN	-0.019687	-0.009253	0.016606	0.024920
WSPM	-0.271568	-0.250980	-0.064196	-0.422990

[52]:
```
corr_by_sta_seas.loc['Dongsi'][['PM2.5']].unstack(0).iloc[1:11,:]
```

[52]:

	PM2.5			
season	Fall	Spring	Summer	Winter
PM10	0.930421	0.738041	0.883716	0.947366
SO2	0.482897	0.627838	0.380398	0.595084
NO2	0.754154	0.651603	0.290598	0.670836
CO	0.796269	0.736529	0.460174	0.842768
O3	-0.125780	-0.071130	0.111629	-0.442939
TEMP	-0.090469	-0.043904	0.004773	-0.057028
PRES	-0.136853	-0.147483	-0.062090	-0.278295
DEWP	0.249597	0.357723	0.477459	0.647441
RAIN	-0.025655	-0.019747	-0.017312	0.009776
WSPM	-0.336423	-0.275606	-0.113547	-0.409859

[53]:
```
corr_by_sta_seas.loc['Huairou'][['PM2.5']].unstack(0).iloc[1:11,:]
```

[53]:

	PM2.5			
season	Fall	Spring	Summer	Winter
PM10	0.928473	0.769247	0.854081	0.915941
SO2	0.284108	0.378809	0.298769	0.434499
NO2	0.595318	0.637524	0.438904	0.769131
CO	0.813953	0.802015	0.622229	0.867832
O3	0.024087	-0.009785	0.220829	-0.477801
TEMP	0.008071	-0.038958	0.147556	0.060622
PRES	-0.115993	-0.112887	-0.048690	-0.240120
DEWP	0.256446	0.310279	0.447094	0.659185
RAIN	-0.023799	-0.019099	0.004945	0.013948
WSPM	-0.228311	-0.238697	-0.101686	-0.305902

In each station during each season...

PM10 is always highly correlated to PM2.5;

SO2 is relatively highly correlated to PM2.5 in Spring and Winter but weakly correlated in Summer and Fall;

NO2 is highly correlated to PM2.5 in Spring, Fall,and Winter, but weakly correlated in Summer;

CO is highly correlated to PM2.5 in Spring, Fall,and Winter, but relatively weakly correlated in Summer;

O3 does not seem highly correlated to PM2.5 but does has somewhat negative correlation between PM2.5 in Winter;

Among the five meteorological conditions, only the dew point in the winter seems highly correlated to PM2.5, all the others, such as temperature, pressure, dew point, precipitation and wind speed do not seem correleated to PM2.5 in any season.

5 Model Analysis

5.1 OLS Regression

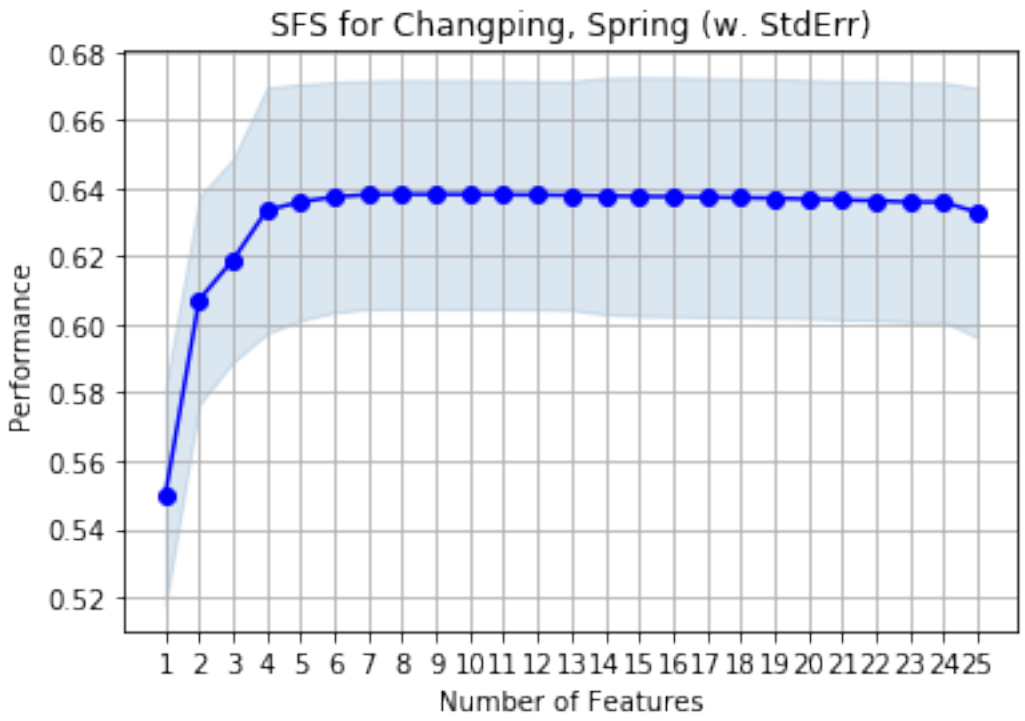
we begin to do OLS regression analysis and see what are statistically significant to the change in PM2.5. First, let's do forward feature selection to decide which features yield the best model in terms of R^2.

5.1.1 Feature Selection on spring data for each station.

[54]:
```
# Changping, Spring:
X = spring.loc['Changping'].values[:,6:31] # note we are excluding PM10
y = spring.loc['Changping'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Changping, Spring (w. StdErr)')
plt.grid()
plt.show()
```

```
8      0.63822
9     0.638208
10    0.638186
7     0.638122
11    0.638113
12    0.638026
13    0.637928
```

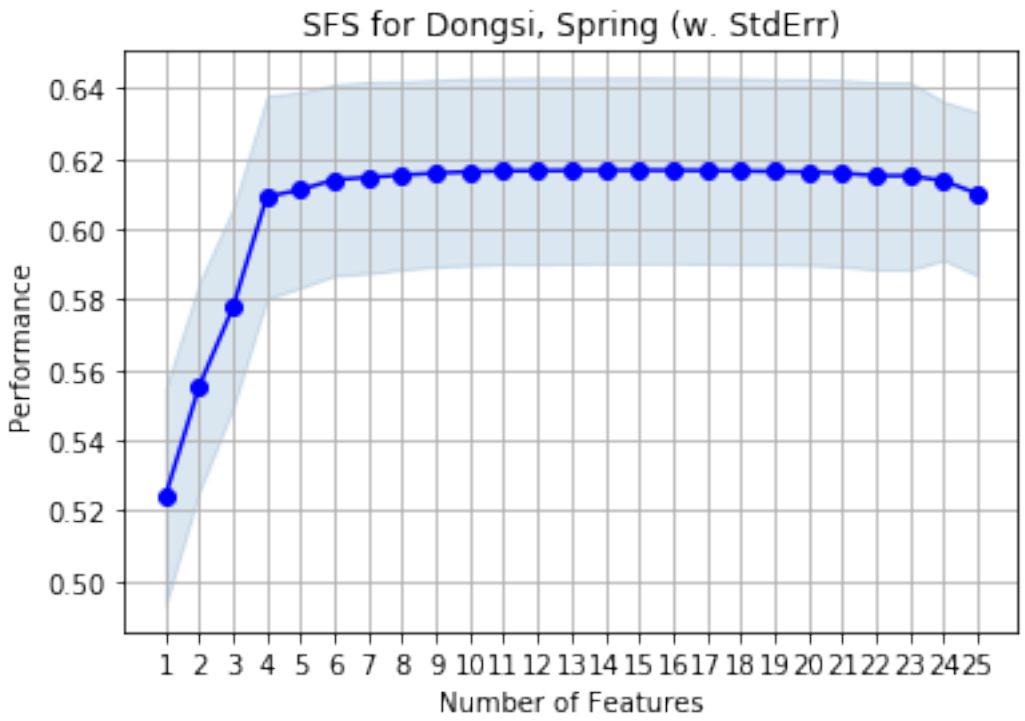
```
14    0.637764
15    0.637604
16    0.637524
6     0.637459
17    0.637367
18    0.637221
19    0.637072
20    0.636828
21     0.63656
22    0.636344
5     0.636002
23    0.635943
24    0.635943
4     0.633529
25    0.632906
3     0.618915
2     0.607229
1     0.549796
Name: avg_score, dtype: object
```



[55]:
```
# Dongsi, Spring:
X = spring.loc['Dongsi'].values[:,6:31] # note we are excluding PM10
y = spring.loc['Dongsi'].values[:,4].ravel()
lr = LinearRegression()
```

```
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Dongsi, Spring (w. StdErr)')
plt.grid()
plt.show()
```

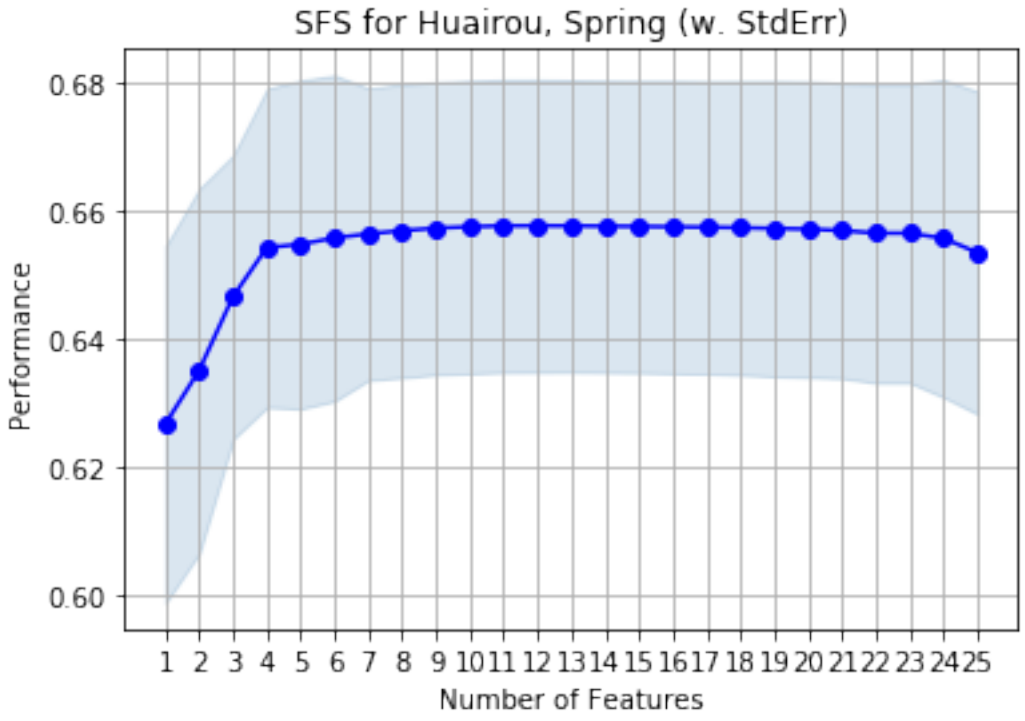
```
15    0.616658
14    0.616657
16    0.616643
13    0.616591
17    0.616588
12     0.61654
11    0.616494
18    0.616464
19    0.616336
10    0.616249
20    0.616192
21    0.615878
9     0.615859
8     0.615279
22    0.615115
23    0.615115
7     0.614637
6     0.613988
24    0.613686
5     0.611139
25    0.610004
4       0.6091
3     0.577699
2     0.555206
1       0.5239
Name: avg_score, dtype: object
```



[56]:
```
# Huairou, Spring:
X = spring.loc['Huairou'].values[:,6:31] # note we are excluding PM10
y = spring.loc['Huairou'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Huairou, Spring (w. StdErr)')
plt.grid()
plt.show()
```

```
12    0.657543
11    0.657528
13    0.657523
14    0.657471
15    0.657431
16    0.657376
```

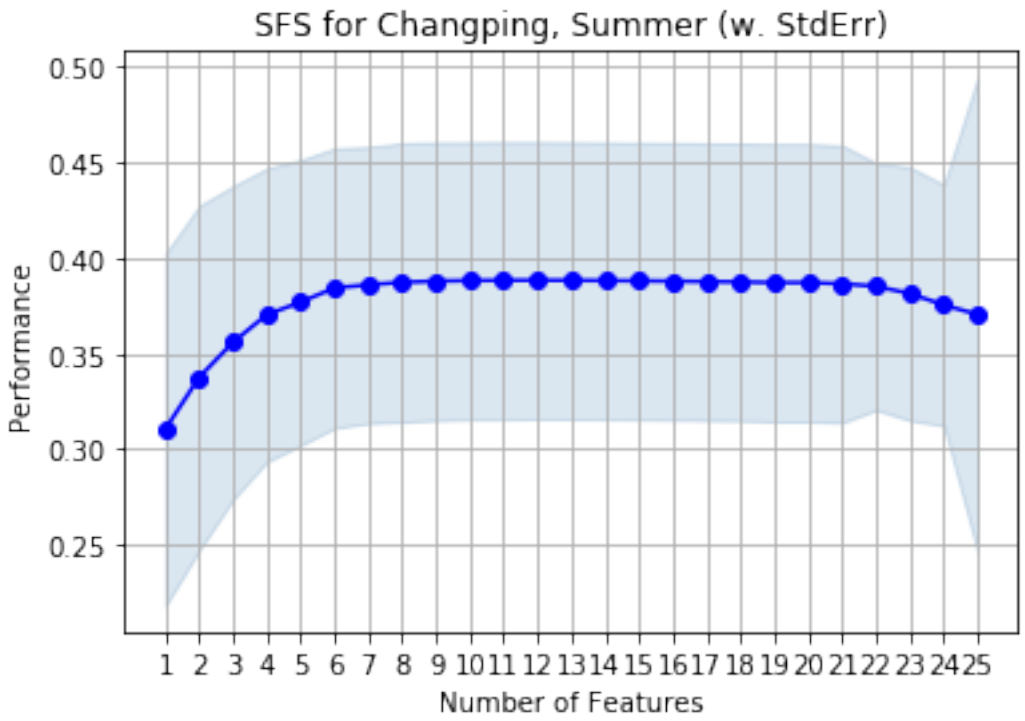
```
10    0.657375
17    0.657314
18    0.657235
9     0.657171
19    0.657125
20    0.657023
21    0.656791
8     0.656768
22    0.656383
23    0.656383
7     0.656267
6     0.655641
24    0.655576
5     0.654652
4      0.65412
25    0.653356
3     0.646456
2     0.634939
1     0.626565
Name: avg_score, dtype: object
```



5.1.2 Feature Selection on summer data for each station.

[57]:
```
# Changping, Summer:
X = summer.loc['Changping'].values[:,6:31] # note we are excluding PM10
y = summer.loc['Changping'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
           k_features=25,
           forward=True,
           floating=False,
           verbose=0,
           scoring='r2',
           cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Changping, Summer (w. StdErr)')
plt.grid()
plt.show()
```

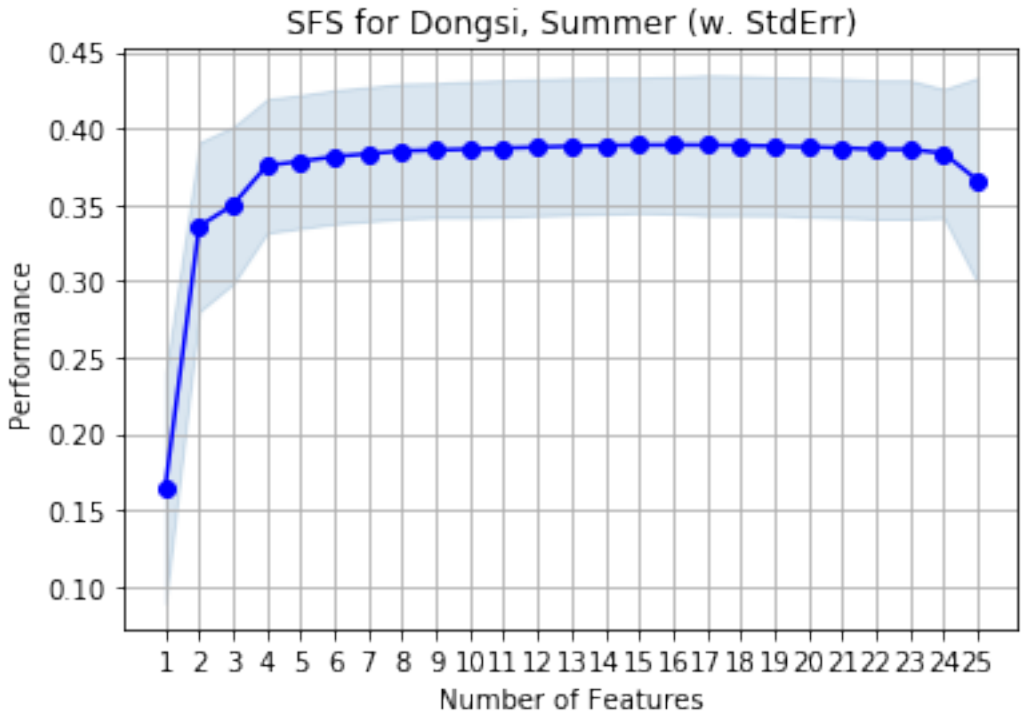
```
12    0.388439
11    0.388362
13     0.38836
10    0.388257
14    0.388251
15    0.388103
9     0.387952
16    0.387935
17     0.38773
18    0.387534
8     0.387345
19    0.387202
20    0.387202
21     0.38657
7     0.386015
22    0.385297
6     0.384408
23    0.381469
5     0.376955
24    0.375527
25    0.370509
4     0.370404
3     0.355919
2      0.33751
1     0.310458
Name: avg_score, dtype: object
```



[58]:
```
# Dongsi, Summer:
X = summer.loc['Dongsi'].values[:,6:31] # note we are excluding PM10
y = summer.loc['Dongsi'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Dongsi, Summer (w. StdErr)')
plt.grid()
plt.show()
```

```
16    0.389083
17    0.388986
15    0.388982
18    0.388812
14    0.388702
19     0.38835
```

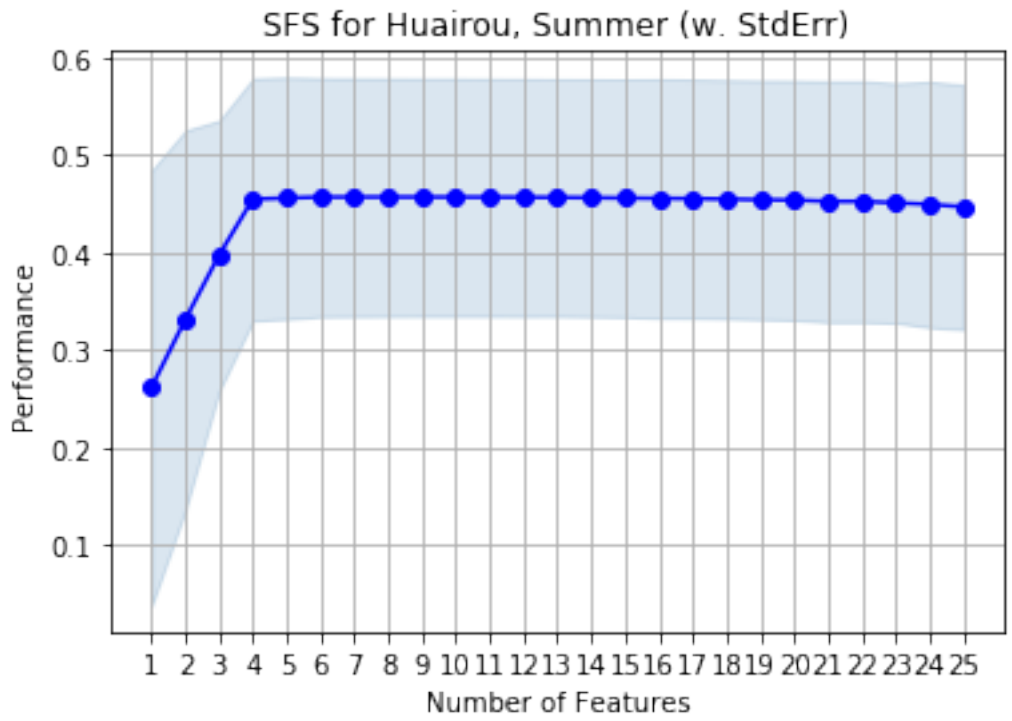
```
13    0.388247
20    0.387868
12     0.38765
21    0.387156
11    0.387007
10    0.386369
22    0.386228
23    0.386228
9     0.385764
8      0.38517
24     0.38369
7      0.38332
6     0.381436
5     0.378376
4     0.375555
25    0.366074
3     0.349839
2     0.335671
1     0.164465
Name: avg_score, dtype: object
```



[59]:
```
# Huairou, Summer:
X = summer.loc['Huairou'].values[:,6:31] # note we are excluding PM10
y = summer.loc['Huairou'].values[:,4].ravel()
```

```
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Huairou, Summer (w. StdErr)')
plt.grid()
plt.show()
```

```
8     0.456739
7     0.456721
9      0.45671
10    0.456666
6     0.456659
11    0.456559
12    0.456449
13    0.456332
14    0.456063
5      0.45576
15    0.455745
16    0.455407
17    0.455173
18    0.454639
4      0.45456
19    0.453997
20    0.453598
21    0.452256
22    0.452256
23    0.450842
24    0.449244
25     0.44668
3     0.396893
2     0.330771
1     0.261278
Name: avg_score, dtype: object
```

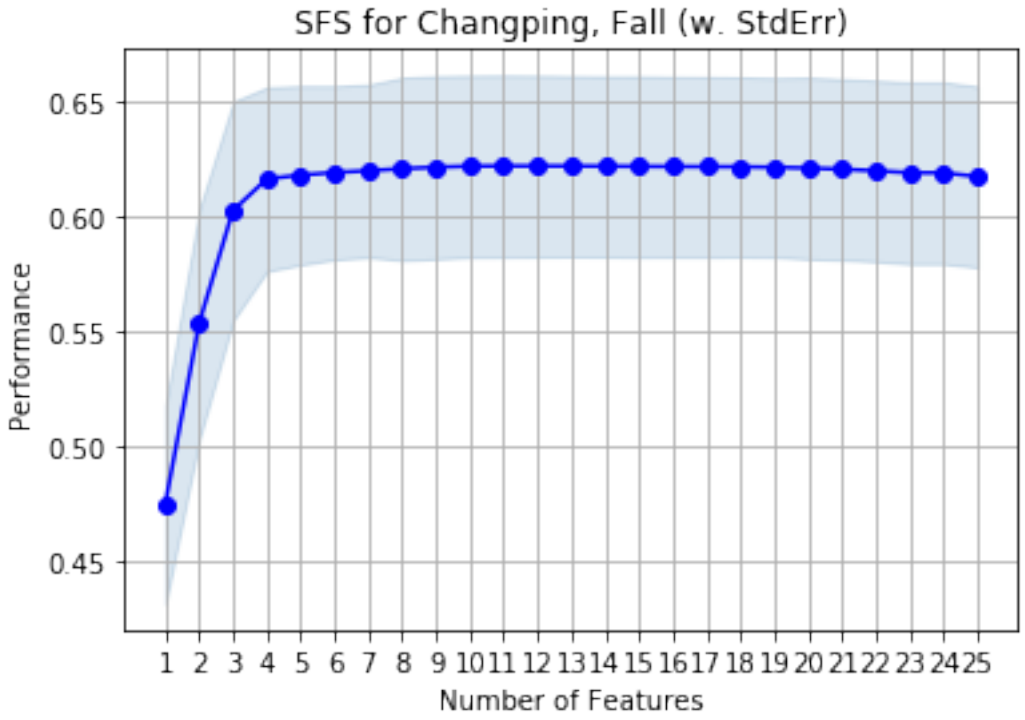


5.1.3 Feature Selection on `fall` data for each station.

[60]:
```
# Changping, Fall:
X = fall.loc['Changping'].values[:,6:31] # note we are excluding PM10
y = fall.loc['Changping'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Changping, Fall (w. StdErr)')
plt.grid()
plt.show()
```

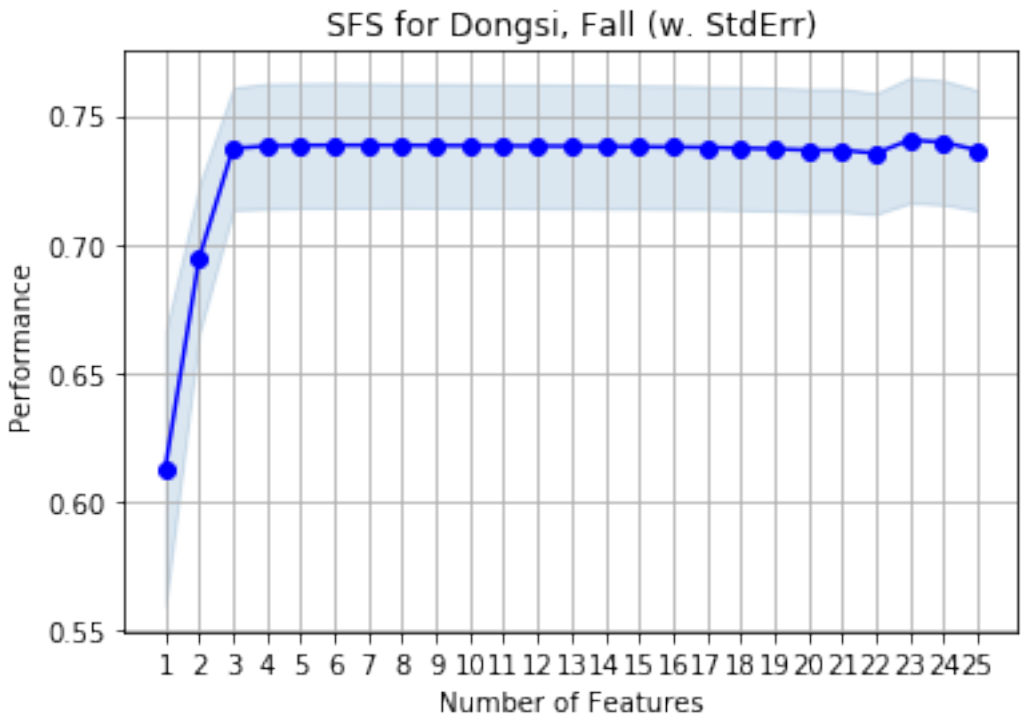
```
11    0.621694
12    0.621691
13    0.621661
```

```
10    0.621605
14     0.62159
15    0.621514
16    0.621441
17    0.621385
18    0.621334
9     0.621161
19    0.621139
20    0.620803
8     0.620522
21    0.620294
7     0.619617
22    0.619598
6     0.618841
23    0.618735
24    0.618735
5     0.617729
25    0.617067
4     0.616053
3       0.6023
2     0.553133
1     0.474428
Name: avg_score, dtype: object
```



[61]:
```
# Dongsi, Fall:
X = fall.loc['Dongsi'].values[:,6:31] # note we are excluding PM10
y = fall.loc['Dongsi'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Dongsi, Fall (w. StdErr)')
plt.grid()
plt.show()
```

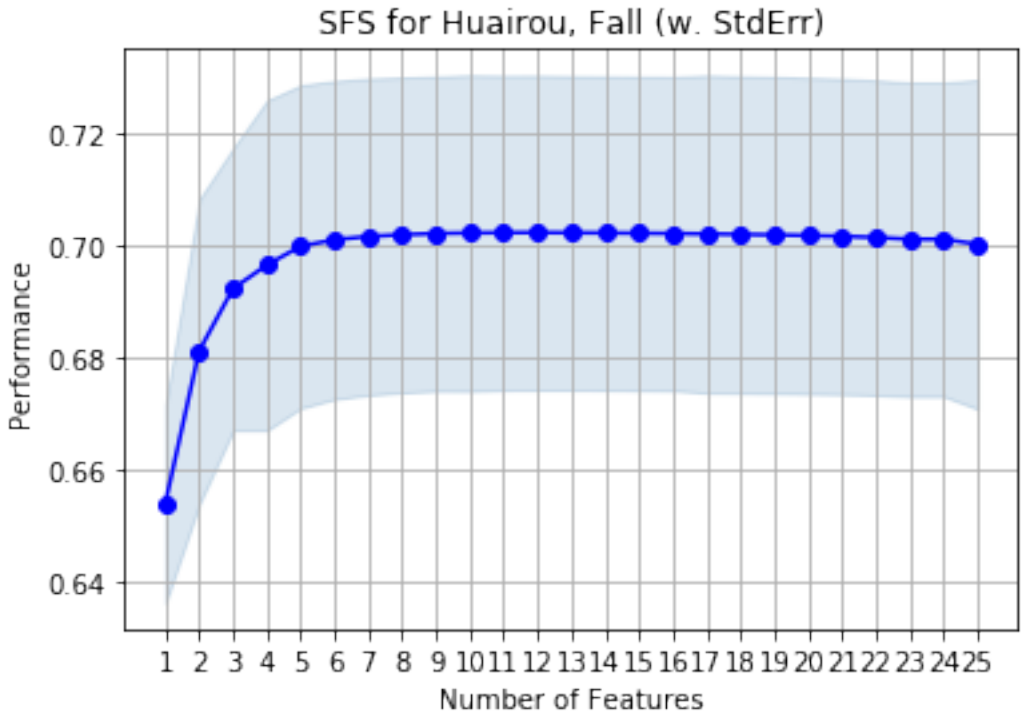
```
23    0.740517
24    0.739588
6     0.738458
7     0.738443
8     0.738403
5     0.738386
9     0.738361
10    0.738295
11    0.738239
12    0.738176
4     0.738171
13    0.738095
14    0.738019
15    0.737894
16    0.737758
17    0.737589
18    0.737324
3     0.737208
19    0.737046
25    0.736574
20    0.736568
21    0.736568
22     0.73531
2     0.694425
1      0.61278
Name: avg_score, dtype: object
```



[62]:
```
# Huairou, Fall:
X = fall.loc['Huairou'].values[:,6:31] # note we are excluding PM10
y = fall.loc['Huairou'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Huairou, Fall (w. StdErr)')
plt.grid()
plt.show()
```

```
12    0.702257
11    0.702235
13    0.702221
14    0.702188
10    0.702184
15     0.70214
```

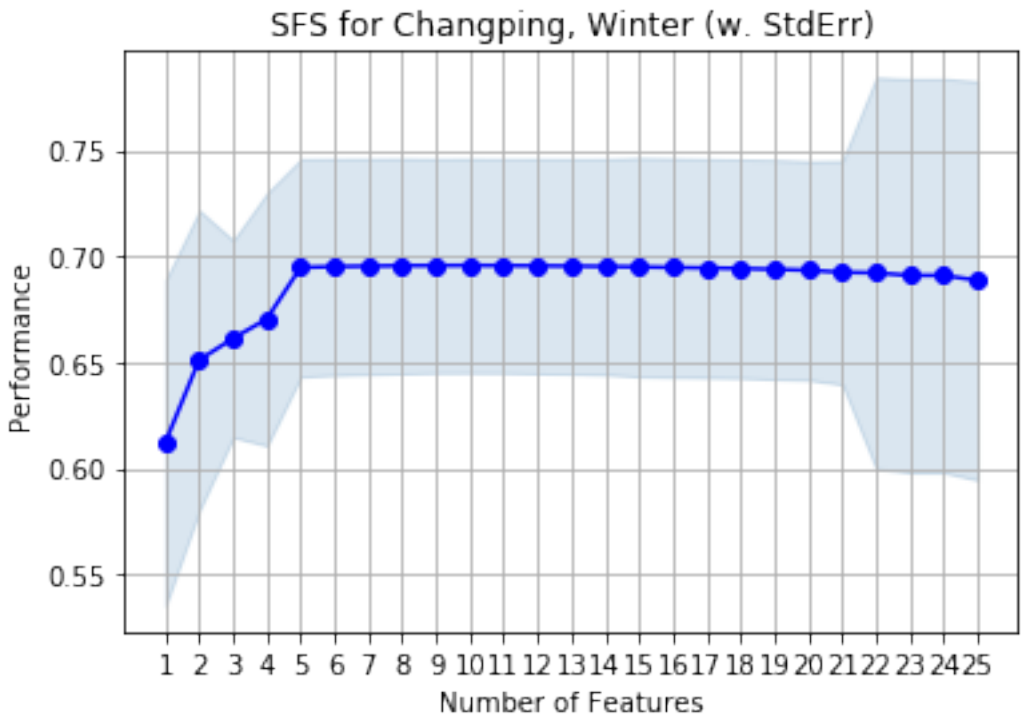
```
16    0.702099
9     0.702094
17    0.702016
18    0.701932
8      0.70187
19    0.701841
20    0.701727
21    0.701596
7     0.701553
22    0.701387
24    0.701067
23    0.701067
6     0.700975
25    0.700172
5     0.699802
4      0.69645
3     0.692203
2     0.681058
1     0.653765
Name: avg_score, dtype: object
```



5.1.4 Feature Selection on winter data for each station.

[63]:
```
# Changping, Winter:
X = winter.loc['Changping'].values[:,6:31] # note we are excluding PM10
y = winter.loc['Changping'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
           k_features=25,
           forward=True,
           floating=False,
           verbose=0,
           scoring='r2',
           cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Changping, Winter (w. StdErr)')
plt.grid()
plt.show()
```

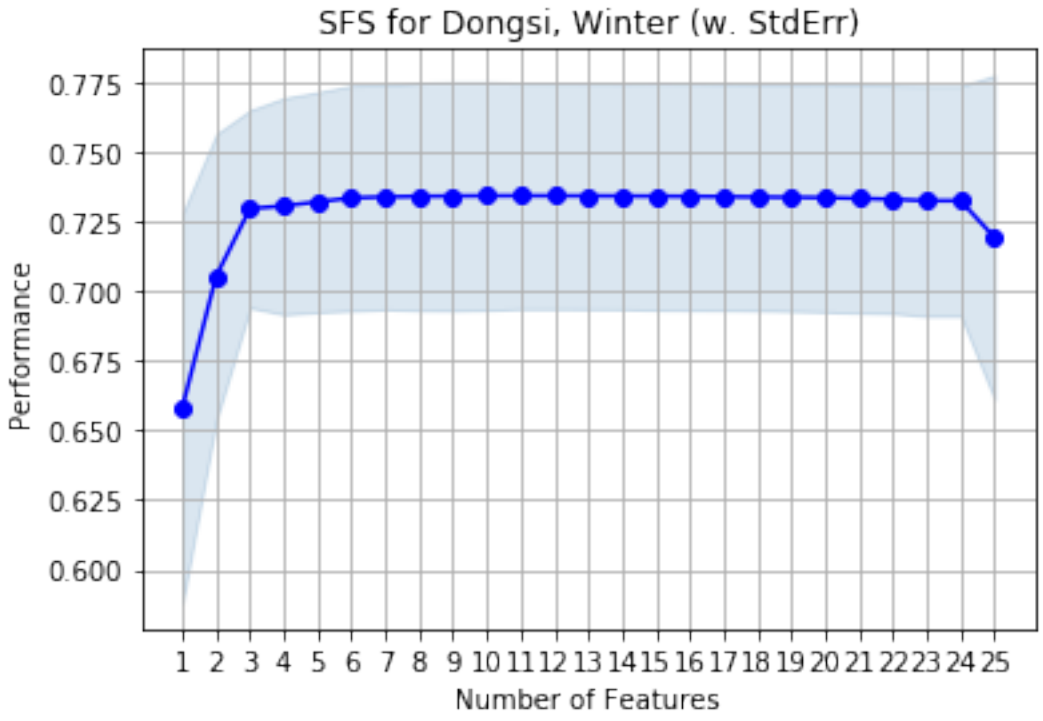
```
10    0.695743
9     0.695686
11    0.695667
8      0.69563
12    0.695556
13    0.695421
7       0.6954
14    0.695249
6     0.695171
15    0.695034
5     0.694778
16    0.694776
17     0.69453
18    0.694282
19    0.693916
20    0.693466
21    0.692471
22    0.692213
24    0.691014
23    0.691014
25    0.688705
4     0.670453
3     0.661253
2     0.651059
1      0.61207
Name: avg_score, dtype: object
```



[64]:
```
# Dongsi, Winter:
X = winter.loc['Dongsi'].values[:,6:31] # note we are excluding PM10
y = winter.loc['Dongsi'].values[:,4].ravel()
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Dongsi, Winter (w. StdErr)')
plt.grid()
plt.show()
```

```
11    0.734175
10    0.734165
12    0.734163
13    0.734124
14    0.734076
9      0.73406
```

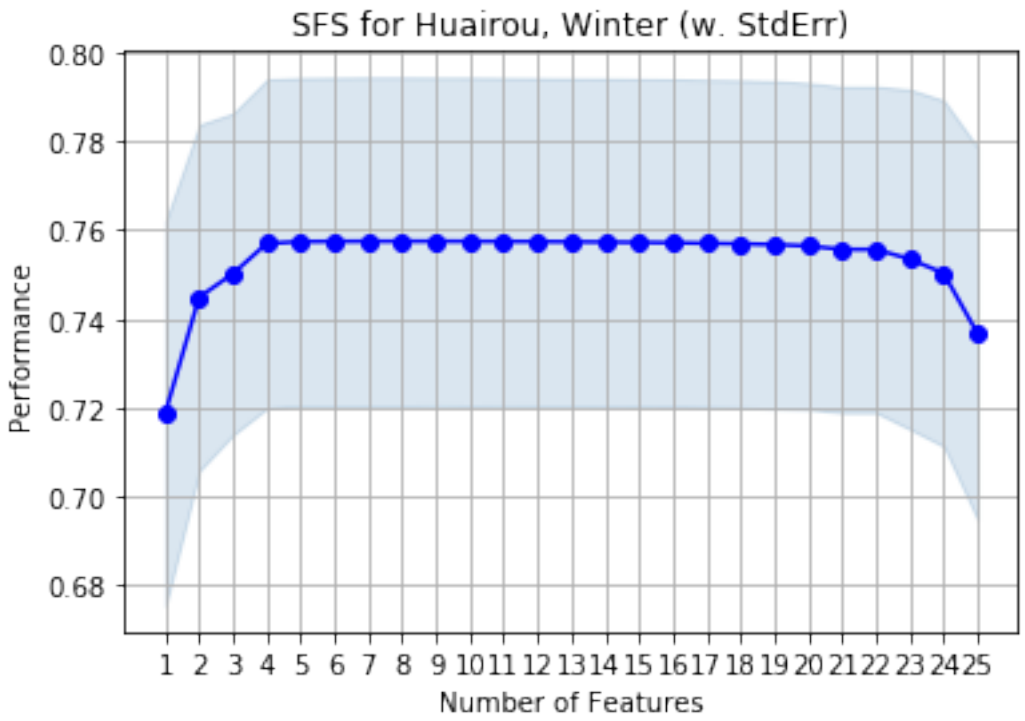
```
15    0.734022
8     0.733966
16     0.73396
17    0.733857
7     0.733766
18    0.733739
19    0.733628
20    0.733506
6     0.733405
21    0.733246
22    0.732917
23     0.73239
24     0.73239
5     0.731979
4     0.730527
3     0.729564
25    0.719305
2     0.705228
1     0.658123
Name: avg_score, dtype: object
```



[65]:
```
# Huairou, Winter:
X = winter.loc['Huairou'].values[:,6:31] # note we are excluding PM10
y = winter.loc['Huairou'].values[:,4].ravel()
```

```
lr = LinearRegression()
sfsfit = sfs(lr,
          k_features=25,
          forward=True,
          floating=False,
          verbose=0,
          scoring='r2',
          cv=5).fit(X, y)
print(pd.DataFrame.from_dict(sfsfit.get_metric_dict()).T.avg_score.
 ↪sort_values(ascending=False))
fig = plot_sfs(sfsfit.get_metric_dict(), kind='std_err')
plt.title('SFS for Huairou, Winter (w. StdErr)')
plt.grid()
plt.show()
```

```
9     0.757496
8     0.757489
7     0.757481
10    0.757473
6     0.757463
11    0.757448
12    0.757421
5     0.757408
13    0.757372
14    0.757312
15    0.757232
16    0.757159
17    0.757029
4     0.756986
18     0.75692
19    0.756741
20    0.756433
21    0.755656
22    0.755656
23    0.753479
24    0.750315
3     0.750192
2     0.744852
25    0.736753
1      0.71873
Name: avg_score, dtype: object
```



After performing Sequential Feature Selection, we see that for each season, the R^2 does not differ that much after around 5 features, thus, we will include `SO2`, `NO2`, `CO`, `O3`, `TEMP`, `PRES`, `DEWP` , `RAIN`, `WSPM`, and `wd` in the OLS regression model in order to gain more insight from all the variables

5.1.5 Next, we will fit our seasonal regression model using these ten selected features.

[66]:
```
# Define regression formula
formula = 'PM2_5 ~ SO2 + NO2 + CO + O3 + TEMP + PRES + DEWP + RAIN + WSPM + wd␣
 ↪- 1'
```

We will seperate our data into 12 groups, for each station and each season.

[67]:
```
# seperate data into 3 regions:
changping = data.loc['Changping']
dongsi = data.loc['Dongsi']
huairou = data.loc['Huairou']
```

[68]:
```
# break down further into 12 data sets
chp_spr = changping.loc[changping.season == 'Spring'].rename(columns={'PM2.5':
 ↪'PM2_5'})
chp_su =changping.loc[changping.season == 'Summer'].rename(columns={'PM2.5':
 ↪'PM2_5'})
```

```
chp_fa = changping.loc[changping.season == 'Fall'].rename(columns={'PM2.5':
 ↪'PM2_5'})
chp_win = changping.loc[changping.season == 'Winter'].rename(columns={'PM2.5':
 ↪'PM2_5'})

ds_spr = dongsi.loc[dongsi.season == 'Spring'].rename(columns={'PM2.5':'PM2_5'})
ds_su =dongsi.loc[dongsi.season == 'Summer'].rename(columns={'PM2.5':'PM2_5'})
ds_fa = dongsi.loc[dongsi.season == 'Fall'].rename(columns={'PM2.5':'PM2_5'})
ds_win = dongsi.loc[dongsi.season == 'Winter'].rename(columns={'PM2.5':'PM2_5'})

hr_spr = huairou.loc[huairou.season == 'Spring'].rename(columns={'PM2.5':
 ↪'PM2_5'})
hr_su =huairou.loc[huairou.season == 'Summer'].rename(columns={'PM2.5':'PM2_5'})
hr_fa = huairou.loc[huairou.season == 'Fall'].rename(columns={'PM2.5':'PM2_5'})
hr_win = huairou.loc[huairou.season == 'Winter'].rename(columns={'PM2.5':
 ↪'PM2_5'})
```

5.1.6 Fit OLS regression for Changping for all seasons

[69]:
```
oslm_chp_spr = smf.ols(formula=formula, data=chp_spr.iloc[:,4:32]).fit().
 ↪summary()
oslm_chp_su = smf.ols(formula=formula, data=chp_su.iloc[:,4:32]).fit().summary()
oslm_chp_fa = smf.ols(formula=formula, data=chp_fa.iloc[:,4:32]).fit().summary()
oslm_chp_win = smf.ols(formula=formula, data=chp_win.iloc[:,4:32]).fit().
 ↪summary()
```

[70]:
```
print(oslm_chp_spr) #Changping, Spring
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.686
Model:                            OLS   Adj. R-squared:                  0.685
Method:                 Least Squares   F-statistic:                     802.6
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                        16:44:44   Log-Likelihood:                -44427.
No. Observations:                8832   AIC:                         8.890e+04
Df Residuals:                    8807   BIC:                         8.908e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]        -90.0422     74.053     -1.216      0.224    -235.203      55.119
wd[ENE]      -86.8537     73.944     -1.175      0.240    -231.800      58.093
wd[ESE]      -88.9841     74.048     -1.202      0.230    -234.136      56.168
wd[N]        -88.4511     73.949     -1.196      0.232    -233.408      56.506
```

```
wd[NE]       -87.9985     73.931     -1.190      0.234    -232.921      56.924
wd[NNE]      -86.8279     73.943     -1.174      0.240    -231.773      58.117
wd[NNW]      -88.6859     73.916     -1.200      0.230    -233.578      56.206
wd[NW]       -87.8232     73.887     -1.189      0.235    -232.659      57.012
wd[S]        -95.7587     74.109     -1.292      0.196    -241.029      49.512
wd[SE]       -89.2254     74.061     -1.205      0.228    -234.403      55.952
wd[SSE]      -90.1658     74.144     -1.216      0.224    -235.505      55.174
wd[SSW]      -89.2769     74.097     -1.205      0.228    -234.524      55.970
wd[SW]       -92.1768     74.002     -1.246      0.213    -237.239      52.885
wd[W]        -89.1017     73.928     -1.205      0.228    -234.019      55.815
wd[WNW]      -89.7802     73.935     -1.214      0.225    -234.710      55.149
wd[WSW]      -95.4469     74.073     -1.289      0.198    -240.647      49.753
SO2            0.2533      0.031      8.238      0.000       0.193       0.314
NO2            0.6179      0.025     24.564      0.000       0.569       0.667
CO             0.0468      0.001     44.634      0.000       0.045       0.049
O3             0.2616      0.012     21.079      0.000       0.237       0.286
TEMP          -0.4712      0.095     -4.949      0.000      -0.658      -0.285
PRES           0.0740      0.073      1.014      0.310      -0.069       0.217
DEWP           1.7275      0.064     27.062      0.000       1.602       1.853
RAIN          -8.0096      1.255     -6.380      0.000     -10.470      -5.549
WSPM           2.0400      0.373      5.464      0.000       1.308       2.772
==============================================================================
Omnibus:                     4009.532   Durbin-Watson:                   0.336
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            48620.782
Skew:                           1.855   Prob(JB):                         0.00
Kurtosis:                      13.879   Cond. No.                     1.09e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.09e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[71]:
```
print(oslm_chp_su) #Changping, Summer
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.487
Model:                            OLS   Adj. R-squared:                  0.486
Method:                 Least Squares   F-statistic:                     348.9
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                        16:44:44   Log-Likelihood:                -44324.
No. Observations:                8832   AIC:                         8.870e+04
Df Residuals:                    8807   BIC:                         8.888e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
```

```
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]        410.9889    104.475      3.934      0.000     206.194     615.784
wd[ENE]      405.1531    104.483      3.878      0.000     200.343     609.963
wd[ESE]      407.7146    104.543      3.900      0.000     202.786     612.643
wd[N]        392.2919    104.388      3.758      0.000     187.667     596.917
wd[NE]       396.4166    104.383      3.798      0.000     191.801     601.033
wd[NNE]      394.1893    104.344      3.778      0.000     189.651     598.728
wd[NNW]      393.5931    104.405      3.770      0.000     188.935     598.251
wd[NW]       394.5886    104.385      3.780      0.000     189.969     599.208
wd[S]        396.4358    104.552      3.792      0.000     191.489     601.383
wd[SE]       402.1497    104.574      3.846      0.000     197.160     607.140
wd[SSE]      395.8978    104.555      3.787      0.000     190.946     600.850
wd[SSW]      389.4516    104.531      3.726      0.000     184.546     594.357
wd[SW]       389.3987    104.530      3.725      0.000     184.496     594.302
wd[W]        389.9839    104.429      3.734      0.000     185.280     594.688
wd[WNW]      393.0363    104.341      3.767      0.000     188.503     597.569
wd[WSW]      390.5748    104.491      3.738      0.000     185.748     595.402
SO2            0.6750      0.057     11.855      0.000       0.563       0.787
NO2            0.5025      0.027     18.824      0.000       0.450       0.555
CO             0.0417      0.001     40.811      0.000       0.040       0.044
O3             0.1401      0.008     16.553      0.000       0.123       0.157
TEMP          -0.7906      0.128     -6.186      0.000      -1.041      -0.540
PRES          -0.4394      0.104     -4.238      0.000      -0.643      -0.236
DEWP           3.0386      0.104     29.310      0.000       2.835       3.242
RAIN          -0.3790      0.294     -1.289      0.198      -0.955       0.197
WSPM           0.9973      0.528      1.890      0.059      -0.037       2.031
==============================================================================
Omnibus:                     4841.934   Durbin-Watson:                   0.232
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           127610.816
Skew:                           2.108   Prob(JB):                         0.00
Kurtosis:                      21.138   Cond. No.                     1.40e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.4e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[72]:
```
print(oslm_chp_fa) #Changping, Fall
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.645
Model:                            OLS   Adj. R-squared:                  0.644
Method:                 Least Squares   F-statistic:                     659.0
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
```

```
Time:                        16:44:44   Log-Likelihood:                -45123.
No. Observations:                8736   AIC:                         9.030e+04
Df Residuals:                    8711   BIC:                         9.047e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]       -294.7026    103.377     -2.851      0.004    -497.346     -92.059
wd[ENE]     -298.4903    103.385     -2.887      0.004    -501.150     -95.831
wd[ESE]     -288.8085    103.434     -2.792      0.005    -491.563     -86.054
wd[N]       -288.2523    103.226     -2.792      0.005    -490.600     -85.904
wd[NE]      -295.3187    103.231     -2.861      0.004    -497.676     -92.961
wd[NNE]     -299.0288    103.279     -2.895      0.004    -501.481     -96.577
wd[NNW]     -287.2554    103.206     -2.783      0.005    -489.564     -84.947
wd[NW]      -289.1687    103.192     -2.802      0.005    -491.450     -86.887
wd[S]       -299.8616    103.388     -2.900      0.004    -502.527     -97.196
wd[SE]      -291.4596    103.437     -2.818      0.005    -494.220     -88.699
wd[SSE]     -294.7507    103.470     -2.849      0.004    -497.576     -91.925
wd[SSW]     -297.6441    103.384     -2.879      0.004    -500.300     -94.988
wd[SW]      -296.5205    103.379     -2.868      0.004    -499.168     -93.873
wd[W]       -291.5943    103.232     -2.825      0.005    -493.953     -89.236
wd[WNW]     -287.5964    103.195     -2.787      0.005    -489.883     -85.309
wd[WSW]     -290.7745    103.328     -2.814      0.005    -493.322     -88.227
SO2            0.3135      0.047      6.648      0.000       0.221       0.406
NO2            1.0761      0.024     44.769      0.000       1.029       1.123
CO             0.0336      0.001     43.361      0.000       0.032       0.035
O3             0.4036      0.016     24.948      0.000       0.372       0.435
TEMP          -1.4996      0.134    -11.222      0.000      -1.761      -1.238
PRES           0.2551      0.101      2.520      0.012       0.057       0.454
DEWP           2.2890      0.100     22.805      0.000       2.092       2.486
RAIN          -4.4049      0.877     -5.021      0.000      -6.125      -2.685
WSPM           4.2350      0.544      7.783      0.000       3.168       5.302
==============================================================================
Omnibus:                     3582.242   Durbin-Watson:                   0.165
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            27144.838
Skew:                           1.784   Prob(JB):                         0.00
Kurtosis:                      10.864   Cond. No.                     1.54e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.54e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[73]:
```
print(oslm_chp_win) #Changping, Winter
```

OLS Regression Results

Dep. Variable:	PM2_5	R-squared:	0.812
Model:	OLS	Adj. R-squared:	0.812
Method:	Least Squares	F-statistic:	1560.
Date:	Sun, 01 Dec 2019	Prob (F-statistic):	0.00
Time:	16:44:44	Log-Likelihood:	-44324.
No. Observations:	8664	AIC:	8.870e+04
Df Residuals:	8639	BIC:	8.887e+04
Df Model:	24		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
wd[E]	685.7037	86.707	7.908	0.000	515.738	855.670
wd[ENE]	685.5594	86.700	7.907	0.000	515.607	855.512
wd[ESE]	690.5524	86.702	7.965	0.000	520.596	860.509
wd[N]	680.8299	86.607	7.861	0.000	511.059	850.601
wd[NE]	685.1492	86.692	7.903	0.000	515.213	855.086
wd[NNE]	683.4294	86.657	7.887	0.000	513.561	853.298
wd[NNW]	682.1363	86.589	7.878	0.000	512.402	851.871
wd[NW]	685.2082	86.608	7.912	0.000	515.435	854.981
wd[S]	677.2684	86.787	7.804	0.000	507.146	847.391
wd[SE]	687.7032	86.772	7.925	0.000	517.609	857.797
wd[SSE]	680.7897	86.819	7.841	0.000	510.603	850.977
wd[SSW]	681.6771	86.741	7.859	0.000	511.645	851.709
wd[SW]	681.0522	86.718	7.854	0.000	511.064	851.041
wd[W]	682.2153	86.629	7.875	0.000	512.402	852.029
wd[WNW]	685.2861	86.655	7.908	0.000	515.421	855.151
wd[WSW]	674.0022	86.679	7.776	0.000	504.090	843.914
SO2	0.5475	0.018	30.548	0.000	0.512	0.583
NO2	1.2238	0.026	46.601	0.000	1.172	1.275
CO	0.0204	0.000	46.810	0.000	0.020	0.021
O3	1.0400	0.036	29.029	0.000	0.970	1.110
TEMP	-3.2791	0.144	-22.740	0.000	-3.562	-2.996
PRES	-0.6795	0.085	-7.983	0.000	-0.846	-0.513
DEWP	4.4531	0.111	40.062	0.000	4.235	4.671
RAIN	-9.8137	13.946	-0.704	0.482	-37.150	17.523
WSPM	2.4323	0.391	6.226	0.000	1.667	3.198

Omnibus:	4294.518	Durbin-Watson:	0.229
Prob(Omnibus):	0.000	Jarque-Bera (JB):	120676.121
Skew:	1.804	Prob(JB):	0.00
Kurtosis:	20.924	Cond. No.	2.08e+06

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly

specified.
[2] The condition number is large, 2.08e+06. This might indicate that there are strong multicollinearity or other numerical problems.

From the OLS Regression Results of Changping we can see that winter has highest R-squared which is 0.812, R- squared in summer is 0.487 which is lowest, because PM2.5 is higher in winter than summer.

For spring of Changping, the p values of wd are large than 0.05, so wd is not significant, and pressure also is not significant because it's p value large than 0.05. The coefficient of Rain and Temp are negative.

For summer of Changping, all of the varibles p values are smaller than 0.05, so all variables are significant. However, the coefficients of wd are large positive number, so wd has importance effect in summer, especially wd(E). Temp, Rain and pres have negative coefficients.

For Fall of Changping, all of the varibles p values are smaller than 0.05, so all variables are significant. However, wd has large negative coefficient, so wd increase will decrease PM2.5. Rain and Temp are negativ.e

For winter of Changping, p value of Rain is large than 0.05, so Rain is not significant, this situation matches reality, because It hardly rains in winter of Beijing. the coefficients of wd are large positive number, but Temp Rain and pres have negative coefficients. –Mary

5.1.7 Fit OLS regression for Dongsi for all seasons

[74]:
```
oslm_ds_spr = smf.ols(formula=formula, data=ds_spr.iloc[:,4:32]).fit().summary()
oslm_ds_su = smf.ols(formula=formula, data=ds_su.iloc[:,4:32]).fit().summary()
oslm_ds_fa = smf.ols(formula=formula, data=ds_fa.iloc[:,4:32]).fit().summary()
oslm_ds_win = smf.ols(formula=formula, data=ds_win.iloc[:,4:32]).fit().summary()
```

[75]:
```
print(oslm_ds_spr) #Dongsi, Spring
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.652
Model:                            OLS   Adj. R-squared:                  0.651
Method:                 Least Squares   F-statistic:                     688.4
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                        16:44:44   Log-Likelihood:                -45593.
No. Observations:                8832   AIC:                          9.124e+04
Df Residuals:                    8807   BIC:                          9.141e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
```

```
wd[E]       -106.9151     85.879     -1.245      0.213    -275.258      61.428
wd[ENE]     -107.4712     85.898     -1.251      0.211    -275.850      60.908
wd[ESE]     -106.6051     85.961     -1.240      0.215    -275.110      61.899
wd[N]       -102.0476     85.816     -1.189      0.234    -270.268      66.173
wd[NE]      -102.2751     85.878     -1.191      0.234    -270.616      66.066
wd[NNE]     -105.0022     85.876     -1.223      0.221    -273.339      63.335
wd[NNW]      -98.7276     85.752     -1.151      0.250    -266.822      69.367
wd[NW]       -98.0533     85.697     -1.144      0.253    -266.040      69.933
wd[S]        -95.4577     85.978     -1.110      0.267    -263.995      73.080
wd[SE]      -103.7707     85.955     -1.207      0.227    -272.263      64.722
wd[SSE]      -97.0024     85.938     -1.129      0.259    -265.461      71.456
wd[SSW]      -96.7251     85.977     -1.125      0.261    -265.261      71.811
wd[SW]      -101.4757     85.934     -1.181      0.238    -269.927      66.975
wd[W]       -103.2091     85.793     -1.203      0.229    -271.384      64.966
wd[WNW]      -99.3679     85.766     -1.159      0.247    -267.490      68.754
wd[WSW]     -100.7240     85.916     -1.172      0.241    -269.139      67.691
SO2            0.2784      0.032      8.652      0.000       0.215       0.342
NO2            0.8465      0.024     35.434      0.000       0.800       0.893
CO             0.0343      0.001     33.958      0.000       0.032       0.036
O3             0.3167      0.015     21.554      0.000       0.288       0.346
TEMP          -1.1383      0.111    -10.213      0.000      -1.357      -0.920
PRES           0.0840      0.084      0.998      0.318      -0.081       0.249
DEWP           1.5923      0.075     21.154      0.000       1.445       1.740
RAIN          -6.8640      1.588     -4.324      0.000      -9.976      -3.752
WSPM           3.6035      0.419      8.597      0.000       2.782       4.425
==============================================================================
Omnibus:                     2983.957   Durbin-Watson:                   0.266
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            28574.915
Skew:                           1.342   Prob(JB):                         0.00
Kurtosis:                      11.393   Cond. No.                     1.24e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.24e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[76]:
```
print(oslm_ds_su) #Dongsi, Summer
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.474
Model:                            OLS   Adj. R-squared:                  0.472
Method:                 Least Squares   F-statistic:                     330.5
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                        16:44:44   Log-Likelihood:                -45155.
No. Observations:                8832   AIC:                         9.036e+04
```

```
Df Residuals:                     8807   BIC:                          9.054e+04
Df Model:                           24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]       -192.3506    114.649     -1.678      0.093    -417.090      32.389
wd[ENE]     -196.7842    114.609     -1.717      0.086    -421.444      27.876
wd[ESE]     -187.9613    114.654     -1.639      0.101    -412.710      36.787
wd[N]       -197.9193    114.513     -1.728      0.084    -422.392      26.554
wd[NE]      -200.8058    114.581     -1.753      0.080    -425.412      23.800
wd[NNE]     -202.3107    114.595     -1.765      0.078    -426.944      22.323
wd[NNW]     -199.8206    114.471     -1.746      0.081    -424.210      24.569
wd[NW]      -200.4056    114.464     -1.751      0.080    -424.782      23.971
wd[S]       -189.5809    114.634     -1.654      0.098    -414.291      35.129
wd[SE]      -185.9963    114.717     -1.621      0.105    -410.869      38.876
wd[SSE]     -183.6483    114.708     -1.601      0.109    -408.502      41.206
wd[SSW]     -191.5456    114.618     -1.671      0.095    -416.225      33.133
wd[SW]      -193.3139    114.612     -1.687      0.092    -417.980      31.352
wd[W]       -197.7522    114.573     -1.726      0.084    -422.342      26.838
wd[WNW]     -200.8240    114.473     -1.754      0.079    -425.217      23.570
wd[WSW]     -196.3153    114.562     -1.714      0.087    -420.884      28.253
SO2            1.5582      0.050     30.986      0.000       1.460       1.657
NO2            0.4288      0.024     17.945      0.000       0.382       0.476
CO             0.0206      0.001     25.543      0.000       0.019       0.022
O3             0.0992      0.007     13.371      0.000       0.085       0.114
TEMP          -0.2493      0.137     -1.820      0.069      -0.518       0.019
PRES           0.1182      0.113      1.045      0.296      -0.103       0.340
DEWP           4.7954      0.109     44.001      0.000       4.582       5.009
RAIN          -0.9721      0.331     -2.939      0.003      -1.620      -0.324
WSPM           3.4585      0.567      6.103      0.000       2.348       4.569
==============================================================================
Omnibus:                     2488.578   Durbin-Watson:                   0.172
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            18204.902
Skew:                           1.154   Prob(JB):                         0.00
Kurtosis:                       9.644   Cond. No.                     1.60e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.6e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[77]:
```
print(oslm_ds_fa) #Dongsi, Fall
```

```
                            OLS Regression Results
==============================================================================
```

Dep. Variable:	PM2_5	R-squared:	0.770
Model:	OLS	Adj. R-squared:	0.769
Method:	Least Squares	F-statistic:	1216.
Date:	Sun, 01 Dec 2019	Prob (F-statistic):	0.00
Time:	16:44:44	Log-Likelihood:	-44958.
No. Observations:	8736	AIC:	8.997e+04
Df Residuals:	8711	BIC:	9.014e+04
Df Model:	24		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
wd[E]	150.0877	100.954	1.487	0.137	-47.806	347.982
wd[ENE]	150.4477	100.960	1.490	0.136	-47.459	348.354
wd[ESE]	147.2836	100.953	1.459	0.145	-50.607	345.174
wd[N]	157.1628	100.930	1.557	0.119	-40.683	355.009
wd[NE]	147.9399	100.948	1.466	0.143	-49.942	345.822
wd[NNE]	151.1080	100.922	1.497	0.134	-46.723	348.939
wd[NNW]	157.1757	100.980	1.557	0.120	-40.769	355.120
wd[NW]	156.8112	100.809	1.556	0.120	-40.799	354.421
wd[S]	149.1276	101.006	1.476	0.140	-48.868	347.123
wd[SE]	150.4165	100.998	1.489	0.136	-47.564	348.397
wd[SSE]	149.9728	101.020	1.485	0.138	-48.050	347.995
wd[SSW]	150.9703	100.959	1.495	0.135	-46.933	348.874
wd[SW]	153.0237	100.924	1.516	0.129	-44.811	350.859
wd[W]	146.1015	100.818	1.449	0.147	-51.526	343.729
wd[WNW]	155.3369	100.699	1.543	0.123	-42.058	352.731
wd[WSW]	150.9201	100.864	1.496	0.135	-46.798	348.638
SO2	0.4652	0.034	13.502	0.000	0.398	0.533
NO2	1.1990	0.021	56.010	0.000	1.157	1.241
CO	0.0381	0.001	56.942	0.000	0.037	0.039
O3	0.5540	0.017	33.506	0.000	0.522	0.586
TEMP	-2.0207	0.129	-15.712	0.000	-2.273	-1.769
PRES	-0.2009	0.098	-2.041	0.041	-0.394	-0.008
DEWP	1.5881	0.097	16.357	0.000	1.398	1.778
RAIN	-2.0909	0.603	-3.467	0.001	-3.273	-0.909
WSPM	5.9182	0.533	11.104	0.000	4.873	6.963

Omnibus:	1407.979	Durbin-Watson:	0.177
Prob(Omnibus):	0.000	Jarque-Bera (JB):	3664.368
Skew:	0.888	Prob(JB):	0.00
Kurtosis:	5.629	Cond. No.	1.71e+06

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.71e+06. This might indicate that there are

strong multicollinearity or other numerical problems.

[78]:
```
print(oslm_ds_win) #Dongsi, Winter
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.787
Model:                            OLS   Adj. R-squared:                  0.786
Method:                 Least Squares   F-statistic:                     1330.
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                        16:44:44   Log-Likelihood:                -46866.
No. Observations:                8664   AIC:                         9.378e+04
Df Residuals:                    8639   BIC:                         9.396e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]       1143.7816    117.820      9.708      0.000     912.825    1374.738
wd[ENE]     1144.5494    117.841      9.713      0.000     913.553    1375.546
wd[ESE]     1143.2093    117.856      9.700      0.000     912.184    1374.235
wd[N]       1147.0781    117.891      9.730      0.000     915.984    1378.172
wd[NE]      1150.8474    117.854      9.765      0.000     919.825    1381.870
wd[NNE]     1152.3542    117.883      9.775      0.000     921.274    1383.434
wd[NNW]     1148.6311    117.845      9.747      0.000     917.627    1379.635
wd[NW]      1148.3298    117.671      9.759      0.000     917.666    1378.993
wd[S]       1140.1293    117.960      9.665      0.000     908.901    1371.358
wd[SE]      1144.3595    117.926      9.704      0.000     913.197    1375.522
wd[SSE]     1136.7013    118.004      9.633      0.000     905.386    1368.017
wd[SSW]     1148.8729    117.904      9.744      0.000     917.753    1379.993
wd[SW]      1154.3983    117.929      9.789      0.000     923.229    1385.567
wd[W]       1153.1002    117.753      9.793      0.000     922.276    1383.924
wd[WNW]     1147.3538    117.610      9.756      0.000     916.809    1377.898
wd[WSW]     1163.1440    117.884      9.867      0.000     932.062    1394.226
SO2            0.5919      0.025     23.559      0.000       0.543       0.641
NO2            0.2577      0.020     12.785      0.000       0.218       0.297
CO             0.0413      0.001     80.872      0.000       0.040       0.042
O3             0.4780      0.032     15.075      0.000       0.416       0.540
TEMP          -2.0072      0.185    -10.859      0.000      -2.370      -1.645
PRES          -1.0910      0.115     -9.468      0.000      -1.317      -0.865
DEWP           4.2368      0.133     31.881      0.000       3.976       4.497
RAIN         -25.3860     10.254     -2.476      0.013     -45.487      -5.285
WSPM           1.4645      0.594      2.467      0.014       0.301       2.628
==============================================================================
Omnibus:                     3115.070   Durbin-Watson:                   0.244
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            34925.739
Skew:                           1.399   Prob(JB):                         0.00
Kurtosis:                      12.430   Cond. No.                     2.10e+06
```

```
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 2.1e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

From the OLS Regression Results of Dongsi we can see that winter has highest R-squared which is 0.787, summer has lowest – 0.487.

For spring of Dongsi, the p values of wd and pres are large than 0.05, so wd and pres are not significant. The coefficient of Rain and Temp are negative.

For summer of Dongsi, the p values of wd and pres are large than 0.05, so wd and pres are not significant. Rain has negative coefficients.

For Fall of Dongsi, the p value of wd is large than 0.05, so so wd is not significant. The coefficient of Rain ,pres and Temp are negative coefficients.

For Fall of Dongsi, all varaibles are significant, wd has large positive coefficient. Temp, Rain and Pres have neative coefficients. –Mary

5.2 Fit OLS regression for Huairou for all seasons

[79]:
```
oslm_hr_spr = smf.ols(formula=formula, data=hr_spr.iloc[:,4:32]).fit().summary()
oslm_hr_su = smf.ols(formula=formula, data=hr_su.iloc[:,4:32]).fit().summary()
oslm_hr_fa = smf.ols(formula=formula, data=hr_fa.iloc[:,4:32]).fit().summary()
oslm_hr_win = smf.ols(formula=formula, data=hr_win.iloc[:,4:32]).fit().summary()
```

[80]:
```
print(oslm_hr_spr) #Huairou, Spring
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.690
Model:                            OLS   Adj. R-squared:                  0.690
Method:                 Least Squares   F-statistic:                     818.4
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                        16:44:44   Log-Likelihood:                -44309.
No. Observations:                8832   AIC:                         8.867e+04
Df Residuals:                    8807   BIC:                         8.884e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]        129.0266     73.196      1.763      0.078     -14.456     272.509
wd[ENE]      126.6956     73.210      1.731      0.084     -16.813     270.205
wd[ESE]      130.0437     73.218      1.776      0.076     -13.480     273.567
```

```
wd[N]        128.8913     73.091      1.763      0.078     -14.383     272.166
wd[NE]       126.2672     73.220      1.724      0.085     -17.261     269.795
wd[NNE]      125.8975     73.210      1.720      0.086     -17.611     269.406
wd[NNW]      130.6003     73.058      1.788      0.074     -12.611     273.812
wd[NW]       130.3976     73.038      1.785      0.074     -12.774     273.569
wd[S]        135.3386     73.258      1.847      0.065      -8.264     278.941
wd[SE]       126.1088     73.274      1.721      0.085     -17.526     269.743
wd[SSE]      131.5698     73.259      1.796      0.073     -12.036     275.175
wd[SSW]      128.0607     73.266      1.748      0.081     -15.557     271.678
wd[SW]       126.8510     73.246      1.732      0.083     -16.729     270.431
wd[W]        122.7775     73.024      1.681      0.093     -20.366     265.921
wd[WNW]      127.8272     73.036      1.750      0.080     -15.341     270.996
wd[WSW]      127.9237     73.221      1.747      0.081     -15.607     271.454
SO2           -0.3344      0.022    -15.367      0.000      -0.377      -0.292
NO2            0.5656      0.024     23.658      0.000       0.519       0.612
CO             0.0720      0.001     75.175      0.000       0.070       0.074
O3             0.2036      0.011     18.953      0.000       0.183       0.225
TEMP          -0.8363      0.090     -9.333      0.000      -1.012      -0.661
PRES          -0.1417      0.072     -1.960      0.050      -0.283   -1.37e-05
DEWP           0.9342      0.064     14.688      0.000       0.810       1.059
RAIN          -9.4035      1.652     -5.692      0.000     -12.642      -6.165
WSPM           2.8116      0.351      8.011      0.000       2.124       3.500
==============================================================================
Omnibus:                     2522.987   Durbin-Watson:                   0.261
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            13196.022
Skew:                           1.277   Prob(JB):                         0.00
Kurtosis:                       8.416   Cond. No.                     1.05e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.05e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[81]:
```
print(oslm_hr_su) #Huairou, Summer
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.572
Model:                            OLS   Adj. R-squared:                  0.571
Method:                 Least Squares   F-statistic:                     490.0
Date:                Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                        16:44:44   Log-Likelihood:                -43256.
No. Observations:                8832   AIC:                         8.656e+04
Df Residuals:                    8807   BIC:                         8.674e+04
Df Model:                          24
Covariance Type:            nonrobust
```

```
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]       -573.1346     90.606     -6.326      0.000    -750.744    -395.525
wd[ENE]     -576.6378     90.569     -6.367      0.000    -754.173    -399.102
wd[ESE]     -567.5306     90.592     -6.265      0.000    -745.112    -389.949
wd[N]       -573.0652     90.505     -6.332      0.000    -750.477    -395.654
wd[NE]      -573.3625     90.515     -6.334      0.000    -750.794    -395.931
wd[NNE]     -571.0008     90.518     -6.308      0.000    -748.437    -393.565
wd[NNW]     -570.1082     90.522     -6.298      0.000    -747.552    -392.664
wd[NW]      -570.9814     90.525     -6.307      0.000    -748.432    -393.530
wd[S]       -570.5019     90.567     -6.299      0.000    -748.033    -392.970
wd[SE]      -569.7701     90.599     -6.289      0.000    -747.365    -392.175
wd[SSE]     -569.2349     90.627     -6.281      0.000    -746.885    -391.585
wd[SSW]     -574.8927     90.574     -6.347      0.000    -752.440    -397.346
wd[SW]      -571.0519     90.595     -6.303      0.000    -748.640    -393.464
wd[W]       -570.0266     90.509     -6.298      0.000    -747.446    -392.607
wd[WNW]     -570.4944     90.516     -6.303      0.000    -747.927    -393.062
wd[WSW]     -573.9039     90.574     -6.336      0.000    -751.450    -396.358
SO2            0.5510      0.062      8.836      0.000       0.429       0.673
NO2            1.0679      0.033     32.249      0.000       1.003       1.133
CO             0.0350      0.001     48.004      0.000       0.034       0.036
O3             0.1289      0.007     19.382      0.000       0.116       0.142
TEMP           0.4559      0.105      4.328      0.000       0.249       0.662
PRES           0.4866      0.090      5.407      0.000       0.310       0.663
DEWP           3.6824      0.093     39.668      0.000       3.500       3.864
RAIN          -0.0971      0.226     -0.430      0.667      -0.540       0.346
WSPM           1.3160      0.463      2.839      0.005       0.407       2.224
==============================================================================
Omnibus:                     1516.246   Durbin-Watson:                   0.220
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            17867.951
Skew:                           0.463   Prob(JB):                         0.00
Kurtosis:                       9.906   Cond. No.                     1.40e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.4e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

[82]:
```
print(oslm_hr_fa) #Huairou, Fall
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                  PM2_5   R-squared:                       0.721
Model:                            OLS   Adj. R-squared:                  0.721
Method:                 Least Squares   F-statistic:                     939.3
```

Date:	Sun, 01 Dec 2019	Prob (F-statistic):	0.00
Time:	16:44:44	Log-Likelihood:	-43973.
No. Observations:	8736	AIC:	8.800e+04
Df Residuals:	8711	BIC:	8.817e+04
Df Model:	24		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
wd[E]	-34.8686	85.399	-0.408	0.683	-202.270	132.533
wd[ENE]	-37.5080	85.392	-0.439	0.660	-204.896	129.880
wd[ESE]	-36.1101	85.389	-0.423	0.672	-203.492	131.272
wd[N]	-37.7788	85.278	-0.443	0.658	-204.944	129.387
wd[NE]	-38.6199	85.362	-0.452	0.651	-205.950	128.710
wd[NNE]	-43.0521	85.352	-0.504	0.614	-210.361	124.257
wd[NNW]	-37.3490	85.229	-0.438	0.661	-204.418	129.720
wd[NW]	-34.3445	85.191	-0.403	0.687	-201.338	132.649
wd[S]	-32.5946	85.414	-0.382	0.703	-200.026	134.837
wd[SE]	-34.1615	85.340	-0.400	0.689	-201.448	133.125
wd[SSE]	-32.2889	85.388	-0.378	0.705	-199.669	135.091
wd[SSW]	-37.9503	85.406	-0.444	0.657	-205.367	129.466
wd[SW]	-41.9034	85.408	-0.491	0.624	-209.323	125.516
wd[W]	-42.2276	85.262	-0.495	0.620	-209.360	124.905
wd[WNW]	-36.5943	85.202	-0.430	0.668	-203.609	130.421
wd[WSW]	-41.9390	85.305	-0.492	0.623	-209.156	125.278
SO2	-0.3544	0.040	-8.952	0.000	-0.432	-0.277
NO2	0.4479	0.024	18.481	0.000	0.400	0.495
CO	0.0689	0.001	80.395	0.000	0.067	0.071
O3	0.3657	0.012	29.919	0.000	0.342	0.390
TEMP	-0.4836	0.110	-4.406	0.000	-0.699	-0.268
PRES	0.0102	0.084	0.121	0.904	-0.154	0.175
DEWP	1.1429	0.082	14.002	0.000	0.983	1.303
RAIN	-5.7587	0.773	-7.448	0.000	-7.274	-4.243
WSPM	1.0931	0.501	2.181	0.029	0.111	2.076

Omnibus:	1571.589	Durbin-Watson:	0.161
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5584.176
Skew:	0.884	Prob(JB):	0.00
Kurtosis:	6.495	Cond. No.	1.31e+06

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.31e+06. This might indicate that there are strong multicollinearity or other numerical problems.

[83]:
```
print(oslm_hr_win) #Huairou, Winter
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                   PM2_5   R-squared:                       0.807
Model:                             OLS   Adj. R-squared:                  0.807
Method:                  Least Squares   F-statistic:                     1509.
Date:                 Sun, 01 Dec 2019   Prob (F-statistic):               0.00
Time:                         16:44:44   Log-Likelihood:                -44243.
No. Observations:                8664   AIC:                          8.854e+04
Df Residuals:                    8639   BIC:                          8.871e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
wd[E]        380.7466     84.117      4.526      0.000     215.857     545.636
wd[ENE]      381.2561     84.109      4.533      0.000     216.383     546.129
wd[ESE]      380.0389     84.133      4.517      0.000     215.119     544.959
wd[N]        381.0549     83.953      4.539      0.000     216.487     545.623
wd[NE]       379.3524     84.067      4.512      0.000     214.561     544.144
wd[NNE]      378.9294     84.022      4.510      0.000     214.225     543.633
wd[NNW]      378.5245     83.936      4.510      0.000     213.990     543.059
wd[NW]       380.6863     83.951      4.535      0.000     216.122     545.250
wd[S]        377.0736     84.068      4.485      0.000     212.280     541.867
wd[SE]       381.7712     84.054      4.542      0.000     217.005     546.537
wd[SSE]      381.6229     84.036      4.541      0.000     216.892     546.354
wd[SSW]      377.1910     84.046      4.488      0.000     212.440     541.942
wd[SW]       380.1976     84.071      4.522      0.000     215.399     544.996
wd[W]        378.4758     83.850      4.514      0.000     214.109     542.843
wd[WNW]      378.3137     83.870      4.511      0.000     213.908     542.720
wd[WSW]      379.9792     83.981      4.525      0.000     215.355     544.603
SO2            0.4084      0.020     20.402      0.000       0.369       0.448
NO2            0.4926      0.032     15.623      0.000       0.431       0.554
CO             0.0446      0.001     72.117      0.000       0.043       0.046
O3             0.4937      0.027     18.146      0.000       0.440       0.547
TEMP          -1.3454      0.140     -9.585      0.000      -1.621      -1.070
PRES          -0.3629      0.083     -4.383      0.000      -0.525      -0.201
DEWP           3.4817      0.110     31.691      0.000       3.266       3.697
RAIN          -8.4048      5.596     -1.502      0.133     -19.374       2.564
WSPM           3.5854      0.438      8.177      0.000       2.726       4.445
==============================================================================
Omnibus:                     5946.504   Durbin-Watson:                   0.276
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           226630.327
Skew:                           2.797   Prob(JB):                         0.00
Kurtosis:                      27.423   Cond. No.                     1.63e+06
==============================================================================
```

```
Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The condition number is large, 1.63e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

From the OLS Regression Results of Huairou we can see that winter has highest R-squared which is 0.807, summer has lowest – 0.572

For spring of Huairou, the p values of wd are large than 0.05, so wd is not significant. SO2, Temp, pres and Rain have negative coefficients.

For summer of Huairou, Rain is not significant because p value is large than 0.05. wd has large negative coefficient.

For Fall of Huairou, wd and pres are not significant because p values are large than 0.05. SO2,Temp,Rain have negative coefficients.

For winter of Huairou, Rain is not significant because p value is large than 0.05,wd has large positive coefficient. Temp and pres have negative coefficients. –Mary

For all the three different Districts in Beijing, R-squared shows seasonal trend matches PM2.5 trend which is high in winter and low in summer.

5.3 Gradient Boosting (GBM)

Next, we will try Gradient Boosting (GBM) and see which variables are more important for prediction of `PM2.5`.

[84]:
```
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import classification_report
from sklearn.model_selection import learning_curve, GridSearchCV
```

This is how we tune the parameters which we will be using in the below `GradientBoostingRegressor`.

(We will just use Changping's Spring data for fast tuning)

First, we tune `learning_rate` and `n_estimators`:

```
p_test1 = {'learning_rate': [0.01, 0.03, 0.05, 0.1], 'n_estimators':[10000,30000, 50000]}

tuning = GridSearchCV(estimator=GradientBoostingRegressor(max_depth=4, min_samples_split=2, mi
tuning.fit(X_train_spr, y_train_spr)
tuning.best_params_, tuning.best_score_
```

CV gives us the best parameters `learning_rate=0.01` and `n_estimators=10000`.

Next, we tune `max_depth`:

```
p_test2 = {'max_depth':[2,4,6,8,10,12] }
tuning = GridSearchCV(estimator=GradientBoostingRegressor(learning_rate=0.01, n_estimators=100
```

```
tuning.fit(X_train_spr, y_train_spr)
tuning.best_params_, tuning.best_score_
```

CV gives us the best parameters `max_depth=10`.

Then, we tune `min_samples_split` and `min_samples_leaf`:

```
p_test3 = {'min_samples_split':[2,4,6,8], 'min_samples_leaf':[1,3,5,7]}
tuning = GridSearchCV(estimator=GradientBoostingRegressor(learning_rate=0.01, n_estimators=1000
tuning.fit(X_train_spr, y_train_spr)
tuning.best_params_, tuning.best_score_
```

CV gives us the best parameters `min_samples_split=2` and `min_samples_leaf=5` and yields $R^2 = 0.8319670932863257$.

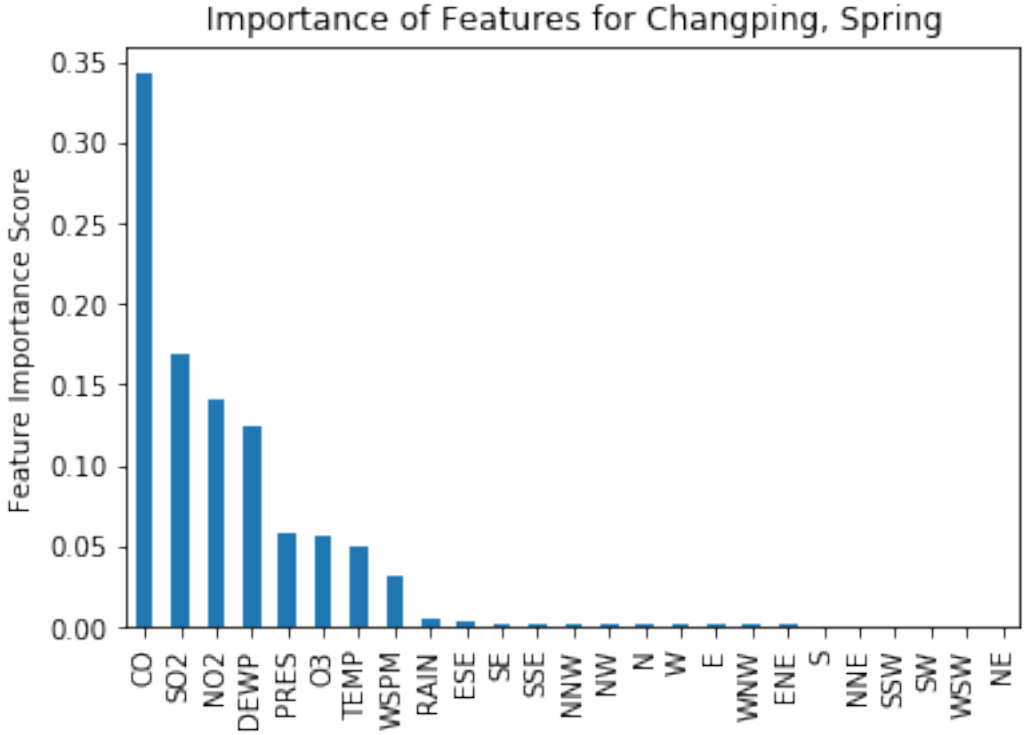
5.4 Now we fit `gbm` to the four seasons of Changping.

5.5 (Do not run these if your computer is slow, just look the outputs)

[85]:
```
# For Changping, Spring
X_train_spr, X_test_spr, y_train_spr, y_test_spr = train_test_split(
    spring.loc['Changping'].iloc[:,6:31], # note we are excluding PM10
    spring.loc['Changping'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_spr = y_train_spr.ravel()
y_test_spr = y_test_spr.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_spr, y_train_spr)
predictors=list(X_train_spr)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Changping, Spring')
plt.ylabel('Feature Importance Score')
chp_spr_r2 = model_gbm.score(X_test_spr, y_test_spr)
print(chp_spr_r2) #the r^2 for this model
chp_spr_fi = feat_imp
print(chp_spr_fi) #the important features
```

```
0.8356382495931237
CO      0.342932
```

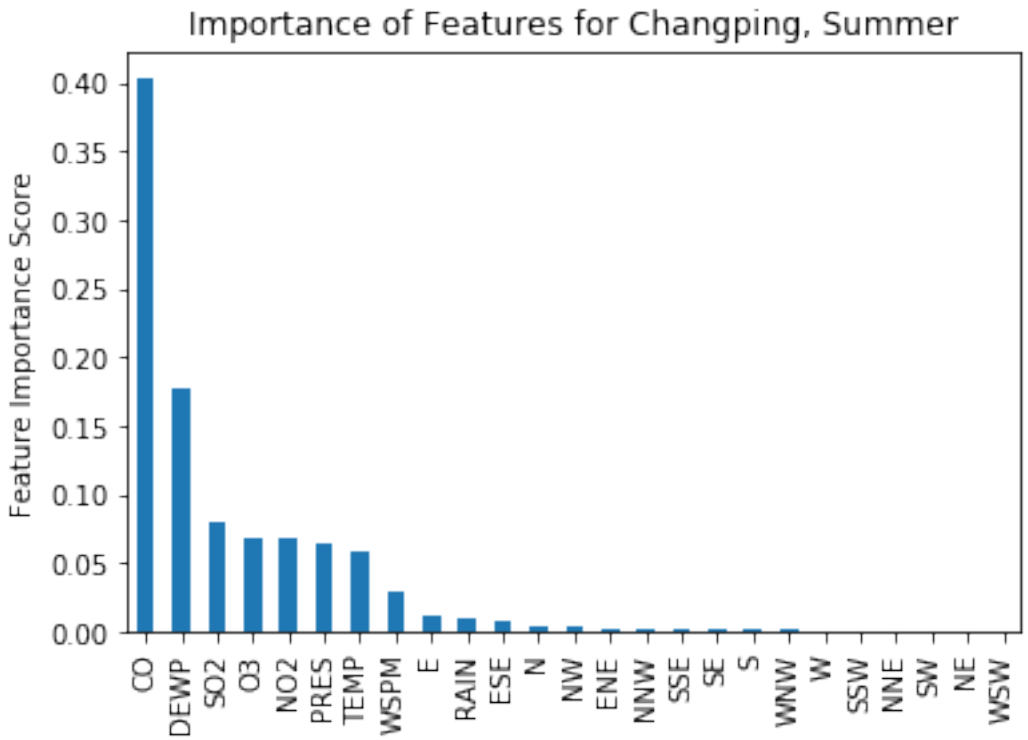
```
SO2     0.169576
NO2     0.141631
DEWP    0.124994
PRES    0.058868
O3      0.055629
TEMP    0.050499
WSPM    0.031245
RAIN    0.005717
ESE     0.003134
SE      0.001887
SSE     0.001587
NNW     0.001583
NW      0.001575
N       0.001475
W       0.001370
E       0.001207
WNW     0.001187
ENE     0.001118
S       0.000861
NNE     0.000546
SSW     0.000472
SW      0.000375
WSW     0.000276
NE      0.000255
dtype: float64
```



[86]:
```
# For Changping, Summer
X_train_su, X_test_su, y_train_su, y_test_su = train_test_split(
    summer.loc['Changping'].iloc[:,6:31], # note we are excluding PM10
    summer.loc['Changping'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_su = y_train_su.ravel()
y_test_su = y_test_su.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_su, y_train_su)
predictors=list(X_train_su)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Changping, Summer')
plt.ylabel('Feature Importance Score')
chp_su_r2 = model_gbm.score(X_test_su, y_test_su)
print(chp_su_r2) #Returns the coefficient of determination R^2 of the prediction
chp_su_fi = feat_imp
print(chp_su_fi) #the important features
```

```
0.7296657729263121
CO      0.403060
DEWP    0.176940
SO2     0.079329
O3      0.068478
NO2     0.067753
PRES    0.064887
TEMP    0.057983
WSPM    0.029687
E       0.011991
RAIN    0.009001
ESE     0.008112
N       0.003573
NW      0.003286
ENE     0.002893
NNW     0.002409
SSE     0.002147
SE      0.002037
```

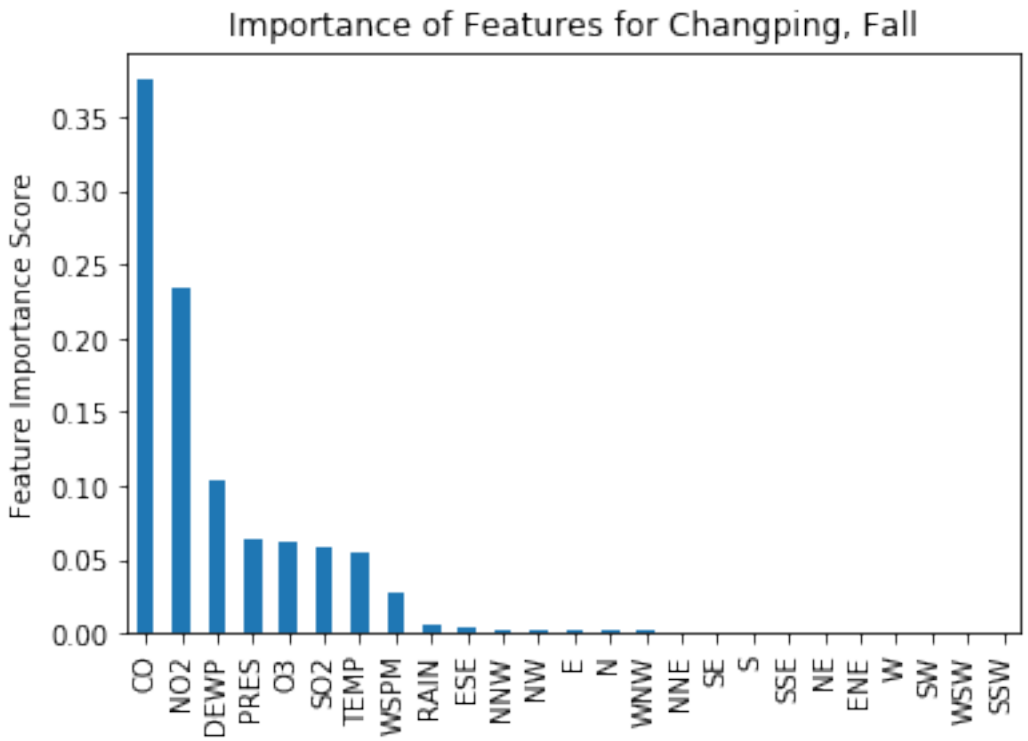
```
S       0.001364
WNW     0.001251
W       0.000806
SSW     0.000745
NNE     0.000728
SW      0.000699
NE      0.000585
WSW     0.000256
dtype: float64
```



[87]:
```
# For Changping, Fall
X_train_fa, X_test_fa, y_train_fa, y_test_fa = train_test_split(
    fall.loc['Changping'].iloc[:,6:31], # note we are excluding PM10
    fall.loc['Changping'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_fa = y_train_fa.ravel()
y_test_fa = y_test_fa.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
```

```
                                    subsample=1,
                                    max_features=6,
                                    random_state=1)
model_gbm.fit(X_train_fa, y_train_fa)
predictors=list(X_train_fa)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Changping, Fall')
plt.ylabel('Feature Importance Score')
chp_fa_r2 = model_gbm.score(X_test_fa, y_test_fa)
print(chp_fa_r2) #the r^2 for this model
chp_fa_fi = feat_imp
print(chp_fa_fi) #the important features
```

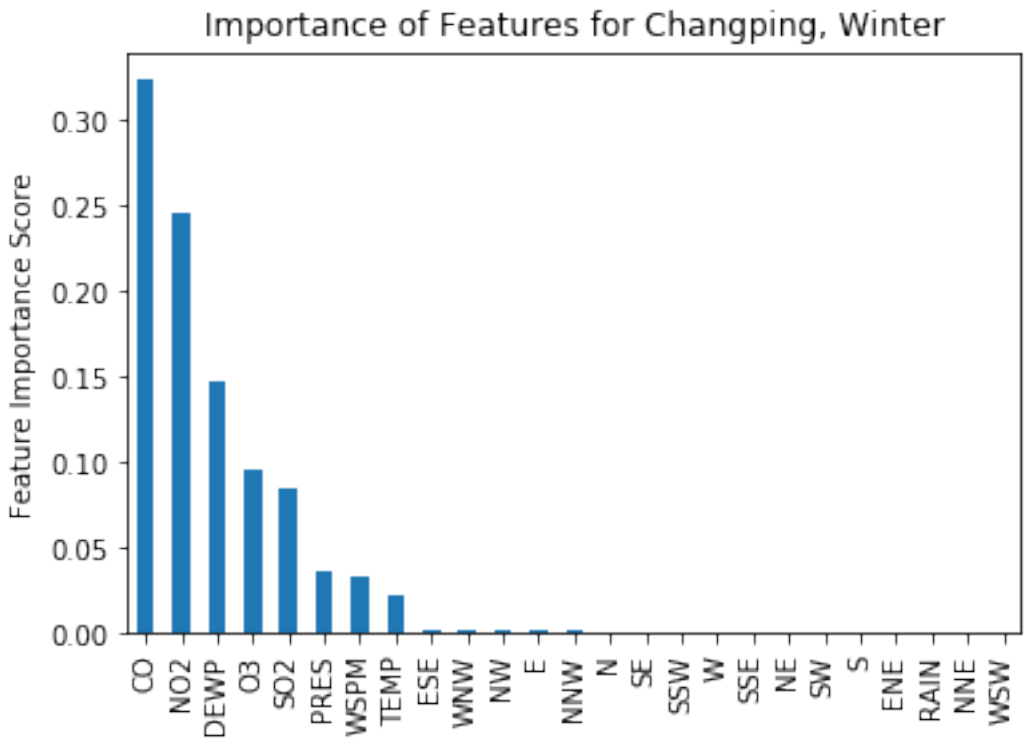
```
0.8698495599666035
CO      0.376069
NO2     0.233673
DEWP    0.103364
PRES    0.064454
O3      0.061389
SO2     0.058206
TEMP    0.054540
WSPM    0.026512
RAIN    0.005210
ESE     0.003166
NNW     0.002466
NW      0.001786
E       0.001638
N       0.001572
WNW     0.001018
NNE     0.000949
SE      0.000793
S       0.000623
SSE     0.000620
NE      0.000608
ENE     0.000510
W       0.000320
SW      0.000212
WSW     0.000162
SSW     0.000141
dtype: float64
```



[88]:
```
# For Changping, Winter
X_train_win, X_test_win, y_train_win, y_test_win = train_test_split(
    winter.loc['Changping'].iloc[:,6:31], # note we are excluding PM10
    winter.loc['Changping'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_win = y_train_win.ravel()
y_test_win = y_test_win.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_win, y_train_win)
predictors=list(X_train_win)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Changping, Winter')
plt.ylabel('Feature Importance Score')
chp_win_r2 = model_gbm.score(X_test_win, y_test_win)
```

```
print(chp_win_r2) #the r^2 for this model
chp_win_fi = feat_imp
print(chp_win_fi) #the important features
```

```
0.9290354862393014
CO      0.323404
NO2     0.244727
DEWP    0.146943
O3      0.095979
SO2     0.084781
PRES    0.036446
WSPM    0.033647
TEMP    0.021542
ESE     0.002189
WNW     0.001933
NW      0.001318
E       0.001169
NNW     0.000900
N       0.000795
SE      0.000567
SSW     0.000534
W       0.000482
SSE     0.000450
NE      0.000394
SW      0.000387
S       0.000365
ENE     0.000331
RAIN    0.000289
NNE     0.000222
WSW     0.000204
dtype: float64
```

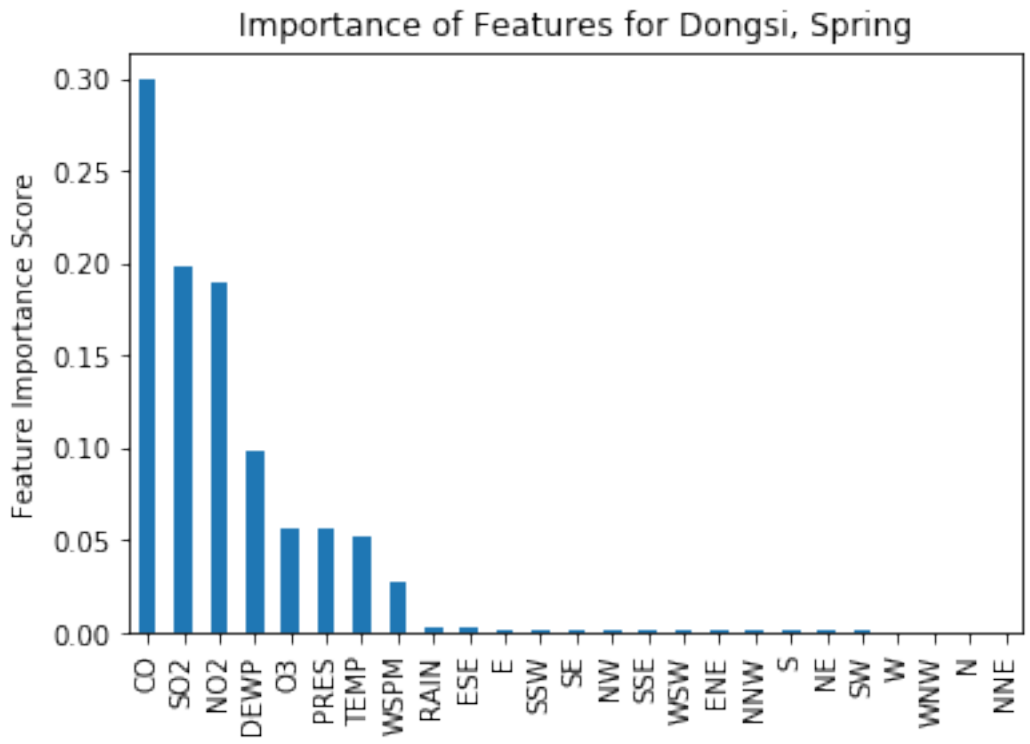


5.6 gbm for the four seasons of Dongsi.

[89]:
```
# For Dongsi, Spring
X_train_spr, X_test_spr, y_train_spr, y_test_spr = train_test_split(
    spring.loc['Dongsi'].iloc[:,6:31], # note we are excluding PM10
    spring.loc['Dongsi'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_spr = y_train_spr.ravel()
y_test_spr = y_test_spr.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_spr, y_train_spr)
predictors=list(X_train_spr)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
```

```
feat_imp.plot(kind='bar', title='Importance of Features for Dongsi, Spring')
plt.ylabel('Feature Importance Score')
ds_spr_r2 = model_gbm.score(X_test_spr, y_test_spr)
print(ds_spr_r2) #the r^2 for this model
ds_spr_fi = feat_imp
print(ds_spr_fi) #the important features
```

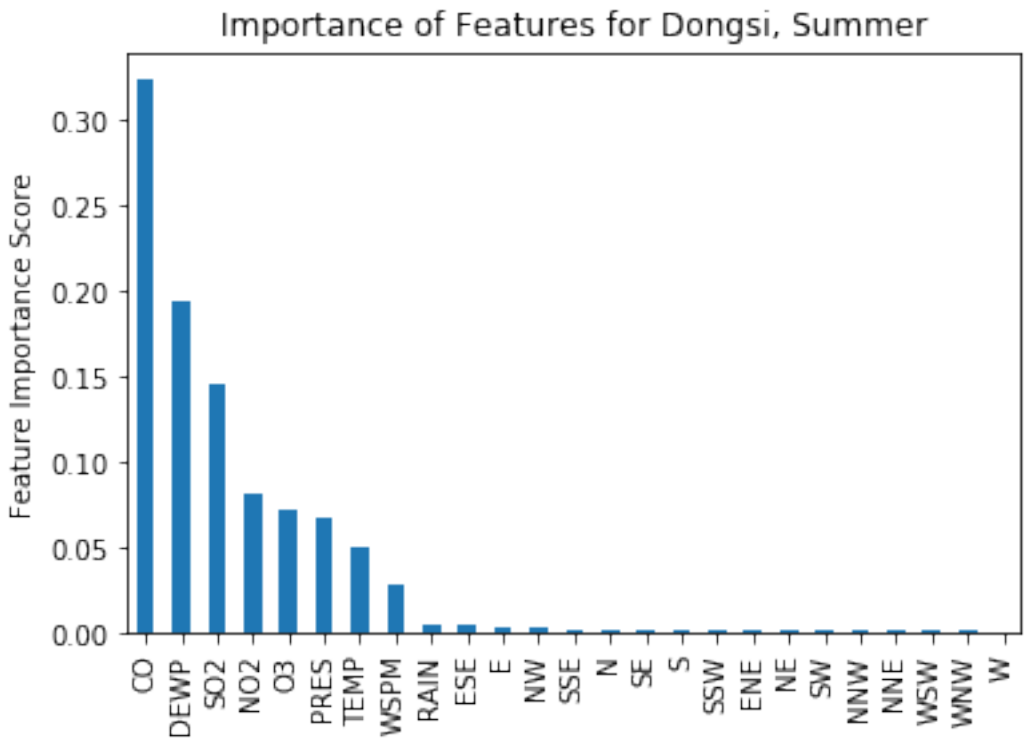
```
0.8123344400670982
CO      0.299399
SO2     0.198033
NO2     0.189554
DEWP    0.097775
O3      0.057138
PRES    0.056336
TEMP    0.051456
WSPM    0.026874
RAIN    0.002484
ESE     0.002260
E       0.002084
SSW     0.001867
SE      0.001657
NW      0.001510
SSE     0.001427
WSW     0.001321
ENE     0.001280
NNW     0.001274
S       0.001220
NE      0.001165
SW      0.001104
W       0.000794
WNW     0.000757
N       0.000739
NNE     0.000491
dtype: float64
```



[90]:
```
# For Dongsi, Summer
X_train_su, X_test_su, y_train_su, y_test_su = train_test_split(
    summer.loc['Dongsi'].iloc[:,6:31], # note we are excluding PM10
    summer.loc['Dongsi'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_su = y_train_su.ravel()
y_test_su = y_test_su.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_su, y_train_su)
predictors=list(X_train_su)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Dongsi, Summer')
plt.ylabel('Feature Importance Score')
ds_su_r2 = model_gbm.score(X_test_su, y_test_su)
```

```
print(ds_su_r2) #Returns the coefficient of determination R^2 of the prediction
ds_su_fi = feat_imp
print(ds_su_fi) #the important features
```

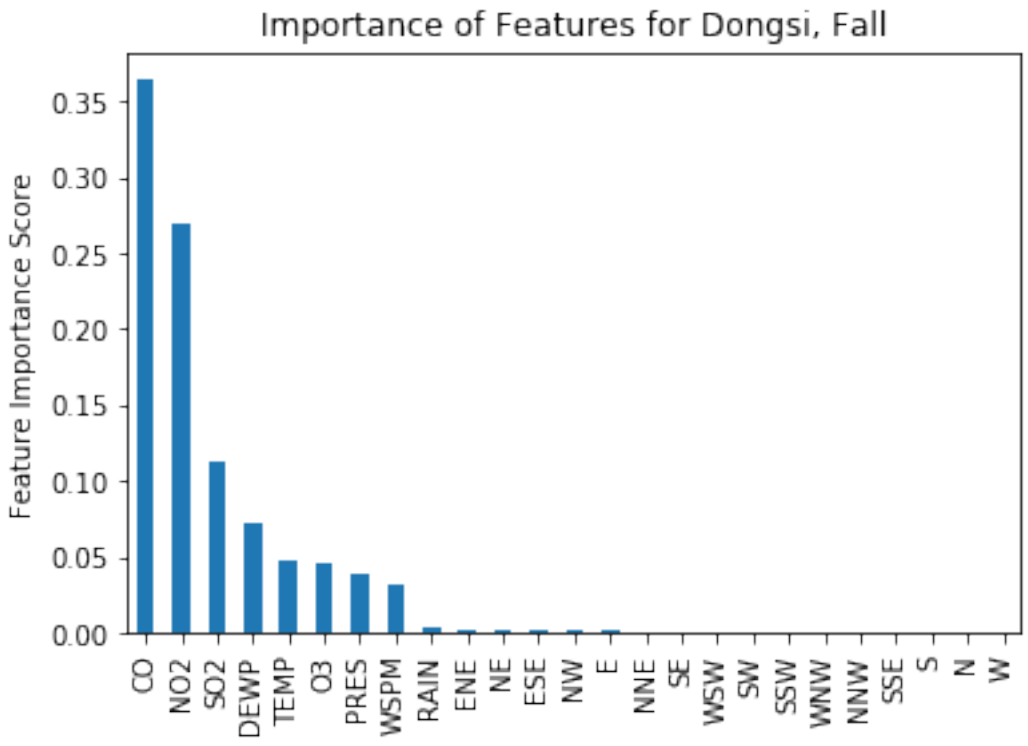
```
0.7821090171008895
CO      0.323429
DEWP    0.194471
SO2     0.144842
NO2     0.080873
O3      0.072262
PRES    0.067790
TEMP    0.050713
WSPM    0.028919
RAIN    0.005309
ESE     0.004728
E       0.002632
NW      0.002559
SSE     0.002400
N       0.002269
SE      0.002255
S       0.002006
SSW     0.001940
ENE     0.001919
NE      0.001758
SW      0.001667
NNW     0.001592
NNE     0.001218
WSW     0.001098
WNW     0.000942
W       0.000408
dtype: float64
```



[91]:
```
# For Dongsi, Fall
X_train_fa, X_test_fa, y_train_fa, y_test_fa = train_test_split(
    fall.loc['Dongsi'].iloc[:,6:31], # note we are excluding PM10
    fall.loc['Dongsi'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_fa = y_train_fa.ravel()
y_test_fa = y_test_fa.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_fa, y_train_fa)
predictors=list(X_train_fa)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Dongsi, Fall')
plt.ylabel('Feature Importance Score')
ds_fa_r2 = model_gbm.score(X_test_fa, y_test_fa)
```

```
print(ds_fa_r2) #the r^2 for this model
ds_fa_fi = feat_imp
print(ds_fa_fi) #the important features
```

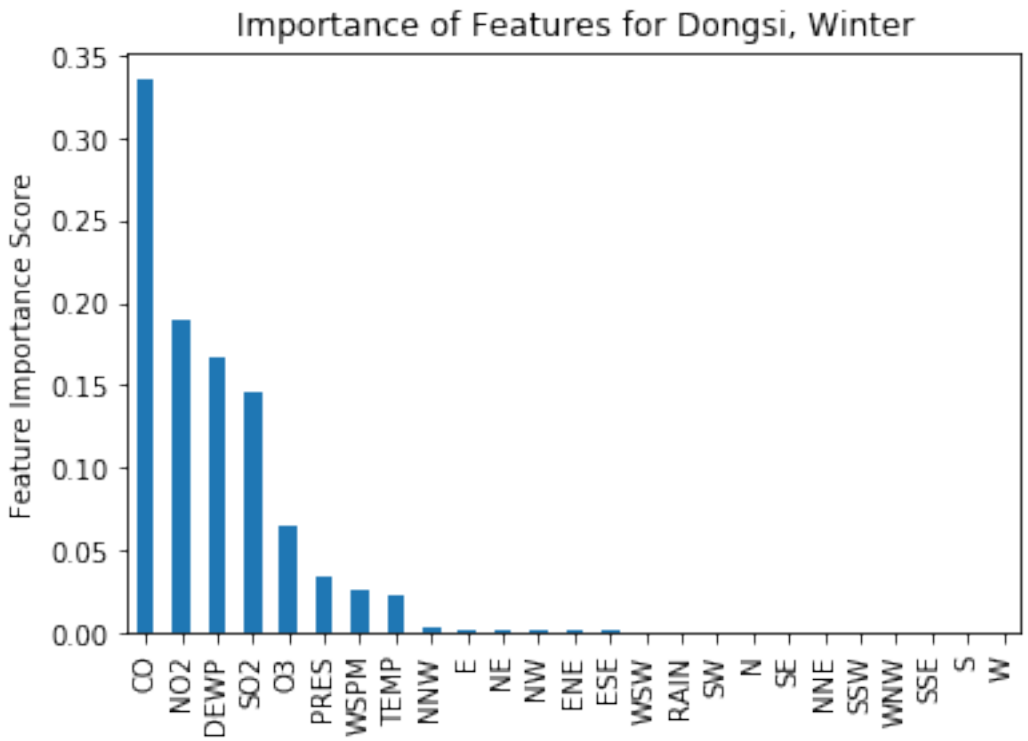
```
0.8998711646663512
CO      0.364385
NO2     0.269789
SO2     0.112006
DEWP    0.072272
TEMP    0.046876
O3      0.046429
PRES    0.038965
WSPM    0.032255
RAIN    0.003401
ENE     0.002138
NE      0.001335
ESE     0.001258
NW      0.001253
E       0.001050
NNE     0.000857
SE      0.000801
WSW     0.000654
SW      0.000641
SSW     0.000637
WNW     0.000627
NNW     0.000548
SSE     0.000526
S       0.000523
N       0.000487
W       0.000286
dtype: float64
```



[92]:
```
# For Changping, Winter
X_train_win, X_test_win, y_train_win, y_test_win = train_test_split(
    winter.loc['Dongsi'].iloc[:,6:31], # note we are excluding PM10
    winter.loc['Dongsi'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_win = y_train_win.ravel()
y_test_win = y_test_win.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_win, y_train_win)
predictors=list(X_train_win)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Dongsi, Winter')
plt.ylabel('Feature Importance Score')
ds_win_r2 = model_gbm.score(X_test_win, y_test_win)
```

```
print(ds_win_r2) #the r^2 for this model
ds_win_fi = feat_imp
print(ds_win_fi) #the important features
```

```
0.9334932026034085
CO      0.335619
NO2     0.189560
DEWP    0.167504
SO2     0.145605
O3      0.064303
PRES    0.033889
WSPM    0.025810
TEMP    0.022414
NNW     0.002527
E       0.002324
NE      0.001815
NW      0.001764
ENE     0.001010
ESE     0.000894
WSW     0.000813
RAIN    0.000811
SW      0.000642
N       0.000589
SE      0.000519
NNE     0.000317
SSW     0.000300
WNW     0.000294
SSE     0.000253
S       0.000233
W       0.000193
dtype: float64
```

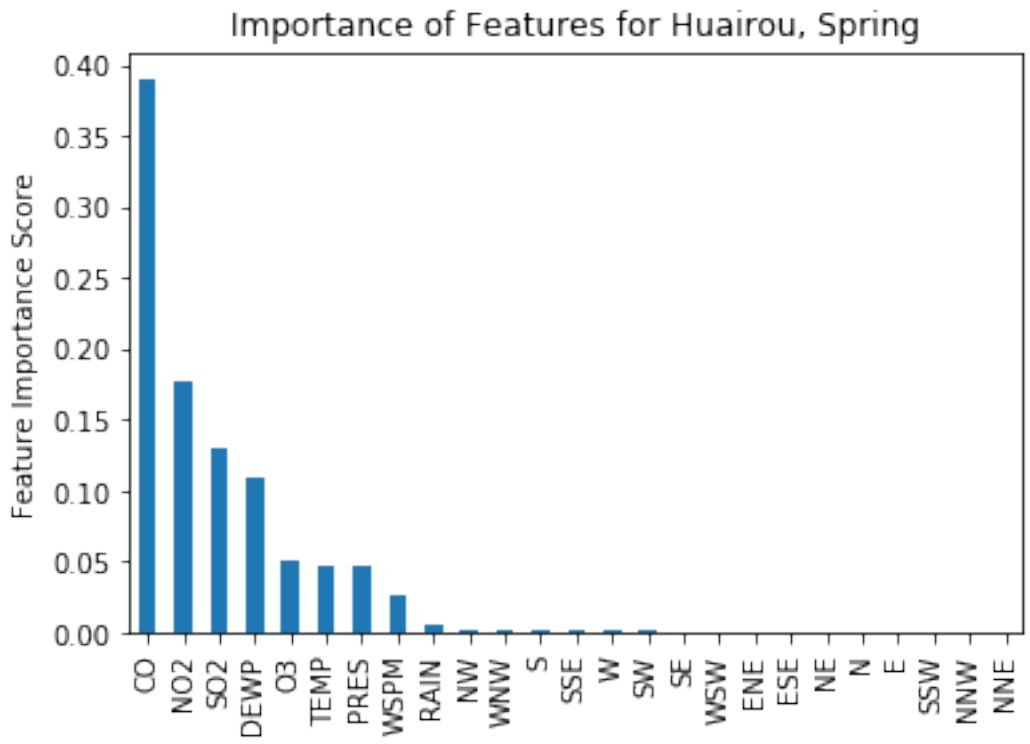


5.7 gbm for the four seasons of Huairou

[93]:
```
# For Huairou, Spring
X_train_spr, X_test_spr, y_train_spr, y_test_spr = train_test_split(
    spring.loc['Huairou'].iloc[:,6:31], # note we are excluding PM10
    spring.loc['Huairou'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_spr = y_train_spr.ravel()
y_test_spr = y_test_spr.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_spr, y_train_spr)
predictors=list(X_train_spr)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
```

```
feat_imp.plot(kind='bar', title='Importance of Features for Huairou, Spring')
plt.ylabel('Feature Importance Score')
hr_spr_r2 = model_gbm.score(X_test_spr, y_test_spr)
print(hr_spr_r2) #the r^2 for this model
hr_spr_fi = feat_imp
print(hr_spr_fi) #the important features
```

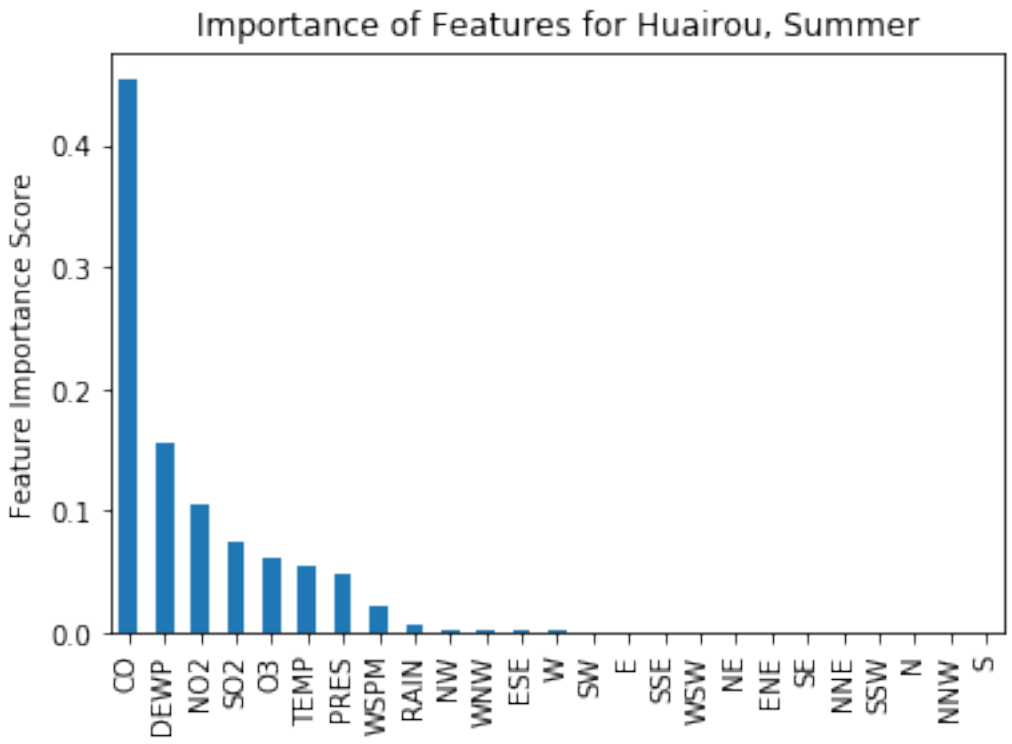
```
0.8697931780904341
CO      0.389787
NO2     0.177129
SO2     0.129496
DEWP    0.110126
O3      0.051441
TEMP    0.047437
PRES    0.047387
WSPM    0.025537
RAIN    0.005679
NW      0.002219
WNW     0.001960
S       0.001487
SSE     0.001483
W       0.001418
SW      0.001162
SE      0.000958
WSW     0.000862
ENE     0.000752
ESE     0.000657
NE      0.000534
N       0.000520
E       0.000518
SSW     0.000503
NNW     0.000489
NNE     0.000459
dtype: float64
```



[94]:
```
# For Huairou, Summer
X_train_su, X_test_su, y_train_su, y_test_su = train_test_split(
    summer.loc['Huairou'].iloc[:,6:31], # note we are excluding PM10
    summer.loc['Huairou'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_su = y_train_su.ravel()
y_test_su = y_test_su.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_su, y_train_su)
predictors=list(X_train_su)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Huairou, Summer')
plt.ylabel('Feature Importance Score')
hr_su_r2 = model_gbm.score(X_test_su, y_test_su)
```

```
print(hr_su_r2) #Returns the coefficient of determination R^2 of the prediction
hr_su_fi = feat_imp
print(hr_su_fi) #the important features
```

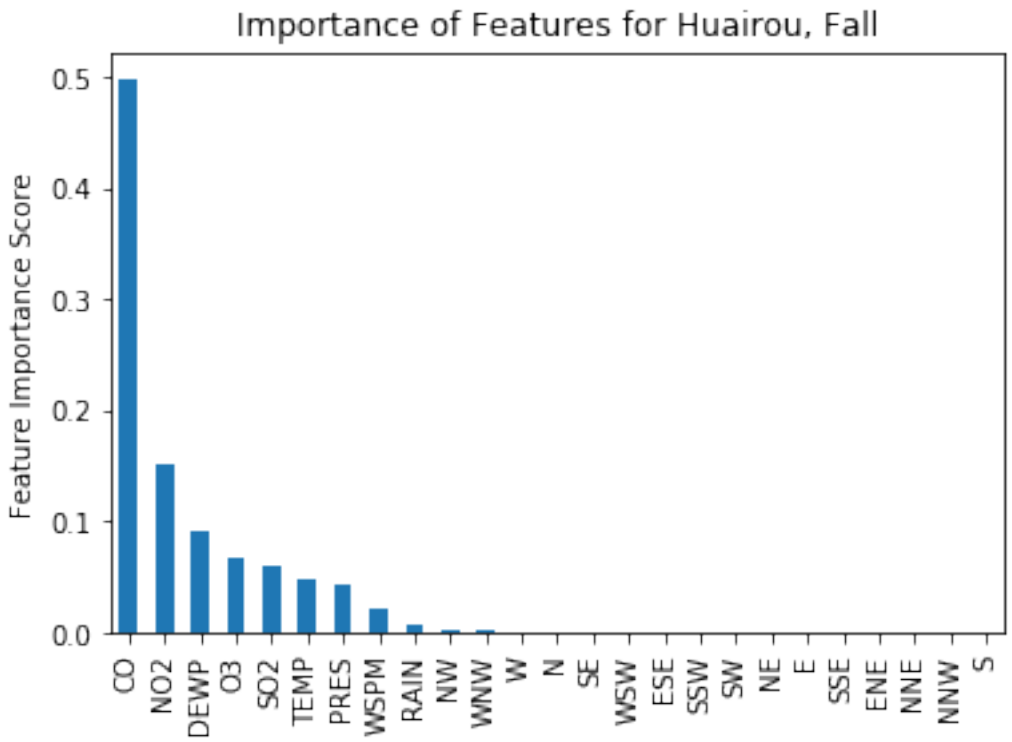
```
0.83138452872731
CO      0.454590
DEWP    0.155472
NO2     0.106226
SO2     0.073735
O3      0.061385
TEMP    0.055826
PRES    0.048138
WSPM    0.022382
RAIN    0.005660
NW      0.001848
WNW     0.001820
ESE     0.001404
W       0.001284
SW      0.001173
E       0.001154
SSE     0.001121
WSW     0.001017
NE      0.001017
ENE     0.000939
SE      0.000905
NNE     0.000721
SSW     0.000600
N       0.000579
NNW     0.000502
S       0.000502
dtype: float64
```



[95]:
```
# For Huairou, Fall
X_train_fa, X_test_fa, y_train_fa, y_test_fa = train_test_split(
    fall.loc['Huairou'].iloc[:,6:31], # note we are excluding PM10
    fall.loc['Huairou'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_fa = y_train_fa.ravel()
y_test_fa = y_test_fa.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_fa, y_train_fa)
predictors=list(X_train_fa)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Huairou, Fall')
plt.ylabel('Feature Importance Score')
hr_fa_r2 = model_gbm.score(X_test_fa, y_test_fa)
```

```
print(hr_fa_r2) #the r^2 for this model
hr_fa_fi = feat_imp
print(hr_fa_fi) #the important features
```

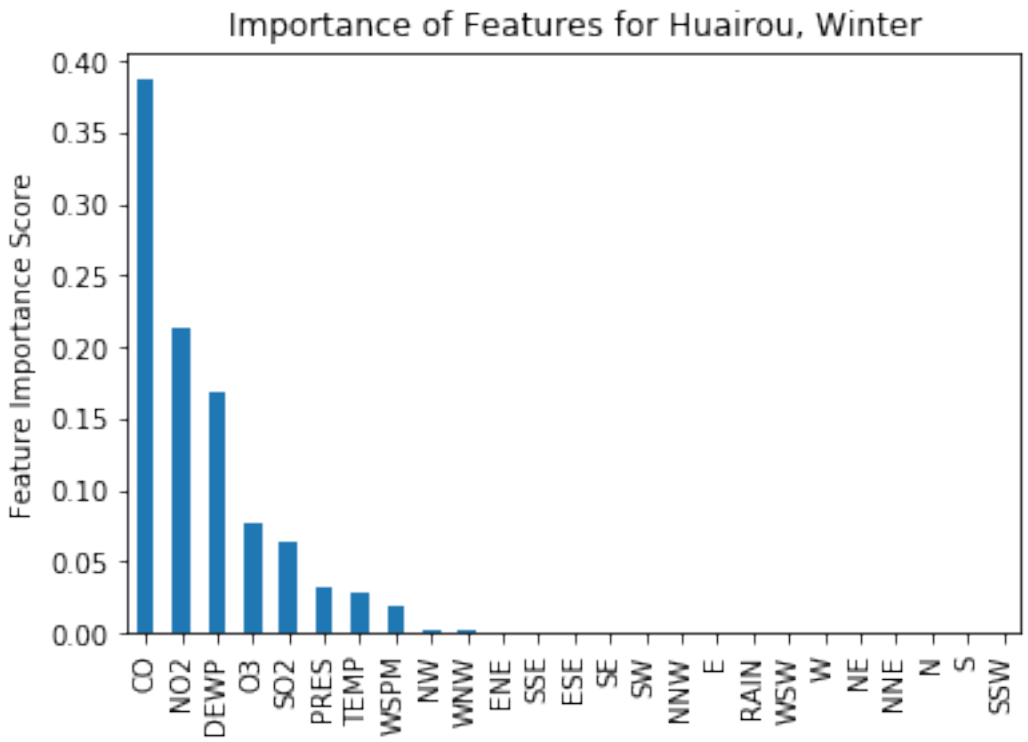
```
0.8999178580559711
CO      0.497652
NO2     0.151782
DEWP    0.091043
O3      0.067523
SO2     0.061147
TEMP    0.047748
PRES    0.042736
WSPM    0.021302
RAIN    0.006184
NW      0.002616
WNW     0.001871
W       0.001156
N       0.000865
SE      0.000837
WSW     0.000657
ESE     0.000604
SSW     0.000589
SW      0.000550
NE      0.000528
E       0.000524
SSE     0.000469
ENE     0.000455
NNE     0.000399
NNW     0.000395
S       0.000367
dtype: float64
```



[96]:
```
# For Huairou, Winter
X_train_win, X_test_win, y_train_win, y_test_win = train_test_split(
    winter.loc['Huairou'].iloc[:,6:31], # note we are excluding PM10
    winter.loc['Huairou'].iloc[:,4], # 4th column is PM2.5
    test_size = 1/3,
    random_state=1)
y_train_win = y_train_win.ravel()
y_test_win = y_test_win.ravel()
model_gbm = GradientBoostingRegressor(learning_rate=0.01,
                                      n_estimators=10000,
                                      max_depth=10,
                                      min_samples_split=2,
                                      min_samples_leaf=5,
                                      subsample=1,
                                      max_features=6,
                                      random_state=1)
model_gbm.fit(X_train_win, y_train_win)
predictors=list(X_train_win)
feat_imp = pd.Series(model_gbm.feature_importances_, predictors).
 ↪sort_values(ascending=False)
feat_imp.plot(kind='bar', title='Importance of Features for Huairou, Winter')
plt.ylabel('Feature Importance Score')
hr_win_r2 = model_gbm.score(X_test_win, y_test_win)
```

```
print(hr_win_r2) #the r^2 for this model
hr_win_fi = feat_imp
print(hr_win_fi) #the important features
```

```
0.9224417681710841
CO      0.387061
NO2     0.213219
DEWP    0.168763
O3      0.077446
SO2     0.064176
PRES    0.031867
TEMP    0.028904
WSPM    0.018818
NW      0.002553
WNW     0.001196
ENE     0.000855
SSE     0.000531
ESE     0.000502
SE      0.000498
SW      0.000480
NNW     0.000468
E       0.000440
RAIN    0.000439
WSW     0.000408
W       0.000392
NE      0.000354
NNE     0.000267
N       0.000161
S       0.000101
SSW     0.000100
dtype: float64
```



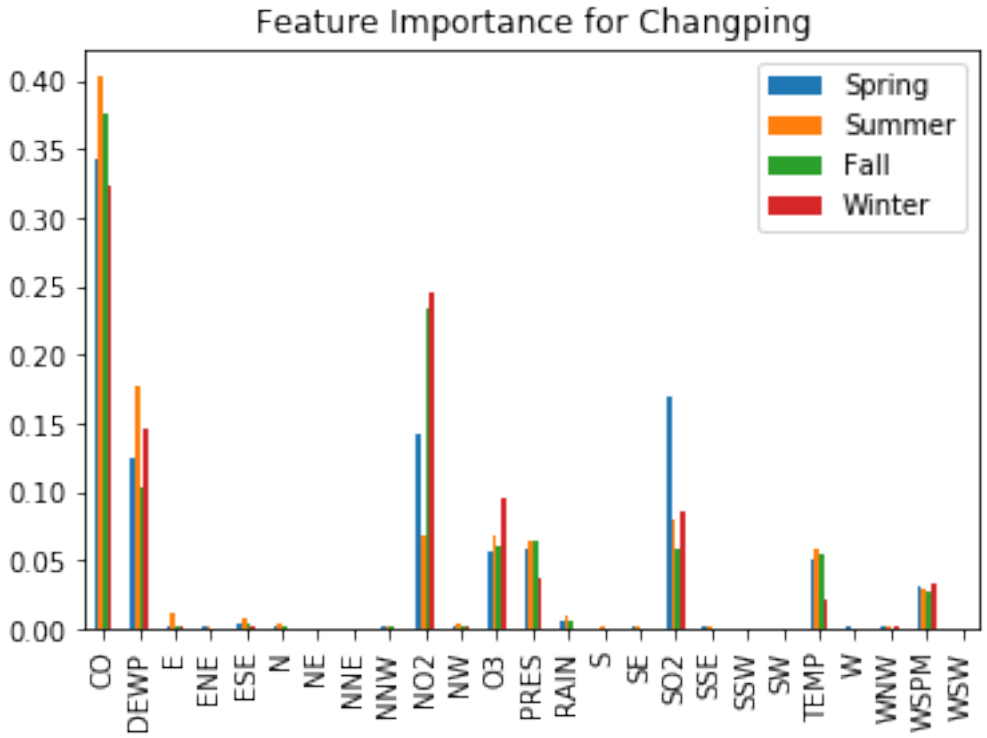
5.8 Summary of the Feature Importance for each station

[97]:
```
# changping
columns=['Spring', 'Summer', 'Fall', 'Winter']
changping_fi = pd.DataFrame([chp_spr_fi.sort_index(), chp_su_fi.sort_index(),␣
↪chp_fa_fi.sort_index(), chp_win_fi.sort_index()], index=columns).T
print(changping_fi)
changping_fi.plot(kind='bar',title='Feature Importance for Changping')
```

```
        Spring    Summer      Fall    Winter
CO    0.342932  0.403060  0.376069  0.323404
DEWP  0.124994  0.176940  0.103364  0.146943
E     0.001207  0.011991  0.001638  0.001169
ENE   0.001118  0.002893  0.000510  0.000331
ESE   0.003134  0.008112  0.003166  0.002189
N     0.001475  0.003573  0.001572  0.000795
NE    0.000255  0.000585  0.000608  0.000394
NNE   0.000546  0.000728  0.000949  0.000222
NNW   0.001583  0.002409  0.002466  0.000900
NO2   0.141631  0.067753  0.233673  0.244727
NW    0.001575  0.003286  0.001786  0.001318
O3    0.055629  0.068478  0.061389  0.095979
```

```
PRES  0.058868  0.064887  0.064454  0.036446
RAIN  0.005717  0.009001  0.005210  0.000289
S     0.000861  0.001364  0.000623  0.000365
SE    0.001887  0.002037  0.000793  0.000567
SO2   0.169576  0.079329  0.058206  0.084781
SSE   0.001587  0.002147  0.000620  0.000450
SSW   0.000472  0.000745  0.000141  0.000534
SW    0.000375  0.000699  0.000212  0.000387
TEMP  0.050499  0.057983  0.054540  0.021542
W     0.001370  0.000806  0.000320  0.000482
WNW   0.001187  0.001251  0.001018  0.001933
WSPM  0.031245  0.029687  0.026512  0.033647
WSW   0.000276  0.000256  0.000162  0.000204
```

[97]: `<matplotlib.axes._subplots.AxesSubplot at 0x7ff601ae2190>`

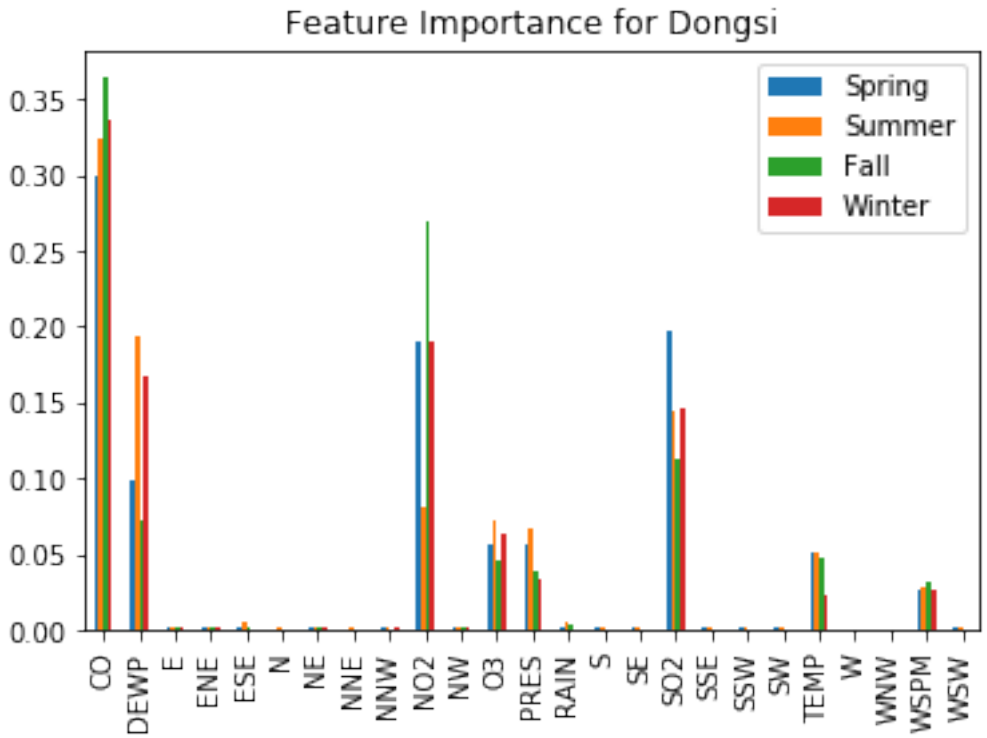


[98]:
```
# Dongsi
dongsi_fi = pd.DataFrame([ds_spr_fi.sort_index(), ds_su_fi.sort_index(),␣
 ↪ds_fa_fi.sort_index(), ds_win_fi.sort_index()], index=columns).T
print(dongsi_fi)
dongsi_fi.plot(kind='bar',title='Feature Importance for Dongsi')
```

```
        Spring    Summer      Fall    Winter
CO    0.299399  0.323429  0.364385  0.335619
```

```
DEWP  0.097775  0.194471  0.072272  0.167504
E     0.002084  0.002632  0.001050  0.002324
ENE   0.001280  0.001919  0.002138  0.001010
ESE   0.002260  0.004728  0.001258  0.000894
N     0.000739  0.002269  0.000487  0.000589
NE    0.001165  0.001758  0.001335  0.001815
NNE   0.000491  0.001218  0.000857  0.000317
NNW   0.001274  0.001592  0.000548  0.002527
NO2   0.189554  0.080873  0.269789  0.189560
NW    0.001510  0.002559  0.001253  0.001764
O3    0.057138  0.072262  0.046429  0.064303
PRES  0.056336  0.067790  0.038965  0.033889
RAIN  0.002484  0.005309  0.003401  0.000811
S     0.001220  0.002006  0.000523  0.000233
SE    0.001657  0.002255  0.000801  0.000519
SO2   0.198033  0.144842  0.112006  0.145605
SSE   0.001427  0.002400  0.000526  0.000253
SSW   0.001867  0.001940  0.000637  0.000300
SW    0.001104  0.001667  0.000641  0.000642
TEMP  0.051456  0.050713  0.046876  0.022414
W     0.000794  0.000408  0.000286  0.000193
WNW   0.000757  0.000942  0.000627  0.000294
WSPM  0.026874  0.028919  0.032255  0.025810
WSW   0.001321  0.001098  0.000654  0.000813
```

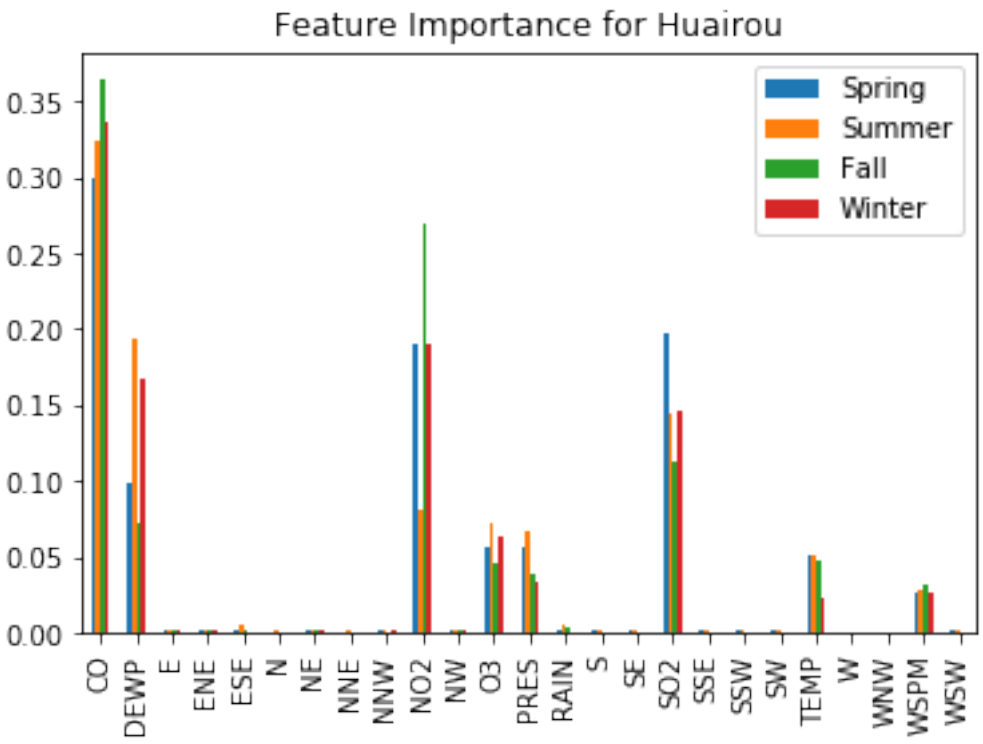
[98]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff60176b1d0>



[99]:
```
# Huairou
huairou_fi = pd.DataFrame([hr_spr_fi.sort_index(), hr_su_fi.sort_index(),␣
 ↪hr_fa_fi.sort_index(), hr_win_fi.sort_index()], index=columns).T
print(huairou_fi)
dongsi_fi.plot(kind='bar',title='Feature Importance for Huairou')
```

```
        Spring    Summer      Fall    Winter
CO    0.389787  0.454590  0.497652  0.387061
DEWP  0.110126  0.155472  0.091043  0.168763
E     0.000518  0.001154  0.000524  0.000440
ENE   0.000752  0.000939  0.000455  0.000855
ESE   0.000657  0.001404  0.000604  0.000502
N     0.000520  0.000579  0.000865  0.000161
NE    0.000534  0.001017  0.000528  0.000354
NNE   0.000459  0.000721  0.000399  0.000267
NNW   0.000489  0.000502  0.000395  0.000468
NO2   0.177129  0.106226  0.151782  0.213219
NW    0.002219  0.001848  0.002616  0.002553
O3    0.051441  0.061385  0.067523  0.077446
PRES  0.047387  0.048138  0.042736  0.031867
RAIN  0.005679  0.005660  0.006184  0.000439
S     0.001487  0.000502  0.000367  0.000101
SE    0.000958  0.000905  0.000837  0.000498
SO2   0.129496  0.073735  0.061147  0.064176
SSE   0.001483  0.001121  0.000469  0.000531
SSW   0.000503  0.000600  0.000589  0.000100
SW    0.001162  0.001173  0.000550  0.000480
TEMP  0.047437  0.055826  0.047748  0.028904
W     0.001418  0.001284  0.001156  0.000392
WNW   0.001960  0.001820  0.001871  0.001196
WSPM  0.025537  0.022382  0.021302  0.018818
WSW   0.000862  0.001017  0.000657  0.000408
```

[99]: <matplotlib.axes._subplots.AxesSubplot at 0x7ff5e0b09e10>



[100]:
```
[chp_spr_r2, chp_su_r2, chp_fa_r2, chp_win_r2]
```

[100]:
```
[0.8356382495931237,
 0.7296657729263121,
 0.8698495599666035,
 0.9290354862393014]
```

5.9 The R^2 from CV for each station and season

[101]:
```
d = {'Changping':[chp_spr_r2, chp_su_r2, chp_fa_r2, chp_win_r2],
     'Dongsi':[ds_spr_r2, ds_su_r2, ds_fa_r2, ds_win_r2],
    'Huairou':[hr_spr_r2, hr_su_r2, hr_fa_r2, hr_win_r2]}
pd.DataFrame(data=d,index=columns)
```

[101]:

	Changping	Dongsi	Huairou
Spring	0.835638	0.812334	0.869793
Summer	0.729666	0.782109	0.831385
Fall	0.869850	0.899871	0.899918
Winter	0.929035	0.933493	0.922442

5.9.1 Exaplain above results (both plots and R^2) here.

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

[ ]:

6 This is Mary's variable desription:

6.1 CO

Carbon monoxide is a colorless, odorless, and tasteless flammable gas that is slightly less dense than air.Carbon monoxide consists of one carbon atom and one oxygen atom and it is one of the main atmospheric pollutants.

[ ]:
```
x=data[["CO"]]
y=data[["PM2.5"]]
plt.scatter(x,y)
plt.title("CO and PM2.5")
plt.ylabel("PM2.5")
plt.xlabel("CO")
plt.show()
```

CO and PM2.5 has positive relationship

6.2 PRES

The atmosphere is formed by air and surrounds the Earth, this column measured what's the weight of air column on each square metre of the Earth's surface corresponding to a pressure ,at sea level is 1013hPa

[ ]:
```
x=data[["PRES"]]
y=data[["PM2.5"]]
plt.scatter(x,y,color="red")
```

```
plt.title("PRES and PM2.5")
plt.ylabel("PM2.5")
plt.xlabel("PRES")
plt.show()
```

PRES and PM2.5 shows like normal distribution, with pressure increase or decrease, PM2.5 will decrease.

6.3 RAIN

Rain is liquid water in the form of droplets that have condensed from atmospheric water vapor and then become heavy enough to fall under gravity.

[ ]:
```
x=data[["RAIN"]]
y=data[["PM2.5"]]
plt.scatter(x,y,color="green")
plt.title("RAIN and PM2.5")
plt.ylabel("PM2.5")
plt.xlabel("RAIN")
plt.show()
```

With rain increase, PM2.5 decrease.

[ ]:
```

```

[ ]:
```

```