Finding the correlation between air pollutants using Data Mining Techiniques

submitted by

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Data Source : https://data.gov.in/catalog/historical-daily-ambient-air-quality-data

Data Exploration

In [20]:

```
#importing libraries for Data Exploration

import pandas as pd
import matplotlib.pyplot as plt
from matplotlib import style
import numpy as np
style.use ('ggplot')
```

In [21]:

```
df=pd.read_csv('ddata.csv')
df.head()
```

Out[21]:

	Stn.Code	Sampling.Date	State	City.Town.Village.Area	loctype	SO2	NO2	RSPM.PM10	SPM	Location.of.Monit
0	150.0	1990-02-01	Telangana	Hyderabad	Residential, Rural and other Areas	4.8	17.4	NaN	NaN	Tarnaka, NEERI L Campus, Hyderab
1	151.0	1990-02-01	Telangana	Hyderabad	Industrial Area	3.1	7.0	NaN	NaN	Nacharam
2	152.0	1990-02-01	Telangana	Hyderabad	Residential, Rural and other Areas	6.2	28.5	NaN	NaN	ABIDS Circle Gen Office Building, Hy
3	150.0	1990-03-01	Telangana	Hyderabad	Residential, Rural and other Areas	6.3	14.7	NaN	NaN	Tarnaka, NEERI L Campus, Hyderab
4	151.0	1990-03-01	Telangana	Hyderabad	Industrial Area	4.7	7.5	NaN	NaN	Nacharam

In [22]:

```
df.describe()
```

Out[22]:

	Stn.Code	SO2	NO2	RSPM.PM10	SPM	PM.2.5
count	95146.000000	91175.000000	93732.000000	92317.000000	48927.000000	1756.000000
mean	295.195352	10.322864	30.796267	108.308604	232.205665	48.247722
std	190.189699	9.781473	21.614489	81.454458	153.108841	38.433731
min	1.000000	0.500000	0.300000	3.000000	0.000000	4.000000
25%	146.000000	5.000000	18.000000	54.000000	123.000000	27.000000
50%	324.000000	8.000000	26.600000	85.000000	193.000000	32.000000
75%	416.000000	13.000000	36.000000	141.000000	311.000000	55.000000
max	814.000000	909.000000	640.000000	6307.033333	1885.000000	318.000000

In [23]:

```
df.drop(['Stn.Code'], axis=1, inplace=True)
df["Sampling.Date"]=pd.to_datetime(df["Sampling.Date"])

df.rename(columns={'City.Town.Village.Area':'City'},inplace=True)
```

In [24]:

```
df.isna().sum()

# Shows the number of missing values in each attribute
```

Out[24]:

```
Sampling.Date                    0
State                            0
City                             0
loctype                          0
SO2                           4896
NO2                           2339
RSPM.PM10                     3754
SPM                          47144
Location.of.Monitoring.Station   608
PM.2.5                       94315
dtype: int64
```

In [25]:

```
import seaborn as sns
```

In [26]:

```
df.rename(columns={'Sampling.Date':'date'}, inplace=True)
df.rename(columns={'City.Town.Village.Area':'City'}, inplace=True)
df.rename(columns={'Location.of.Monitoring.Station':'location'}, inplace=True)
df.rename(columns={'RSPM.PM10' :'RSPM10'}, inplace=True)


# Percentage of missing values in each column
print( df.isnull().sum(axis = 0) * 100 / df.shape[0] )
```

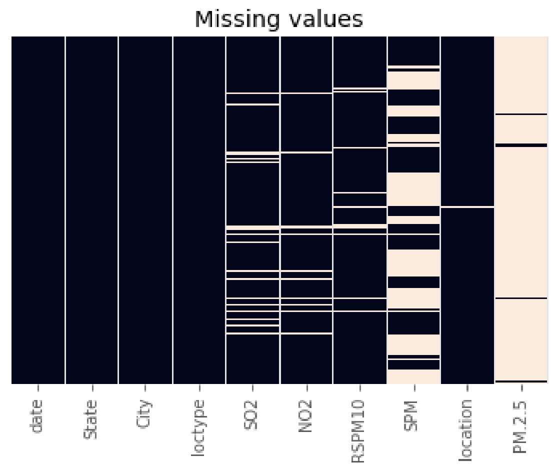
```
date         0.000000
State        0.000000
City         0.000000
loctype      0.000000
SO2          5.096231
NO2          2.434658
RSPM10       3.907527
SPM         49.072040
location     0.632865
PM.2.5      98.172185
dtype: float64
```

In [27]:

```python
sns.heatmap(df.isnull(), yticklabels=False, cbar=False).set_title('Missing values')
```

Out[27]:

```
Text(0.5,1,'Missing values')
```

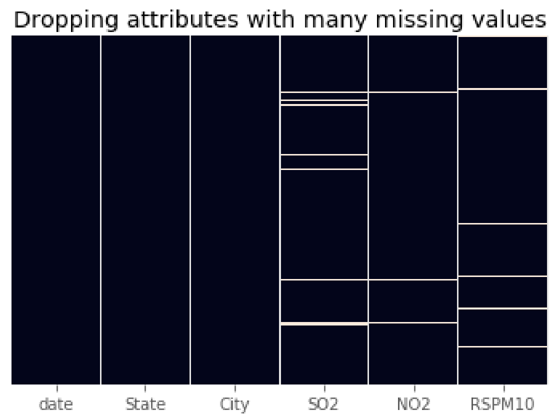


In [28]:

```python
df.drop(['PM.2.5','SPM', 'loctype', 'location'], axis=1, inplace=True)

sns.heatmap(df.isnull(), yticklabels=False, cbar=False).set_title('Dropping attributes with many
missing values')
```

Out[28]:

```
Text(0.5,1,'Dropping attributes with many missing values')
```



Removing Duplicates and Splitting Data on Cities

In [29]:

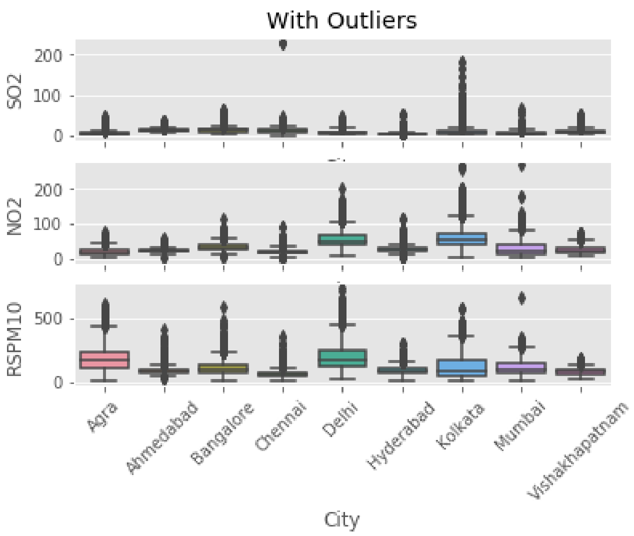
```python
df.drop_duplicates(inplace=True)

dfs = dict(tuple(df.groupby('City')))

for l, DF in dfs.items():
    dfs[l]['SO2']    = dfs[l].groupby(['date'])['SO2'].transform('mean')
    dfs[l]['NO2']    = dfs[l].groupby(['date'])['NO2'].transform('mean')
    dfs[l]['RSPM10'] = dfs[l].groupby(['date'])['RSPM10'].transform('mean')
    dfs[l].drop_duplicates(subset=['date'], keep=False)

df = pd.concat(dfs.values(), ignore_index=True)
```

Outlier Analysis

Removing outliers using Tukey's fences: $$\text{IQR} = Q_3 - Q_1$$ Taking data points only within range $$\left[Q_1 - 1.5 \text{IQR}, Q_3 + 1.5 \text{IQR}\right]$$ $$ \text{where} Q_1 \text{and} Q_3 \text{are first and third quartile}$$

In [30]:

```
locations = ['Agra', 'Ahmedabad', 'Bangalore', 'Chennai', 'Delhi', 'Hyderabad', 'Kolkata', 'Mumbai'
,
             'Vishakhapatnam' ]

fig1, axes = plt.subplots(3, 1)
for i, y in enumerate(['SO2', 'NO2', 'RSPM10']):
    sns.boxplot(x = 'City', y = y,   data = df, order = locations, ax = axes[i])
for i in range(2):
    axes[i].set_xticklabels('')
axes[2].set_xticklabels(locations, rotation = 45)
axes[0].set_title('With Outliers')
fig1

import math
df = pd.DataFrame()
for l, df_i in dfs.items():
    q = ''
    for attr in ['SO2', 'NO2','RSPM10']:
        Q1 = df_i[attr].quantile(0.25)
        Q3 = df_i[attr].quantile(0.75)
        IQR = Q3 - Q1
        if  not (math.isnan(Q1) and math.isnan(Q3)):
            q += f'({Q1} - 1.5 * {IQR}) <= {attr} <= ({Q3} + 1.5 * {IQR}) and '
    dfs[l] = df_i.query(q[:-5])
```

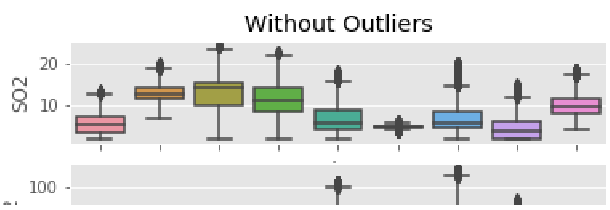


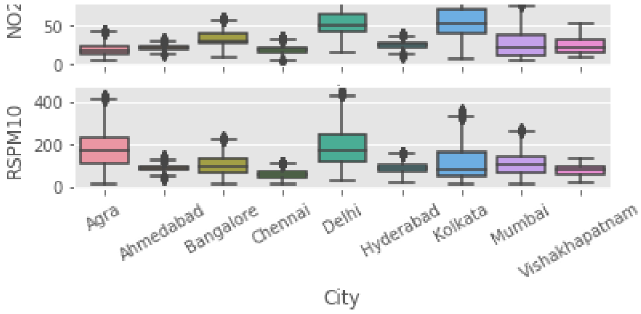
In [31]:

```
df = pd.concat(dfs.values(), ignore_index=True)

fig2, axes = plt.subplots(3, 1)

for i, y in enumerate(['SO2', 'NO2', 'RSPM10']):
    sns.boxplot(x = 'City', y = y,   data = df, order = locations, ax = axes[i])
for i in range(2):
    axes[i].set_xticklabels('')
axes[2].set_xticklabels(locations, rotation = 30)
axes[0].set_title('Without Outliers')
```

Out[31]:

```
Text(0.5,1,'Without Outliers')
```





Treating Missing Values

In [32]:

```
import warnings
warnings.filterwarnings("ignore")
for df_i in dfs.values():
    df_i.fillna(method = 'pad', inplace=True)
```

In [33]:

```
''' Replacing remaining missing values with median '''

for df_i in dfs.values():
    so2 = df_i.SO2.quantile(0.5)
    no2 = df_i.NO2.quantile(0.5)
    rspm = df_i.RSPM10.quantile(0.5)
    df_i.SO2.fillna(so2, inplace=True)
    df_i.NO2.fillna(no2, inplace=True)
    df_i.RSPM10.fillna(rspm, inplace=True)

df = pd.concat(dfs.values(), ignore_index=True)

print(df.isnull().sum(axis = 0))

# Saving treated dataset as new csv file
df.to_csv("final.csv")
```

```
date      0
State     0
City      0
SO2       0
NO2       0
RSPM10    0
dtype: int64
```

Scaling Features

In [34]:

```
df.head() # Before scaling
```

Out[34]:

	date	State	City	SO2	NO2	RSPM10
0	2004-09-13	Uttar Pradesh	Agra	7.0	7.5	67.0
1	2004-09-16	Uttar Pradesh	Agra	7.7	8.4	62.0
2	2004-09-20	Uttar Pradesh	Agra	7.3	7.8	156.0
3	2004-09-23	Uttar Pradesh	Agra	7.5	7.1	181.0
4	2004-09-27	Uttar Pradesh	Agra	8.2	8.9	303.0

In [35]:

In [35]:

```python
df["Scale_SO2"]    = (df["SO2"]/max(df.SO2))
df["Scale_NO2"]    = (df["NO2"]/max(df.NO2))
df["Scale_RSPM10"] = (df["RSPM10"]/max(df.RSPM10))

df.head()
```

Out[35]:

	date	State	City	SO2	NO2	RSPM10	Scale_SO2	Scale_NO2	Scale_RSPM10
0	2004-09-13	Uttar Pradesh	Agra	7.0	7.5	67.0	0.157303	0.060926	0.148641
1	2004-09-16	Uttar Pradesh	Agra	7.7	8.4	62.0	0.173034	0.068237	0.137549
2	2004-09-20	Uttar Pradesh	Agra	7.3	7.8	156.0	0.164045	0.063363	0.346090
3	2004-09-23	Uttar Pradesh	Agra	7.5	7.1	181.0	0.168539	0.057677	0.401553
4	2004-09-27	Uttar Pradesh	Agra	8.2	8.9	303.0	0.184270	0.072299	0.672213

Algorithm

In [36]:

```python
import statsmodels.api as sm
from sklearn.model_selection import train_test_split, cross_val_score
```

In [38]:

```python
# Applying the Linear Regression Algorithm for Bangalore

df = pd.read_csv('final.csv')
d = df.loc[df.City == 'Bangalore']

from itertools import combinations

s = set(['SO2', 'NO2', 'RSPM10'])
model = []

for (x1, x2) in combinations(s, 2):
    yi = set.difference(s, set([x1, x2])).pop()
    X = df[[x1, x2]]
    y = df[yi]
    model.append(([x1, x2], yi, sm.OLS(y, X).fit()))
```

In [39]:

```python
print(model[0][0], model[0][1])
print(model[0][2].summary())
```

```
['NO2', 'RSPM10'] SO2
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                    SO2   R-squared:                       0.628
Model:                            OLS   Adj. R-squared:                  0.628
Method:                 Least Squares   F-statistic:                 6.849e+04
Date:                Mon, 17 Dec 2018   Prob (F-statistic):               0.00
Time:                        10:53:00   Log-Likelihood:            -2.6949e+05
No. Observations:               81209   AIC:                         5.390e+05
Df Residuals:                   81207   BIC:                         5.390e+05
Df Model:                           2                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
NO2            0.2033      0.001    152.684      0.000       0.201       0.206
RSPM10         0.0157      0.000     42.396      0.000       0.015       0.016
==============================================================================
Omnibus:                     2507.247   Durbin-Watson:                   0.208
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             6010.551
```

```
Skew:                           0.142   Prob(JB):                         0.00
Kurtosis:                       4.302   Cond. No.                         7.40
==============================================================================

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

In [40]:

```
print(model[1][0], model[1][1])
print(model[1][2].summary())
```

```
['NO2', 'SO2'] RSPM10
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                 RSPM10   R-squared:                       0.741
Model:                            OLS   Adj. R-squared:                  0.741
Method:                 Least Squares   F-statistic:                 1.164e+05
Date:                Mon, 17 Dec 2018   Prob (F-statistic):               0.00
Time:                        10:53:02   Log-Likelihood:            -4.5122e+05
No. Observations:               81209   AIC:                         9.025e+05
Df Residuals:                   81207   BIC:                         9.025e+05
Df Model:                           2                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
NO2            2.7371      0.010    263.047      0.000       2.717       2.758
SO2            1.3793      0.033     42.396      0.000       1.316       1.443
==============================================================================
Omnibus:                    10865.741   Durbin-Watson:                   0.391
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            25845.616
Skew:                           0.782   Prob(JB):                         0.00
Kurtosis:                       5.279   Cond. No.                         5.40
==============================================================================

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

In [41]:

```
print(model[2][0], model[2][1])
print(model[2][2].summary())
```

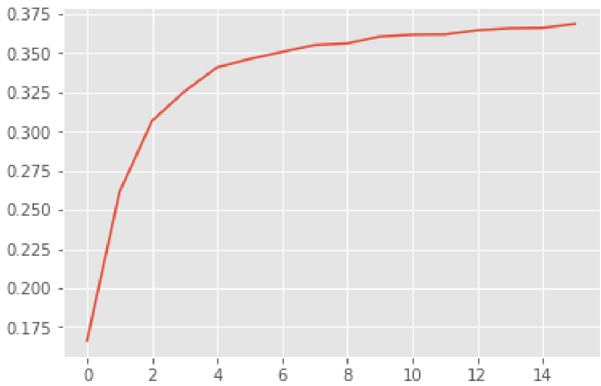
```
['RSPM10', 'SO2'] NO2
                            OLS Regression Results                            
==============================================================================
Dep. Variable:                    NO2   R-squared:                       0.795
Model:                            OLS   Adj. R-squared:                  0.795
Method:                 Least Squares   F-statistic:                 1.571e+05
Date:                Mon, 17 Dec 2018   Prob (F-statistic):               0.00
Time:                        10:53:03   Log-Likelihood:            -3.3793e+05
No. Observations:               81209   AIC:                         6.759e+05
Df Residuals:                   81207   BIC:                         6.759e+05
Df Model:                           2                                         
Covariance Type:            nonrobust                                         
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
RSPM10         0.1681      0.001    263.047      0.000       0.167       0.169
SO2            1.0970      0.007    152.684      0.000       1.083       1.111
==============================================================================
Omnibus:                    15905.302   Durbin-Watson:                   0.382
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            40494.585
Skew:                           1.078   Prob(JB):                         0.00
Kurtosis:                       5.706   Cond. No.                         16.3
==============================================================================

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

$$\text{By comparing the different R-squared values for each Multiple Linear Regression model, we can conclude that the best model is when SO}_2 \\ \text{ and RSPM 10 are independent varaibles and NO}_2 \text{is the dependent variable}$$

is when SO}_2 \\ \text{ and RSPM-10 are independent varaibles and NO}_2 \text{is the dependent variable}$$

In [43]:

```
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier

X_train, X_test, y_train, y_test = train_test_split(df[['RSPM10', 'SO2', 'NO2']],
                                                    df.City,
                                                    test_size = 0.33,
                                                    random_state = 42)

err_rate = []

for i in range(1, 32, 2):
    knn = KNeighborsClassifier(n_neighbors=i)
    knn.fit(X_train, y_train)
    pred_i = knn.predict(X_test)
    err_rate.append(np.mean(pred_i != y_test))

Y = err_rate
X = range(16)
plt.plot(X, Y)
plt.show()
```



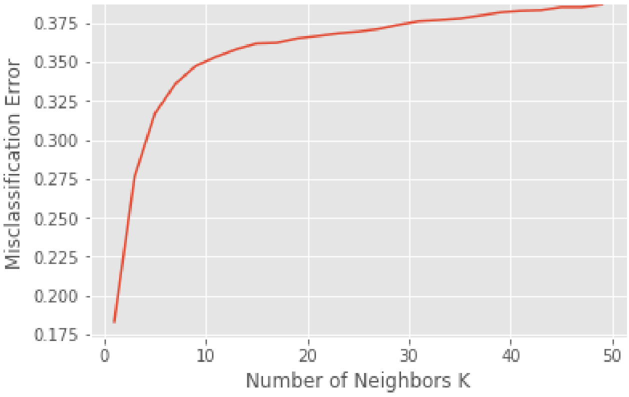
The above graph tells that error rate increases as k value increases

Cross Validation

In [44]:

```
l = list(range(1,50))
neighbors = list(filter(lambda x: x % 2 != 0, l))
cv_scores = []

# perform 10-fold cross validation
for k in neighbors:
    knn = KNeighborsClassifier(n_neighbors=k)
    scores = cross_val_score(knn, X_train, y_train, cv=10, scoring='accuracy')
    cv_scores.append(scores.mean())


# changing to misclassification error
MSE = [1 - x for x in cv_scores]

# determining best k
optimal_k = neighbors[MSE.index(min(MSE))]
print ("The optimal number of neighbors is %d" % optimal_k)

# plot misclassification error vs k
plt.plot(neighbors, MSE)
plt.xlabel('Number of Neighbors K')
plt.ylabel('Misclassification Error')
plt.show()
```

```
The optimal number of neighbors is 1
```



It can be seen that kNN model doesn't work as good as the Linear Regression Model as the optimal value for kNNN is just 1