Experiment No: 4

Aim: Implementation of Statistical Hypothesis Test using Scipy and Sci-kit learn.

Theory:

a) **Pearson's Correlation Coefficient (r)**

Pearson's correlation measures the linear relationship between two continuous variables. It assumes that the data is normally distributed and calculates how closely the variables follow a straight-line relationship. The coefficient ranges from -1 to 1, where values closer to 1 or -1 indicate a strong relationship, while 0 means no correlation. It is sensitive to outliers and works best for data with a linear trend.

b) **Spearman's Rank Correlation (ρ)**

Spearman's correlation evaluates the monotonic relationship between two variables based on their rankings. It does not assume a normal distribution and works well for both linear and non-linear relationships. Since it uses ranks instead of raw values, it is less affected by outliers. A high Spearman's coefficient indicates that as one variable increases, the other tends to increase (or decrease) consistently, but not necessarily at a constant rate.

c) **Kendall's Rank Correlation (τ)**

Kendall's correlation measures the ordinal association between two variables. It is based on concordant and discordant pairs, where concordant means both variables increase together, and discordant means one increases while the other decreases. Kendall's Tau is particularly useful for small datasets and is more robust against tied ranks than Spearman's correlation.

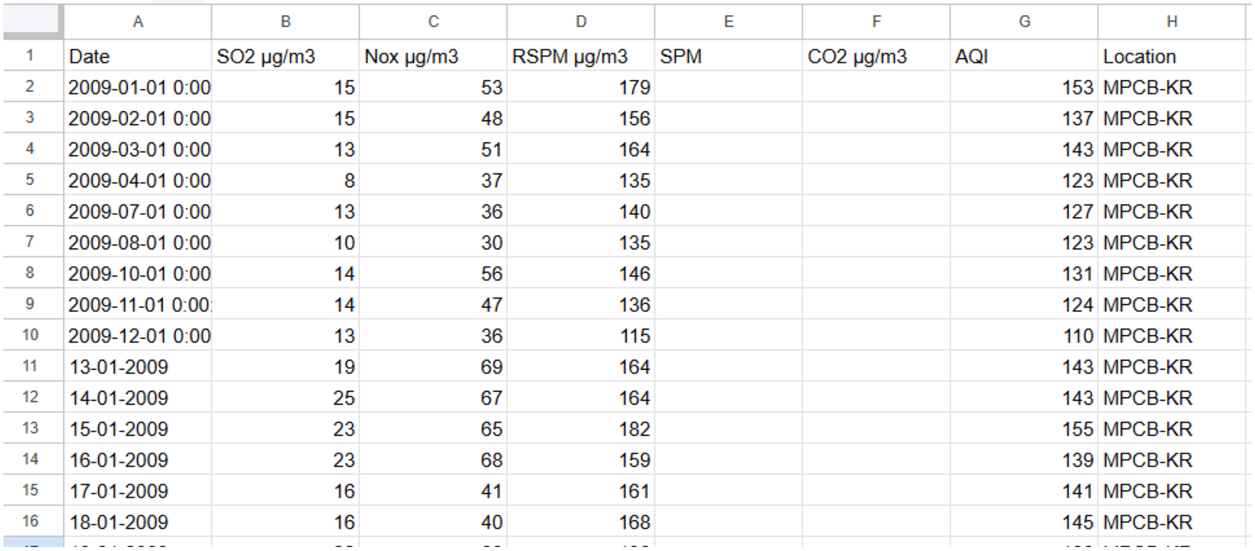
d) **Chi-Squared Test (χ^2)**

The Chi-Square test assesses the association between two categorical variables. It helps determine if one variable depends on another by comparing observed and expected frequencies in a contingency table. A low p-value (< 0.05) indicates a significant relationship, meaning the two variables are not independent. This test is commonly used to analyze relationships between binned numerical data or categorical variables.

Correlation Analysis of AQI Dataset

Air Quality Index (AQI) is an important measure of air pollution levels, influenced by pollutants such as SO_2, NOx, RSPM, and CO_2. Understanding the correlation between these pollutants and AQI can help determine which factors significantly impact air

quality. This experiment aims to perform Pearson’s, Spearman’s, Kendall’s correlation, and the Chi-Squared test to analyze the relationship between SO_2 levels and AQI using statistical methods.
The following image is the image of my first few instances of my AQI dataset :

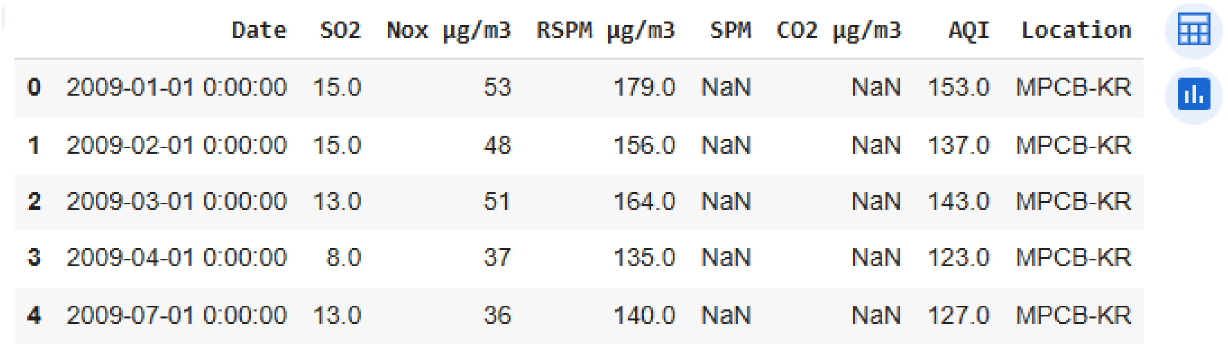


	A	B	C	D	E	F	G	H
1	Date	SO2 µg/m3	Nox µg/m3	RSPM µg/m3	SPM	CO2 µg/m3	AQI	Location
2	2009-01-01 0:00	15	53	179			153	MPCB-KR
3	2009-02-01 0:00	15	48	156			137	MPCB-KR
4	2009-03-01 0:00	13	51	164			143	MPCB-KR
5	2009-04-01 0:00	8	37	135			123	MPCB-KR
6	2009-07-01 0:00	13	36	140			127	MPCB-KR
7	2009-08-01 0:00	10	30	135			123	MPCB-KR
8	2009-10-01 0:00	14	56	146			131	MPCB-KR
9	2009-11-01 0:00	14	47	136			124	MPCB-KR
10	2009-12-01 0:00	13	36	115			110	MPCB-KR
11	13-01-2009	19	69	164			143	MPCB-KR
12	14-01-2009	25	67	164			143	MPCB-KR
13	15-01-2009	23	65	182			155	MPCB-KR
14	16-01-2009	23	68	159			139	MPCB-KR
15	17-01-2009	16	41	161			141	MPCB-KR
16	18-01-2009	16	40	168			145	MPCB-KR

Steps:

Load and Preprocess the Data

```
from google.colab import files
uploaded = files.upload()
import pandas as pd
df = pd.read_csv('PNQ_AQI.csv')
# Convert SO2 and AQI to numeric
df['SO2'] = pd.to_numeric(df['SO2'], errors='coerce')
df['AQI'] = pd.to_numeric(df['AQI'], errors='coerce')
# Drop NaN values
df_clean = df[['SO2', 'AQI']].dropna()
df.head()
```

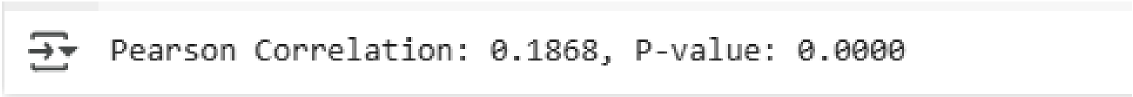


```
                 Date   SO2  Nox µg/m3  RSPM µg/m3  SPM  CO2 µg/m3    AQI  Location
0  2009-01-01 0:00:00  15.0         53       179.0  NaN        NaN  153.0   MPCB-KR
1  2009-02-01 0:00:00  15.0         48       156.0  NaN        NaN  137.0   MPCB-KR
2  2009-03-01 0:00:00  13.0         51       164.0  NaN        NaN  143.0   MPCB-KR
3  2009-04-01 0:00:00   8.0         37       135.0  NaN        NaN  123.0   MPCB-KR
4  2009-07-01 0:00:00  13.0         36       140.0  NaN        NaN  127.0   MPCB-KR
```

1. **Pearson’s Correlation**

```
from scipy.stats import pearsonr

pearson_corr, pearson_p = pearsonr(df_clean['SO2'], df_clean['AQI'])
print(f"Pearson Correlation: {pearson_corr:.4f}, P-value: {pearson_p:.4f}")
```



```
Pearson Correlation: 0.1868, P-value: 0.0000
```

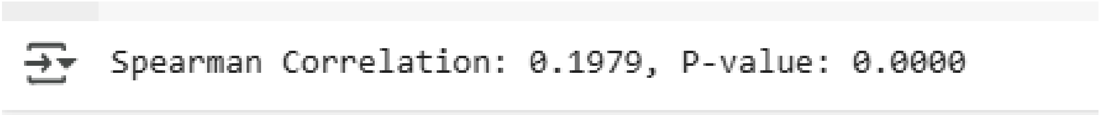
Interpretation

- Weak positive linear relationship between SO_2 and AQI.
- Since p-value < 0.05, the correlation is statistically significant.

2. **Spearman’s Rank Correlation**

```
from scipy.stats import spearmanr

spearman_corr, spearman_p = spearmanr(df_clean['SO2'], df_clean['AQI'])
print(f"Spearman Correlation: {spearman_corr:.4f}, P-value: {spearman_p:.4f}")
```



```
Spearman Correlation: 0.1979, P-value: 0.0000
```

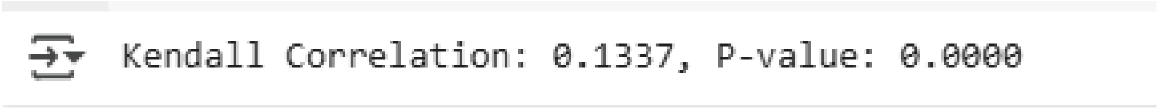
Interpretation

- Weak positive monotonic relationship (not necessarily linear).
- p-value < 0.05, so the correlation is significant.

3. **Kendall’s Rank Correlation**

```
from scipy.stats import kendalltau

kendall_corr, kendall_p = kendalltau(df_clean['SO2'], df_clean['AQI'])
print(f"Kendall Correlation: {kendall_corr:.4f}, P-value: {kendall_p:.4f}")
```



```
Kendall Correlation: 0.1337, P-value: 0.0000
```

Interpretation

- Weak positive ordinal association between variables.
- p-value < 0.05, meaning the correlation is statistically significant.

4. **Chi-Squared Test**

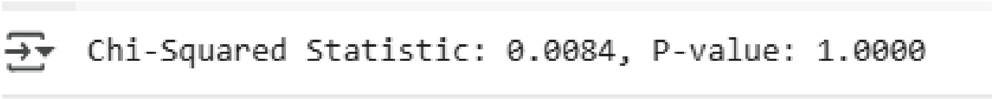
```
import numpy as np
from scipy.stats import chi2_contingency

# Categorizing SO2 and AQI into Low, Medium, High
df_clean['SO2_category'] = pd.cut(df_clean['SO2'], bins=3, labels=['Low', 'Medium', 'High'])
df_clean['AQI_category'] = pd.cut(df_clean['AQI'], bins=3, labels=['Good', 'Moderate', 'Unhealthy'])

# Create contingency table
contingency_table = pd.crosstab(df_clean['SO2_category'], df_clean['AQI_category'])

# Perform Chi-Square Test
chi2_stat, chi2_p, _, _ = chi2_contingency(contingency_table)

print(f"Chi-Squared Statistic: {chi2_stat:.4f}, P-value: {chi2_p:.4f}")
```



```
Chi-Squared Statistic: 0.0084, P-value: 1.0000
```

Interpretation

- No significant association between the categorical variables tested.
- p-value = 1.0, meaning the variables are independent (no relationship).

Conclusion:

In this analysis, four statistical tests were applied to assess the relationships between SO_2 levels and AQI:

1. Pearson's correlation showed a weak positive linear relationship between SO_2 and AQI, with a correlation of 0.1868. Since the p-value is 0.0000, this relationship is statistically significant.
2. Spearman's rank correlation confirmed a weak positive monotonic relationship between SO_2 and AQI, with a correlation of 0.1979. The p-value of 0.0000 indicates statistical significance.

3. Kendall’s Tau also revealed a weak positive association between SO_2 and AQI, with a correlation of 0.1337. The p-value of 0.0000 suggests that this correlation is significant.
4. The Chi-Squared test showed no significant association between the categorical variables tested, with a Chi-Squared statistic of 0.0084 and a p-value of 1.0000. Since the p-value is much greater than 0.05, we fail to reject the null hypothesis, meaning the variables are independent.

Although the correlation tests indicate a weak but statistically significant positive relationship between SO_2 and AQI, the Chi-Square test suggests no significant dependency between the categorical variables analyzed.