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 (χ²)

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 SO₂, NOx, RSPM, and CO₂. Understanding the correlation between these pollutants and AQI can help determine which factors significantly impact air Bhumisha Parchani D15C 38

| | 2009-10-01 0:00 | 14 | 50 | 140 | 131 MPGB-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 |
| 17 | 19-01-2009 | 22 | 68 | 190 | 160 MPCB-KR |
| 18 | 20-01-2009 | 20 | 61 | 194 | 163 MPCB-KR |
| 19 | 21-01-2009 | 20 | 61 | 191 | 161 MPCB-KR |
| 20 | 22-01-2009 | 21 | 67 | 179 | 153 MPCB-KR |
| 21 | 23-01-2009 | 21 | 71 | 195 | 163 MPCB-KR |
| 22 | 24-01-2009 | 23 | 65 | 212 | 175 MPCB-KR |
| 23 | 25-01-2009 | 25 | 35 | 168 | 145 MPCB-KR |
| 24 | 26-01-2009 | 26 | 27 | 167 | 145 MPCB-KR |
| 25 | 27-01-2009 | 24 | 40 | 162 | 141 MPCB-KR |
| 26 | 29-01-2009 | BDL - NA | 30 | 174 | 149 MPCB-KR |
| 27 | 30-01-2009 | BDL - NA | 30 | 200 | 167 MPCB-KR |
| 28 | 2009-01-02 0:00 | BDL - NA | 16 | 140 | 127 MPCB-KR |
| 29 | 2009-02-02 0:00 | BDL - NA | 20 | 133 | 122 MPCB-KR |
| 30 | 2000 02 02 0 00 | DD4 NA | 47 | 400 | 440 MOOD MD |

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 | 502 | 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 |

 \blacksquare

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 SO₂ 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 SO₂ levels and AQI:

- 1. Pearson's correlation showed a weak positive linear relationship between SO₂ 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 SO₂ 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 SO₂ 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 SO₂ and AQI, the Chi-Square test suggests no significant dependency between the categorical variables analyzed.