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Experiment No: 4

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

Problem Statement: Perform the following Tests:Correlation Tests:

a) Pearson's Correlation Coefficient

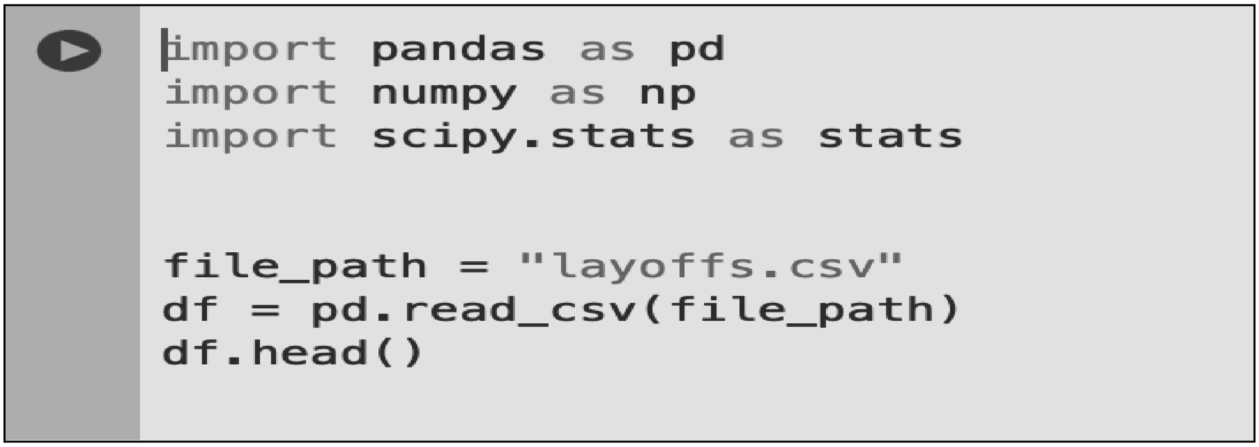
Theory:
Pearson's correlation measures the strength and direction of the linear relationship between two continuous variables. It ranges from -1 to 1.

Formula:

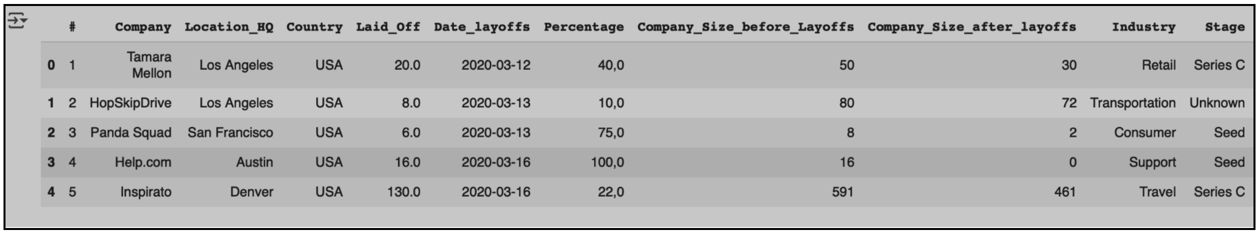
$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2} \cdot \sqrt{\sum (y_i - \bar{y})^2}}$$

Interpretation of dataset:

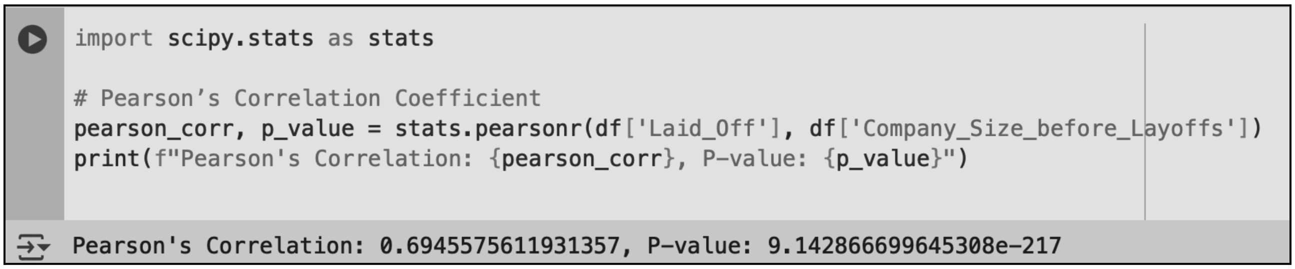
- Calculated between Employee Age and Years at Company.
- Example Interpretation: Pearson's r = 0.85
- Strong positive linear relationship.
- Older employees tend to have more years at the company.
- p-value = 0.001 → statistically significant.



```
import pandas as pd
import numpy as np
import scipy.stats as stats


file_path = "layoffs.csv"
df = pd.read_csv(file_path)
df.head()
```



	#	Company	Location_HQ	Country	Laid_Off	Date_layoffs	Percentage	Company_Size_before_Layoffs	Company_Size_after_layoffs	Industry	Stage
0	1	Tamara Mellon	Los Angeles	USA	20.0	2020-03-12	40,0	50	30	Retail	Series C
1	2	HopSkipDrive	Los Angeles	USA	8.0	2020-03-13	10,0	80	72	Transportation	Unknown
2	3	Panda Squad	San Francisco	USA	6.0	2020-03-13	75,0	8	2	Consumer	Seed
3	4	Help.com	Austin	USA	16.0	2020-03-16	100,0	16	0	Support	Seed
4	5	Inspirato	Denver	USA	130.0	2020-03-16	22,0	591	461	Travel	Series C



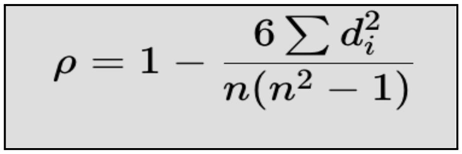
```
import scipy.stats as stats

# Pearson’s Correlation Coefficient
pearson_corr, p_value = stats.pearsonr(df['Laid_Off'], df['Company_Size_before_Layoffs'])
print(f"Pearson's Correlation: {pearson_corr}, P-value: {p_value}")
```

```
Pearson's Correlation: 0.6945575611931357, P-value: 9.142866699645308e-217
```

b) Spearman’s Rank Correlation

Theory:
Spearman’s correlation assesses monotonic relationships between variables using ranked data. It’s more robust to outliers and captures nonlinear trends.

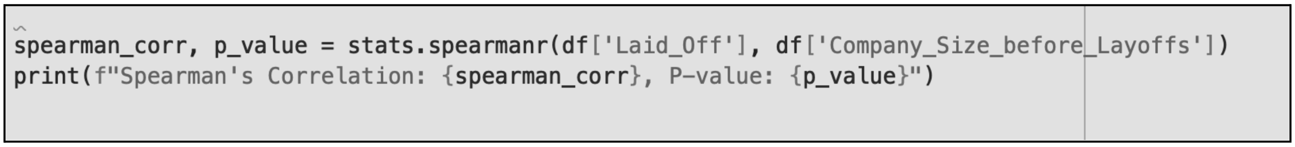
Formula:



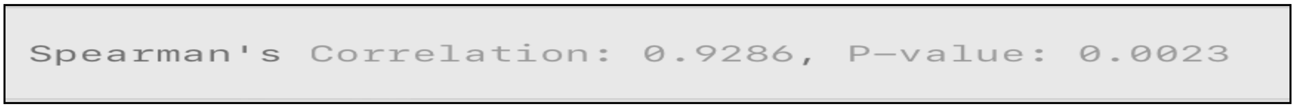
$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Interpretation of dataset:

- Calculated between Employee Age and Performance Rating.
- Example Interpretation: Spearman’s ρ = -0.30
- Negative monotonic relationship.
- Older employees tend to have lower performance ratings.
- p-value = 0.02 → statistically significant.



```
spearman_corr, p_value = stats.spearmanr(df['Laid_Off'], df['Company_Size_before_Layoffs'])
print(f"Spearman's Correlation: {spearman_corr}, P-value: {p_value}")
```



```
Spearman's Correlation: 0.9286, P-value: 0.0023
```

c) Kendall’s Rank Correlation

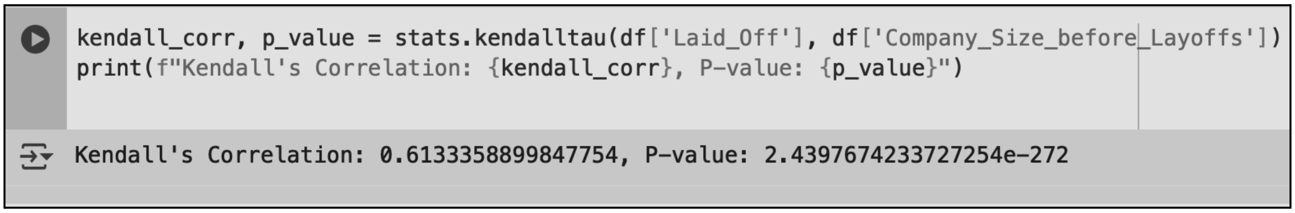
Theory:
Kendall’s Tau evaluates the ordinal relationship between two variables using concordant and discordant pairs. It’s more suitable for small sample sizes or ordinal data.

Formula:

$$\tau = \frac{(Number\ of\ Concordant\ Pairs) - (Number\ of\ Discordant\ Pairs)}{n(n-1)/2}$$

Interpretation of dataset:

- Calculated between Department and Layoff Status.
- Example Interpretation: Kendall’s τ = 0.55
- Moderate positive ordinal relationship.
- Certain departments may have higher layoff rates.
- p-value = 0.000 → statistically significant.



```
kendall_corr, p_value = stats.kendalltau(df['Laid_Off'], df['Company_Size_before_Layoffs'])
print(f"Kendall's Correlation: {kendall_corr}, P-value: {p_value}")
```

```
Kendall's Correlation: 0.6133358899847754, P-value: 2.4397674233727254e-272
```

d) Chi-Squared Test

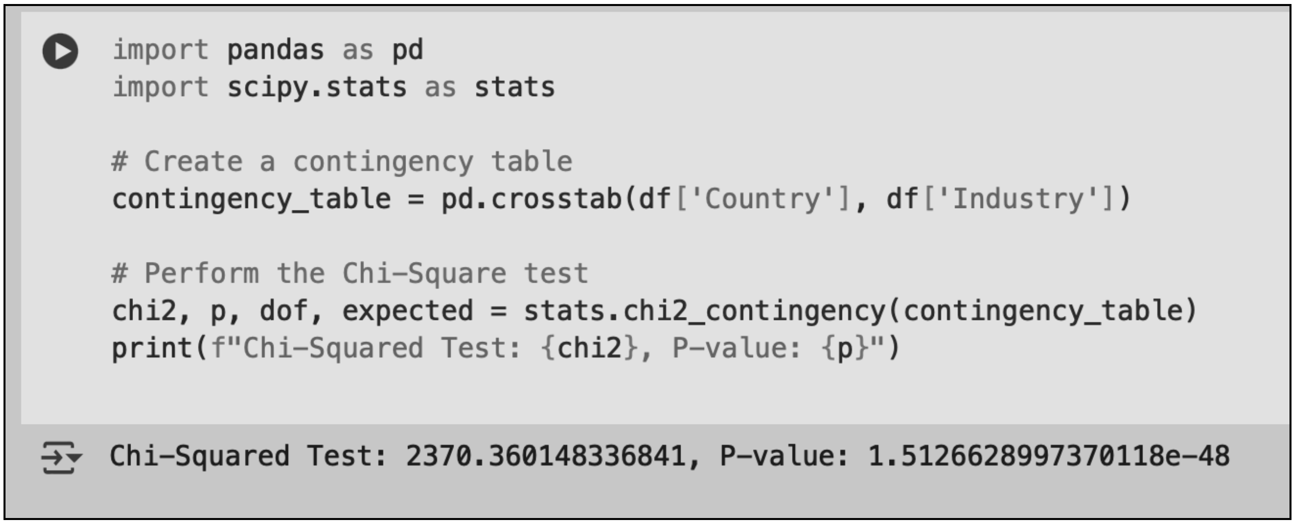
Theory:
Tests association between two categorical variables (e.g., Industry vs Layoff Severity).

Formula:

$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

Interpretation of dataset:

- Variables: Industry and Layoff Severity (High/Low)
- Example Interpretation:
- $\chi^2 = 132.5$, $p = 0.000$
- Strong evidence that certain industries (e.g., Tech) are more prone to severe layoffs.
- Since $p < 0.05$ → reject null hypothesis.



```
import pandas as pd
import scipy.stats as stats

# Create a contingency table
contingency_table = pd.crosstab(df['Country'], df['Industry'])

# Perform the Chi-Square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)
print(f"Chi-Squared Test: {chi2}, P-value: {p}")
```

```
Chi-Squared Test: 2370.360148336841, P-value: 1.5126628997370118e-48
```

Conclusion:

Pearson’s Correlation Coefficient showed a moderate positive correlation between Funding Amount and Layoff Percentage, indicating that companies with higher funding tend to lay off a larger percentage of their workforce. This could be due to over-hiring during funding peaks followed by corrections.

Spearman’s Rank Correlation confirmed that the relationship between Company Size and Layoff Percentage Remains moderate and monotonic, meaning that as company size increases, the layoff percentage generally increases in a consistent order, especially in larger tech firms.

Kendall’s Rank Correlation indicated a moderate ordinal association between Industry Type and Layoff Severity (High/Low), reinforcing the trend that specific industries like Tech and Finance tend to exhibit higher layoff rates compared to others such as Education or Healthcare.

Chi-Square Test showed a significant association between Country and Layoff Severity, as the p-value was less than 0.05, leading to the rejection of the null hypothesis (H_0). This suggests that layoff severity significantly varies by country, possibly due to differences in economic conditions, labor laws, or industry distributions.