Install the Necessary Libraries

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```
!pip install astroML numpy pandas scipy matplotlib seaborn
```

```
Collecting astroML
  Downloading astroML-1.0.2.post1-py3-none-any.whl (134 kB)
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0:00:00
ent already satisfied: numpy in /usr/local/lib/python3.10/dist-
packages (1.23.5)
Requirement already satisfied: pandas in
/usr/local/lib/python3.10/dist-packages (1.5.3)
Requirement already satisfied: scipy in
/usr/local/lib/python3.10/dist-packages (1.11.4)
Requirement already satisfied: matplotlib in
/usr/local/lib/python3.10/dist-packages (3.7.1)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.10/dist-packages (0.13.1)
Requirement already satisfied: scikit-learn>=0.18 in
/usr/local/lib/python3.10/dist-packages (from astroML) (1.2.2)
Requirement already satisfied: astropy>=3.0 in
/usr/local/lib/python3.10/dist-packages (from astroML) (5.3.4)
Requirement already satisfied: python-dateutil>=2.8.1 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in
/usr/local/lib/python3.10/dist-packages (from pandas) (2023.3.post1)
Requirement already satisfied: contourpy>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.2.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (4.47.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (23.2)
Requirement already satisfied: pillow>=6.2.0 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
/usr/local/lib/python3.10/dist-packages (from matplotlib) (3.1.1)
Requirement already satisfied: pyerfa>=2.0 in
/usr/local/lib/python3.10/dist-packages (from astropy>=3.0->astroML)
```

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(2.0.1.1)
Requirement already satisfied: PyYAML>=3.13 in
/usr/local/lib/python3.10/dist-packages (from astropy>=3.0->astroML)
(6.0.1)
Requirement already satisfied: six>=1.5 in
/usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.8.1-
>pandas) (1.16.0)
Requirement already satisfied: joblib>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.18-
>astroML) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=0.18-
>astroML) (3.2.0)
Installing collected packages: astroML
Successfully installed astroML-1.0.2.post1
```

1. In the class, we demonstrated the Central Limit Theorem for a sample drawn from a uniform distribution. Reproduce a similar plot for a sample drawn the from chi-square distribution with degrees of freedom equal to 3, for samples drawn once, 5 times, and 10 times. Either plot all of these on one multipanel figure similar to AstroML figure 3.20. (Hint: look up numpy.random.chisquare and show the distribution of x from 0 to 10)

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns


def first_plot(sample_size: int =1)->None:

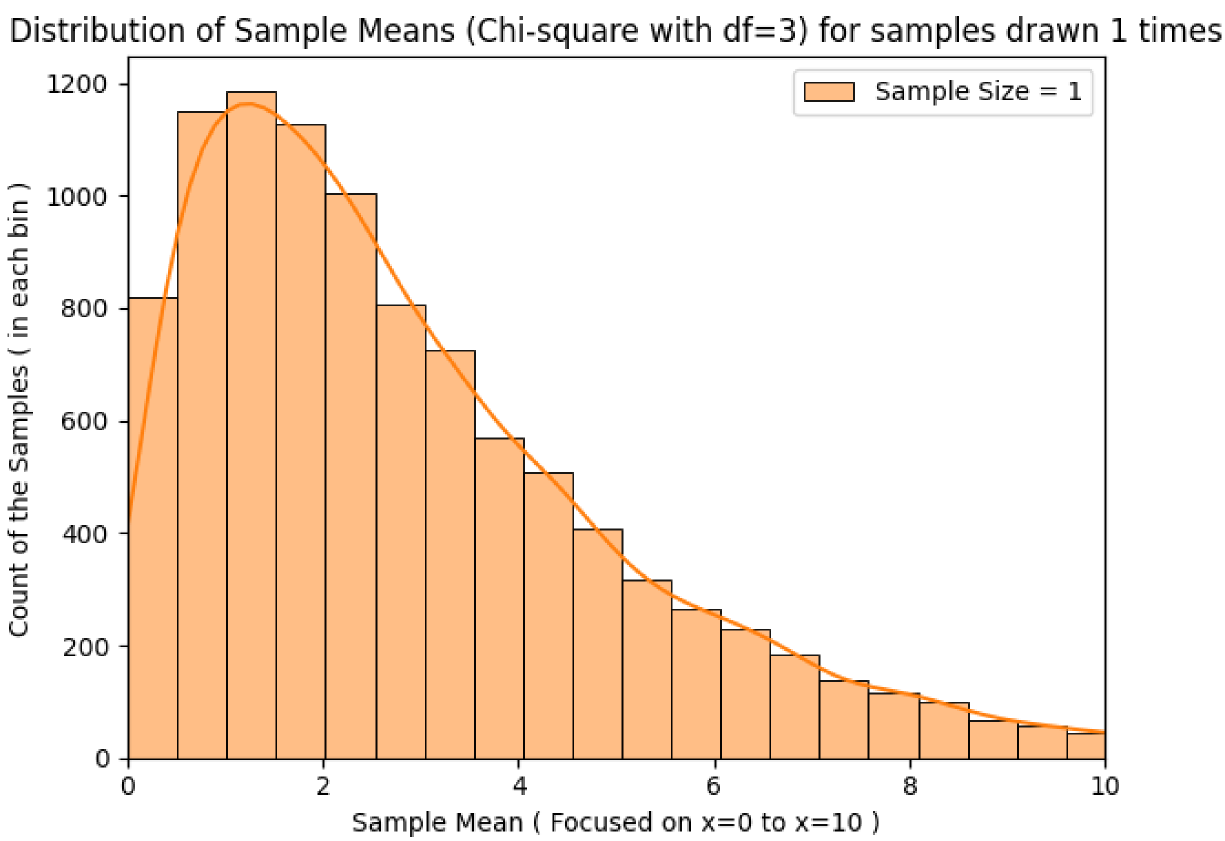
    np.random.seed(42)  # Set the seed to draw the random samples
    df = 3              # Define the degrees of freedom for the chi-
square distribution
```

```
    # Generate and plot samples for given Sample Size
    # Draw samples from the chi-square distribution
    samples = np.random.chisquare(df, size=(sample_size, 10000))

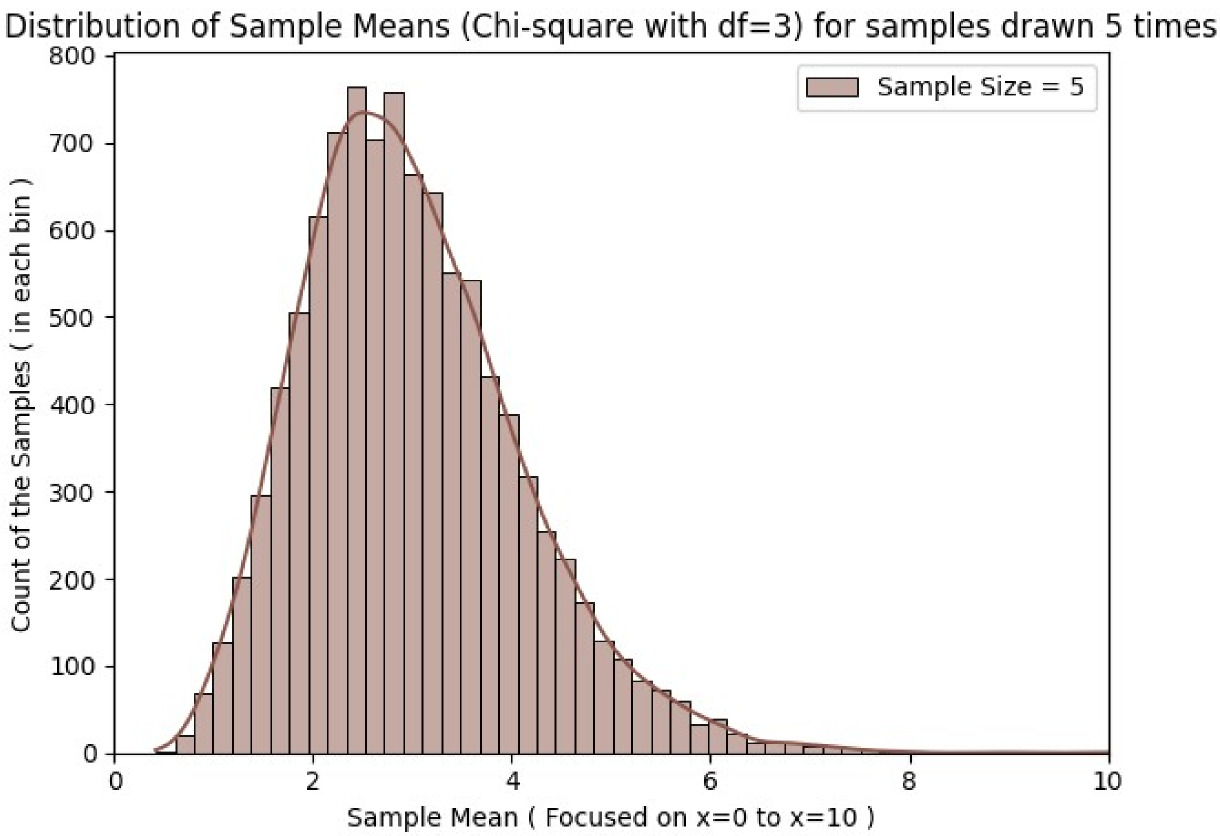
    # Calculate sample means
    sample_means = np.mean(samples, axis=0)

    # Plot the Required Figures
    sns.histplot(sample_means, kde=True, bins=50,  label=f'Sample Size
= {sample_size}', color='C'+str(sample_size))
    plt.legend()
    plt.title(f'Distribution of Sample Means (Chi-square with df={df})
for samples drawn {sample_size} times')
    plt.xlabel('Sample Mean ( Focused on x=0 to x=10 )')
    plt.ylabel('Count of the Samples ( in each bin )')
    plt.xlim(0, 10)
    plt.tight_layout()
    plt.show()

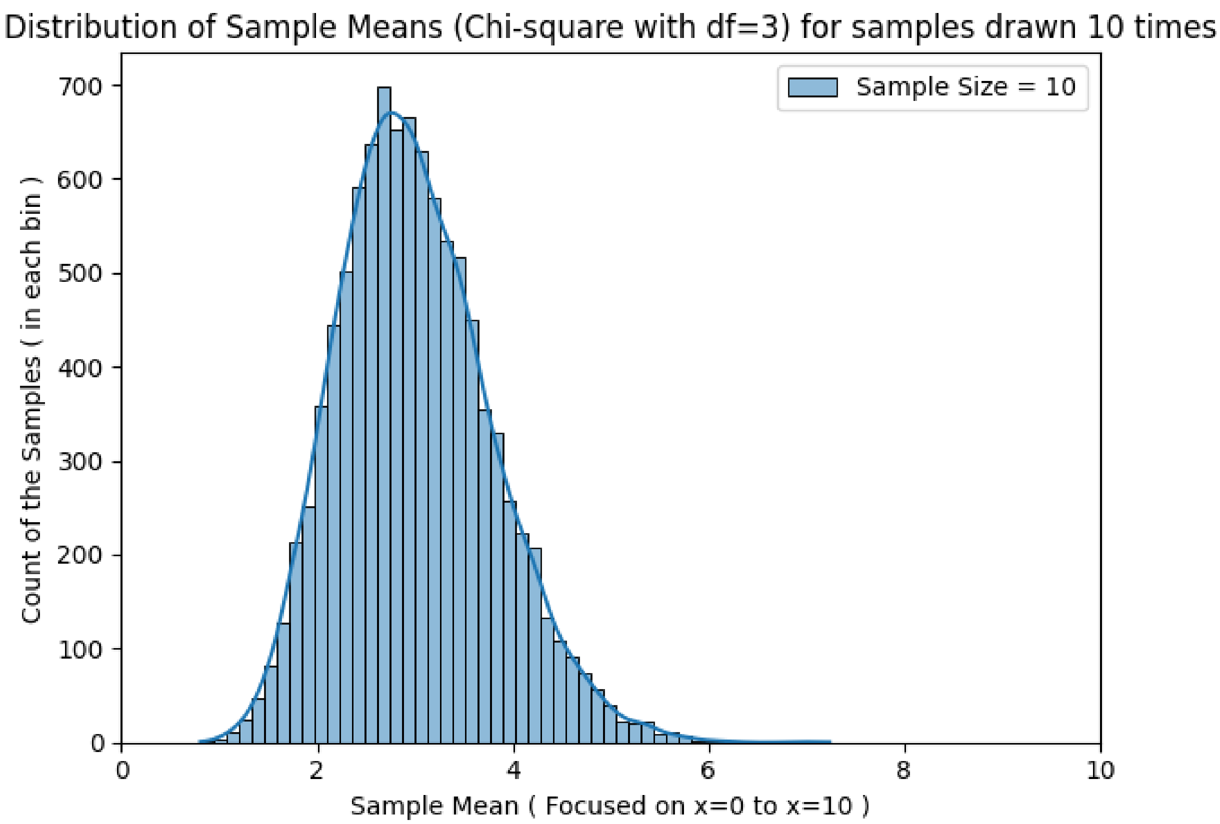
# Plot for samples drawn 1 times
first_plot(1)
```



```
# Plot for samples drawn 5 times
first_plot(5)
```




```
# Plot for samples drawn 10 times
first_plot(10)
```

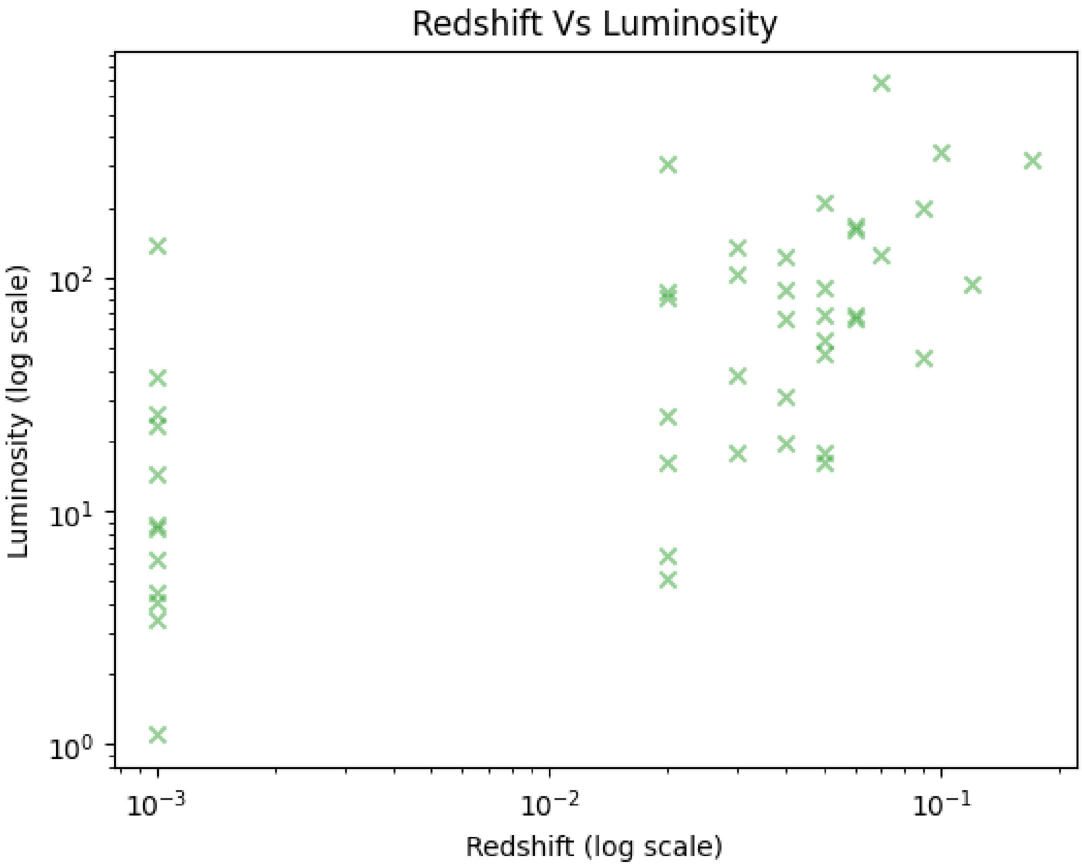


2. The luminosity and redshift of galaxy clusters from XMM-BCS survey (details available at arXiv:1512.01244) can be downloaded http://www.iith.ac.in/~shantanud/test.dat. Plot the luminosity as a function of redshift on a log-log scale. By eye, do you think the datasets are correlated? Calculate the Spearman, Pearson and Kendall-tau correlation coefficients and the p-value for the null hypothesis.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import spearmanr, pearsonr, kendalltau
```

```python
def second_plot()->None:

    # Load the data Stored on Local Machine in same folder
    data = pd.read_csv('galaxy_cluster_data.txt', sep='\s+',
header=None, names=['luminosity', 'redshift'])

    # Droped the first row in the dataset as we have loaded the
    # dataset with different column names
    data = data.drop([0])

    # Convert columns to numeric (if needed)
    # I am getting TypeError: unsupported operand type(s) for +:
'float' and 'str'
    # Hence I have used below function
    data['luminosity'] = pd.to_numeric(data['luminosity'],
errors='coerce')
    data['redshift'] = pd.to_numeric(data['redshift'],
errors='coerce')

    # Ploting the luminosity as a function of redshift on a log-log
scale
    plt.scatter(x=data['redshift'], y=data['luminosity'], alpha=0.5,
c='C2', marker='x')
    plt.xscale('log')
    plt.yscale('log')
    plt.xlabel('Redshift (log scale)')
    plt.ylabel('Luminosity (log scale)')
    plt.title(' Redshift Vs Luminosity ')
    plt.show()

    # Calculate correlation coefficients and p-values
    spearman_corr, spearman_p_value = spearmanr(data['redshift'],
data['luminosity'])
    pearson_corr, pearson_p_value = pearsonr(data['redshift'],
data['luminosity'])
    kendall_corr, kendall_p_value = kendalltau(data['redshift'],
data['luminosity'])

    # Print the results
    print(f"\n\nSpearman correlation coefficient: {spearman_corr:.4f},
Spearman p-value: {spearman_p_value:.4f}")
    print(f"\n\nPearson correlation coefficient: {pearson_corr:.4f},
Pearson p-value: {pearson_p_value:.4f}")
    print(f"\n\nKendall Tau correlation coefficient:
{kendall_corr:.4f},   Kendall Tau p-value: {kendall_p_value:.4f}")

# Call the function to display plot
second_plot()
```

```
# Before calculating the correlation coefficient, We observe
# that there is a Linear-Positive Relationship among Redshift and
Luminosity
```

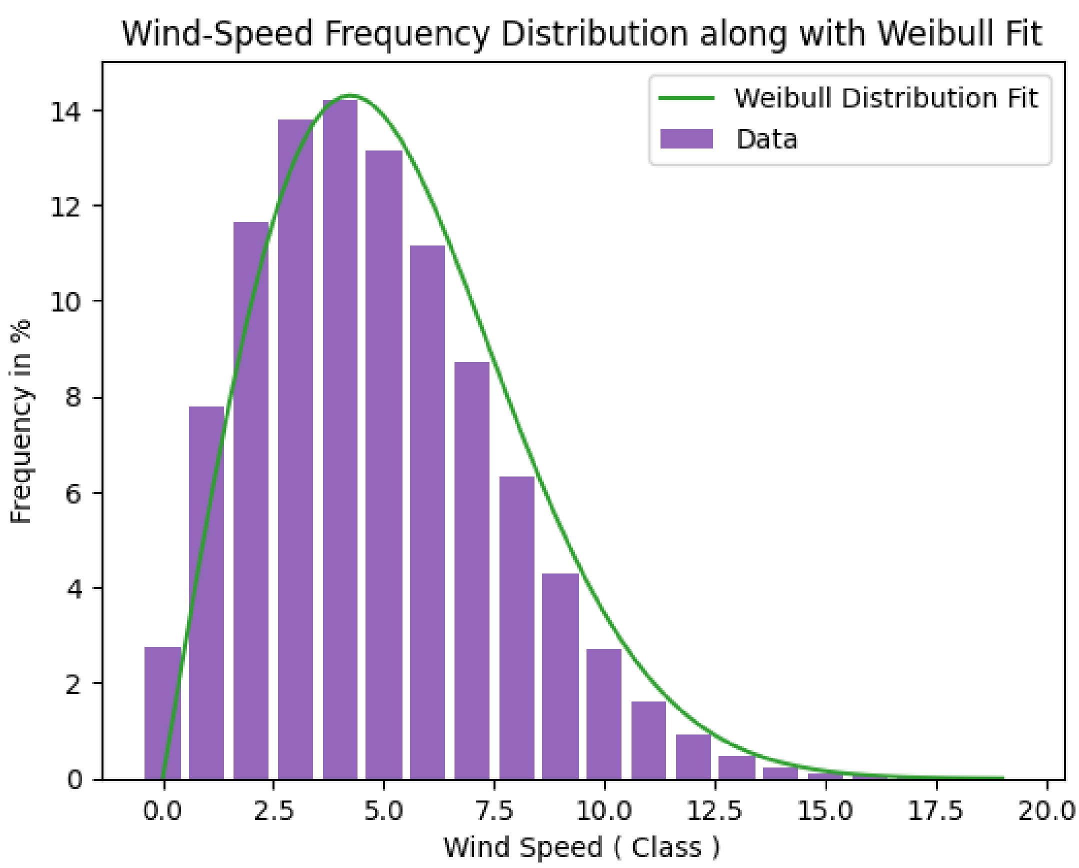



```
Spearman correlation coefficient: 0.6596,   Spearman p-value: 0.0000

Pearson correlation coefficient: 0.5144,   Pearson p-value: 0.0003

Kendall Tau correlation coefficient: 0.5030,   Kendall Tau p-value:
0.0000
```

3. Wind speed data from the Swiss Wind Power data website can be found at http://wind-data.ch/tools/weibull.php. Using the data provided on the website, plot the probability distribution and overlay the best-fit Weibull distribution (with the parameters shown on the website). (20 points) (Hint : A on the website is same as λ, which was used in class to parameterize the Weibull distribution.)

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from scipy.stats import weibull_min

def third_plot()->None:
    # Load the data Stored on Local Machine in same folder
    data = pd.read_csv('wind_data.txt', sep='\t', header=None,
names=['Class', 'Frequency in %'])

    # Droped the first row in the dataset as we have loaded the
    # dataset with different column names
    data = data.drop([0])

    # Convert columns to numeric (if needed)
    # TypeError: ufunc 'isfinite' not supported for the input types,
and the inputs could
    # not be safely coerced to any supported types according to the
casting rule ''safe''
    # Hence I have used below function
    data['Class'] = pd.to_numeric(data['Class'], errors='coerce')
    data['Frequency in %'] = pd.to_numeric(data['Frequency in %'],
errors='coerce')


    # Weibull distribution parameters (replace these with the actual
parameters)
    shape = 2.0  # shape parameter (c or k)
    scale = 6.0  # scale parameter (λ or c)
    location = 0.0  # location parameter (δ)
```

```
    # Plot the data in the histogram for the % frequencies
    plt.bar(data['Class'], data['Frequency in %'], label='Data',
color='C4')

    # Overlay the Weibull distribution
    x = np.linspace(0, max(data['Class']), 100)
    y_fit = weibull_min.pdf(x, shape, loc=location, scale=scale)
    plt.plot(x, y_fit * 100, 'C12', label='Weibull Distribution Fit')

    plt.xlabel('Wind Speed ( Class )')
    plt.ylabel('Frequency in %')
    plt.title('Wind-Speed Frequency Distribution along with Weibull
Fit')
    plt.legend()
    plt.show()

# Call the function to display plot
third_plot()
```



4. Generate two arrays of size 1000 drawn from a Gaussian distribution of mean of zero and standard deviation of one. Calculate Pearson correlation coefficient and its p–value using scipy module. Also check if the p– value agrees with that calculated using the Student-t distibution.

```
import numpy as np
from scipy.stats import pearsonr, t

def fourth_plot(t_dis_tail: int=2)->None:

    np.random.seed(42)  # Set the seed to draw the random samples

    # Generate two Numpy arrays of size 1000 drawn from a Gaussian
distribution
    gaussian_generated_one = np.random.normal(0, 1, 1000)
    gaussian_generated_two = np.random.normal(0, 1, 1000)

    # Calculate Pearson correlation coefficient and its p-value
    correlation_pearson, pearson_p_value =
pearsonr(gaussian_generated_one, gaussian_generated_two)

    # Degrees of freedom for the Student-t distribution
    df = len(gaussian_generated_one) - 2  # for Pearson correlation

    # Calculate p-value using the Student-t distribution
    t_distribution_p_value = t_dis_tail * (1 -
t.cdf(np.abs(correlation_pearson) * np.sqrt(df) / np.sqrt(1 -
correlation_pearson**2), df))

    print(f"\n\nPearson correlation coefficient:
{correlation_pearson:.4f}")
    print(f"\n\nP-value using scipy.stats.pearsonr:
{pearson_p_value:.4f}")
    print(f"\n\nP-value using Student-t distribution:
{t_distribution_p_value:.4f}")

    # check if the p–value agrees with that calculated using the
Student-t distibution.
    if np.isclose(pearson_p_value, t_distribution_p_value, rtol=1e-4):
        print("\n\nP-values agree.")
```

```python
    else:
        print("\n\nP-values do not agree.")

# Taking the t-distribution tail as 1 ( Half )
fourth_plot(t_dis_tail=1)
```

```
Pearson correlation coefficient: -0.0404


P-value using scipy.stats.pearsonr: 0.2018


P-value using Student-t distribution: 0.1009


P-values do not agree.
```

```python
# Taking the t-distribution tail as 1 ( Half )
fourth_plot(t_dis_tail=2)
```

```
Pearson correlation coefficient: -0.0404


P-value using scipy.stats.pearsonr: 0.2018


P-value using Student-t distribution: 0.2018


P-values agree.
```