EP20BTECH11015-Assignment-2

January 21, 2023

0.1 EP20BTECH11015 - Assignment - 2

```
[ ]: import numpy as np
     from scipy import stats as st
     from scipy.optimize import curve_fit
     import astropy as ap
     import astroML.stats as aml
     import pandas as pd
     import matplotlib.pyplot as plt
```

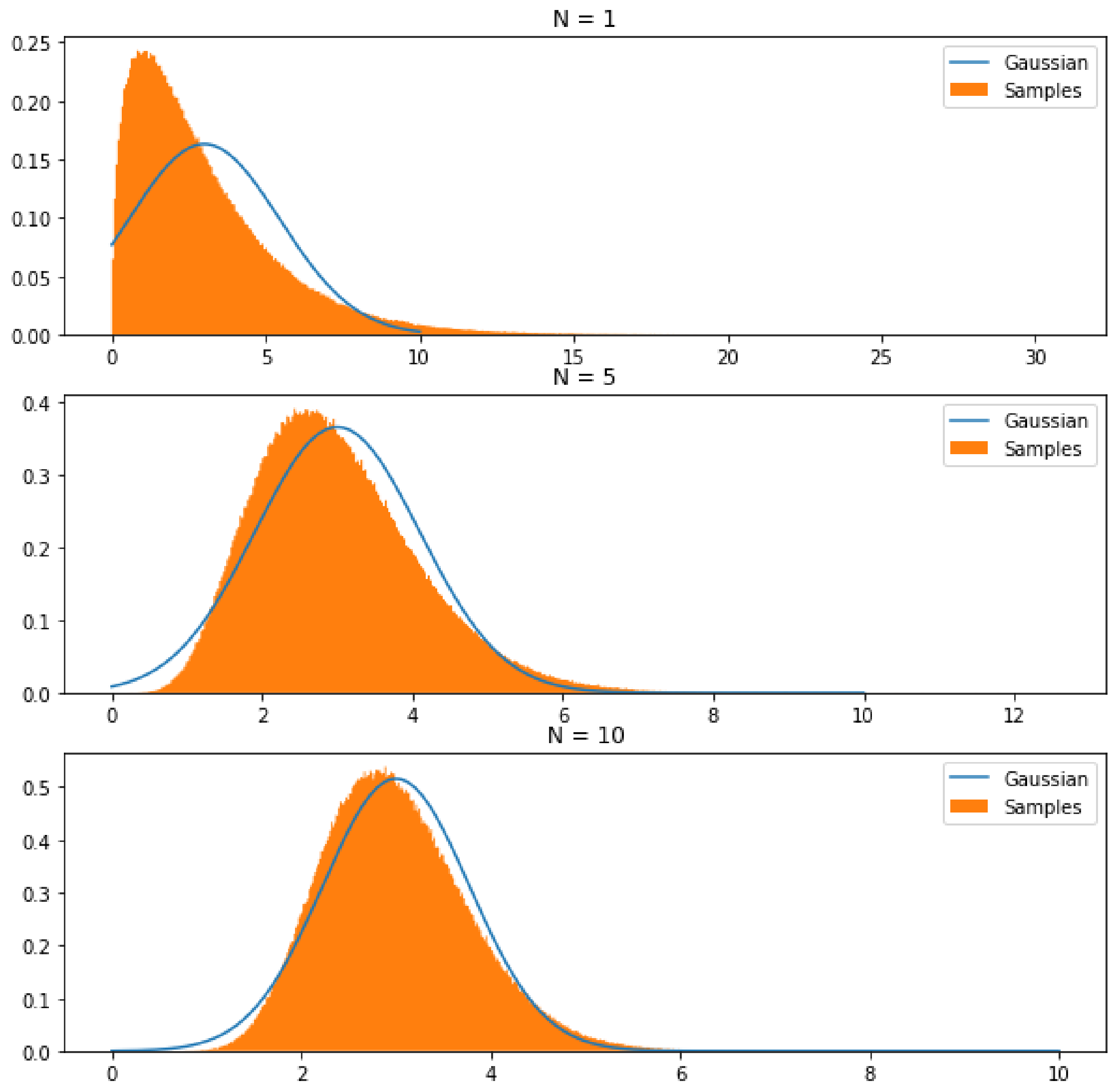
0.1.1 Q1

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.

```
[ ]: N = [1, 5, 10]

     plt.figure(figsize=(10, 10))
     for i in range(len(N)):

         # generating random numbers
         chisample = np.random.chisquare(3, (N[i], 10**6))
         # mean of the samples
         chimean = chisample.mean(axis=0)

         plt.subplot(3, 1, i+1)


         #plotting the gaussian
         x = np.linspace(0, 10, 1000)
         gauss = st.norm.pdf(x, chimean.mean(), np.sqrt(chimean.var()))
         plt.plot(x, gauss, label='Gaussian')
         # plotting the histogram

         plt.hist(chimean, bins=500, density=True, histtype='stepfilled',␣
      ↪label='Samples')
```

```
    plt.title('N = {}'.format(N[i]))
    plt.legend()



plt.show()
```



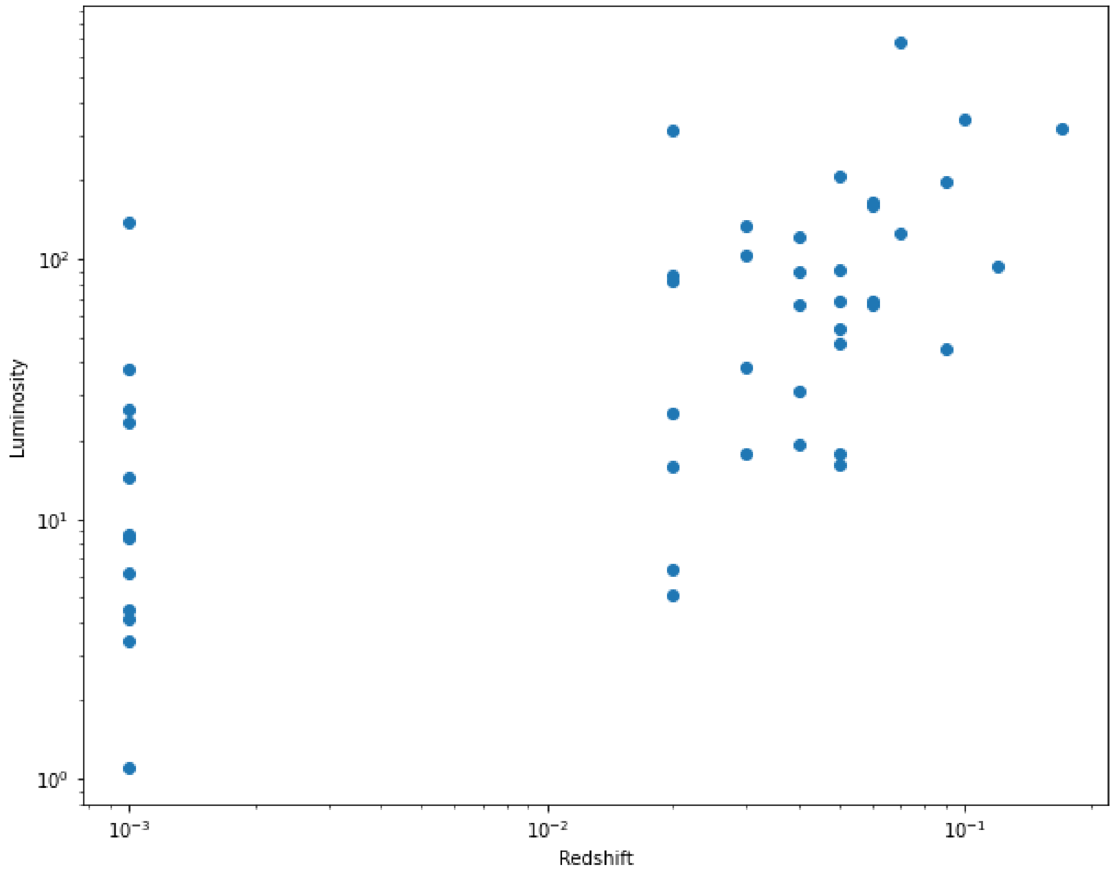
0.1.2 Q2

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.

```
[ ]: data = np.loadtxt('test.dat')

     plt.figure(figsize=(10,8))
     plt.scatter(data[:, 1], data[:, 0])
     plt.ylabel('Luminosity')
     plt.xlabel('Redshift')
     plt.xscale('log')
     plt.yscale('log')
     plt.show()
```



By the eye, the luminosity seems to be somewhat increasing with the redshift. This indicates a moderate positive correlation between them.

```
[ ]: spearman = st.spearmanr(data[:, 1], data[:, 0])
     print("SPEARMAN_R\n Correlation Coefficient: {}\n p-value: {}\n".
      ↪format(spearman[0], spearman[1]))
```

```
kendall = st.kendalltau(data[:, 1], data[:, 0])
print("KENDALL_TAU\n Correlation Coefficient: {}\n p-value: {}\n".
  ↪format(kendall[0], kendall[1]))

pearson = st.pearsonr(data[:, 1], data[:, 0])
print("PEARSON_R\n Correlation Coefficient: {}\n p-value: {}\n".
  ↪format(pearson[0], pearson[1]))
```

```
SPEARMAN_R
 Correlation Coefficient: 0.6596325957535454
 p-value: 6.166489759081011e-07

KENDALL_TAU
 Correlation Coefficient: 0.5029584682704178
 p-value: 2.9696862274734036e-06

PEARSON_R
 Correlation Coefficient: 0.5144497852670242
 p-value: 0.0002546471657612425
```

The correlation coeffiecients are around 0.5-0.6, which is a moderate positive correlation.

The p-value is very small, which indicates that the null hypothesis is rejected.

0.1.3 Q3

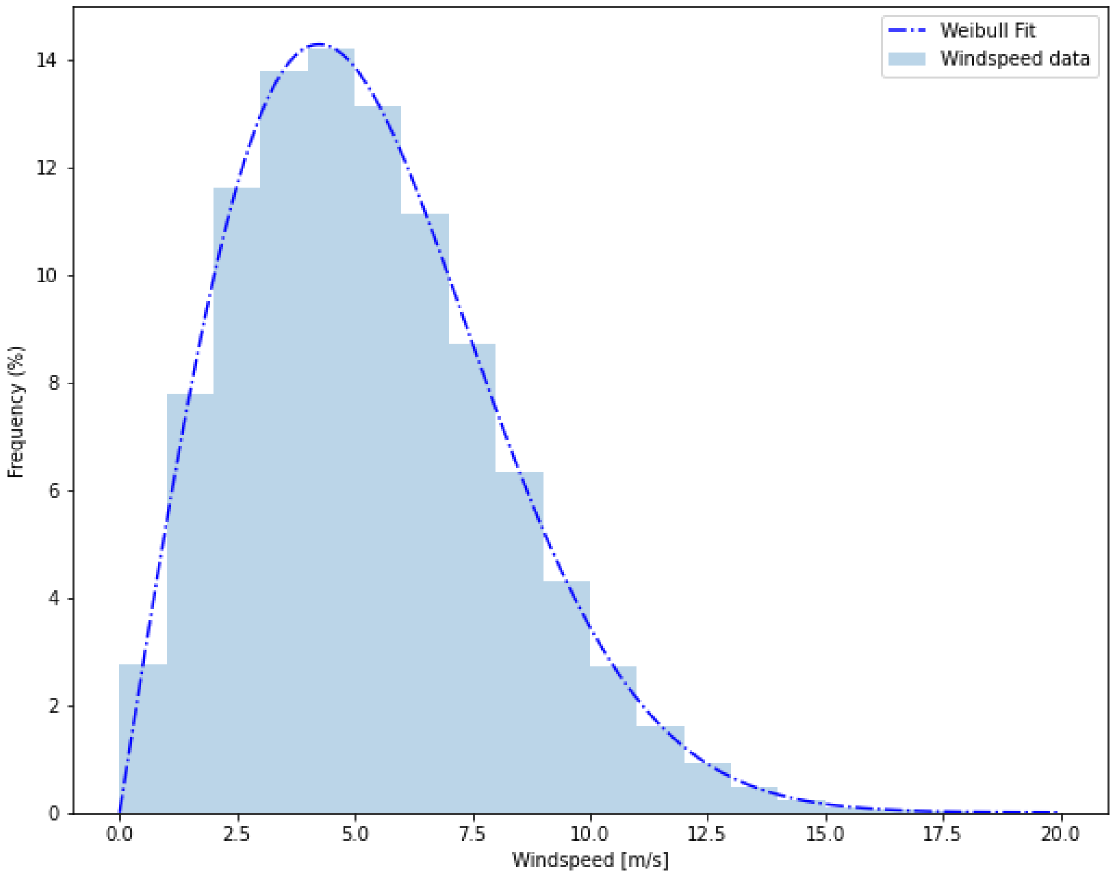
Wind speed data from the Swiss Wind Power data website can be found at http://wind-data.ch/tools/weibull.php.

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).

(Hint : A on the website is same as , which was used in class to parameterize the Weibull distribution.)

```
[ ]: data = pd.read_csv('weibull.dat', sep='\t', header=None)

     plt.figure(figsize=(10,8))

     #Plotting the frequencies
     plt.bar(np.linspace(0.5, 20.5, 21)[:-1], data[1],width=1, label='Windspeed␣
       ↪data', alpha=0.3)

     #Plotting the Weibull Fit
     plt.plot(np.linspace(0, 20, 1000), st.dweibull(2, 0, 6).pdf(np.linspace(0, 20,␣
       ↪1000))*200, label='Weibull Fit', c='b', ls = '-.')
```

```
plt.xlabel('Windspeed [m/s]')
plt.ylabel('Frequency (%)')
plt.legend()
plt.show()
```



0.1.4 Q4

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.

[ ]:
```
#Generating two random normal distributed samples
norm = [st.norm(0, 1).rvs(1000), st.norm(0, 1).rvs(1000)]

#p-value from pearson_r
pearson = st.pearsonr(*norm)
```

```
print("Pearson correlation coefficient r = %.5f\np-value of Pearson = %.
 ↪5f"%pearson)

#p-value from Student's t.cdf
st_t = pearson.statistic * np.sqrt((1000 - 2) / (1 - pearson.statistic ** 2))

pearson_p_manual = 2*(1 - st.t.cdf(np.abs(st_t), 998))
#Absolute value of t is taken because -ve values of r give p-value > 1

print('p-value from Students t = %.5f\nThe p-values match in both cases'␣
 ↪%pearson_p_manual)
```

```
Pearson correlation coefficient r = -0.03782
p-value of Pearson = 0.23218
p-value from Students t = 0.23218
The p-values match in both cases
```