ee21b154

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1 Assignment 3

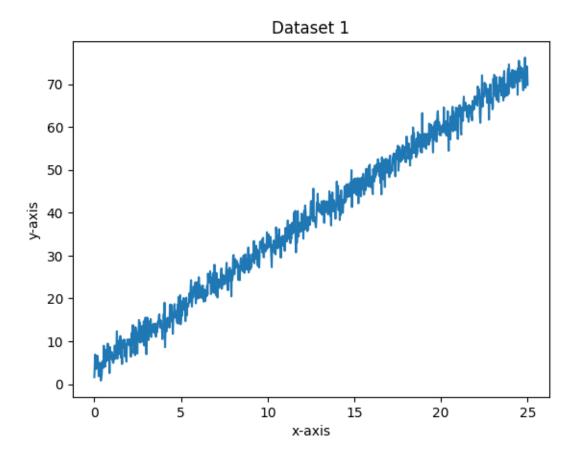
1.1 Plotting and Visualization

In this assignment we are trying to plot a reasonable curve for a bunch of known and unknown dataset. We are trying to predict the possible and use the curve_fit fuction to estimate if the predicted graph is accurate.

1.1.1 For Dataset 1

```
[92]: import numpy as np
import matplotlib.pyplot as plt
import statistics
from scipy.optimize import curve_fit
%matplotlib inline
```

```
[93]: Text(0.5, 1.0, 'Dataset 1')
```

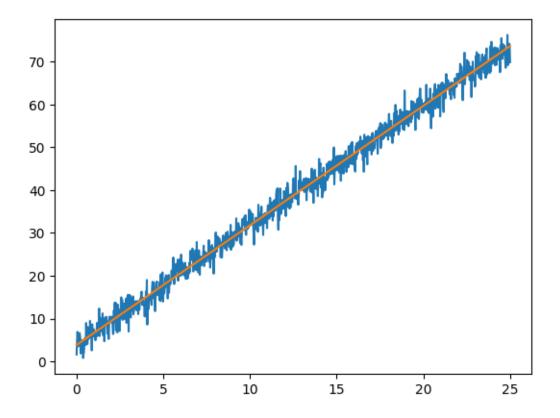


Using linalg.lstsq for this dataset as we know that it's a straight line, with 2 parameters varying linearly with x.

```
[94]: M = np.column_stack([x, np.ones(len(x))])
# Using the lstsq function to solve for p_1 and p_2
(p1, p2), _, _, _ = np.linalg.lstsq(M, y, rcond=None)
print(f"The estimated equation is {p1} t + {p2}")
def stline(x, m, c):
    z=[]
    for i in range(len(x)):
        z.append(p1*x[i]+p2) #defining a straight line function
    return z

yest = stline(x, p1, p2) #Plotting the obtained linear curve through lstsq
plt.plot(x,y,x,yest )
```

The estimated equation is 2.791124245414918 t + 3.848800101430742



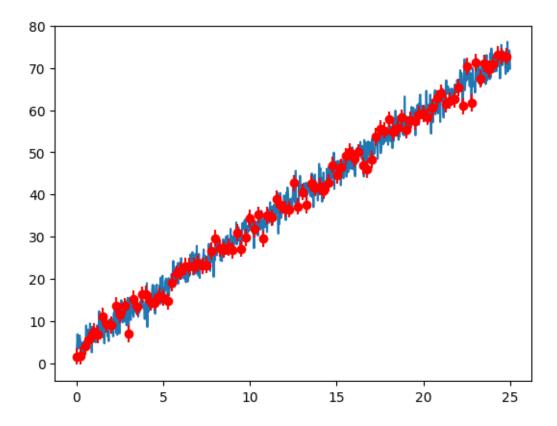
The error bar for this can be plotted as the standard deviation of the estimated value and actual value

```
[95]: y_err=y-yest
plt.plot(x,y)
plt.errorbar(x[::10], y[::10], yerr=np.std(y_err), fmt='ro')
%timeit np.linalg.lstsq(M, y) #timeit function
```

<magic-timeit>:1: FutureWarning: `rcond` parameter will change to the default of
machine precision times ``max(M, N)`` where M and N are the input matrix
dimensions.

To use the future default and silence this warning we advise to pass `rcond=None`, to keep using the old, explicitly pass `rcond=-1`.

 $35.4 \mu s \pm 8 \mu s$ per loop (mean \pm std. dev. of 7 runs, 10,000 loops each)

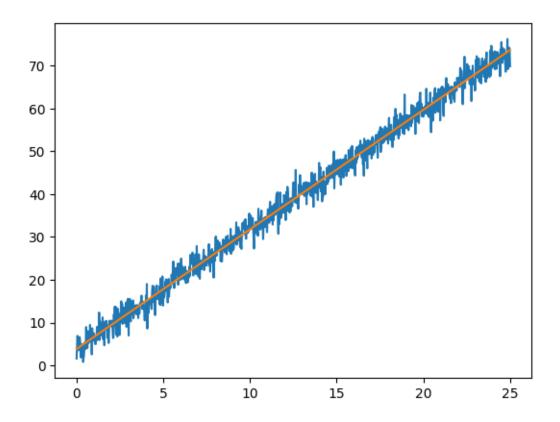


We are using curve_fit on the linear fuction to check which one of these methods of drawing a graph might be feasible

```
[96]: from scipy.optimize import curve_fit
  (zp1, zp2), pcov = curve_fit( stline,x, y)
  print(f"Estimated function: exp(-{zp1}t) + {zp2}")

zest = stline(x, zp1, zp2)
  plt.plot(x, y, x, zest)
```

Estimated function: exp(-1.0t) + 1.0



```
[97]: cuy_err=y-zest

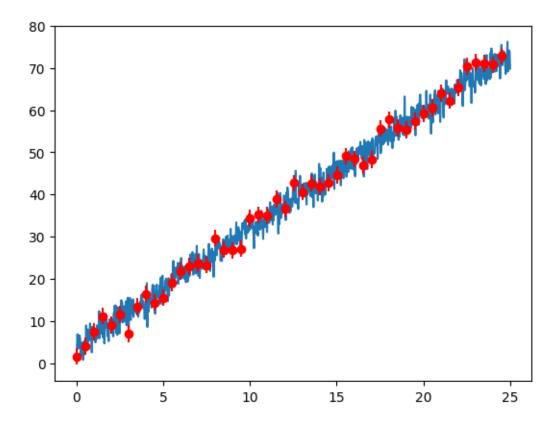
plt.plot(x, y)

plt.errorbar(x[::20], y[::20], np.std(cuy_err), fmt='ro') #erroe bar for when_

curvefit used

%timeit curve_fit(stline,x, y) #timeit function
```

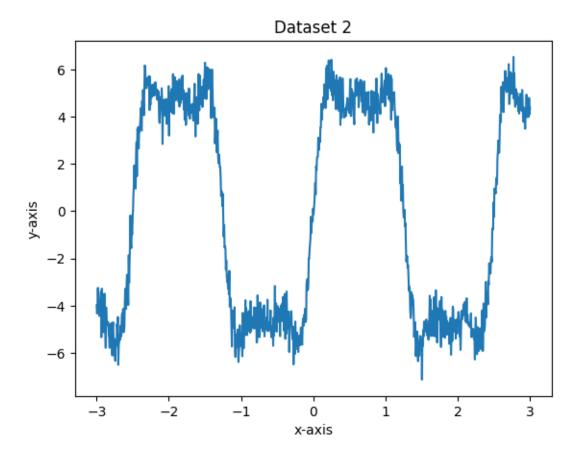
 $1.42 \text{ ms} \pm 32.5 \text{ } \mu\text{s}$ per loop (mean \pm std. dev. of 7 runs, 1,000 loops each)



Clearly we can see that when lstsq was used for plotting cure for a known linear graph, it was much faster compared to using curvefit(which is mostly used for non-linear functions)

1.1.2 For Dataset 2

[98]: Text(0.5, 1.0, 'Dataset 2')



Fourier series equation

$$f(x) = \frac{4}{\pi} \sum_{n=1,3,5,\dots}^{\infty} \frac{1}{n} \sin\left(\frac{n\pi x}{L}\right).$$

The given Dataset is said to be a Fourier series. Hence, we define functions for n=1,3,5... and see the best fit for the given data.

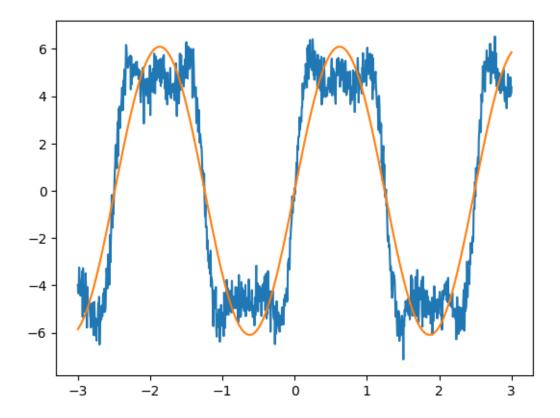
```
[99]: #Fourier equations
    def fourier_1(x,a,1):
        return a*(4/np.pi)*(np.sin(np.pi*x/1)) #For n=1
    def fourier_3(x,a,1):
        return a*(4/np.pi)*((np.sin(np.pi*x/1))+((np.sin((np.pi*x*3)/1))/3)) #For n=3
    def fourier_5(x,a,1):
```

```
return a*(4/np.pi)*((np.sin(np.pi*x/1))+((np.sin((np.pi*x*3)/1))/3)+((np.sin((np.pi*x*5)/1))/5)) #For n=5
```

For n=1

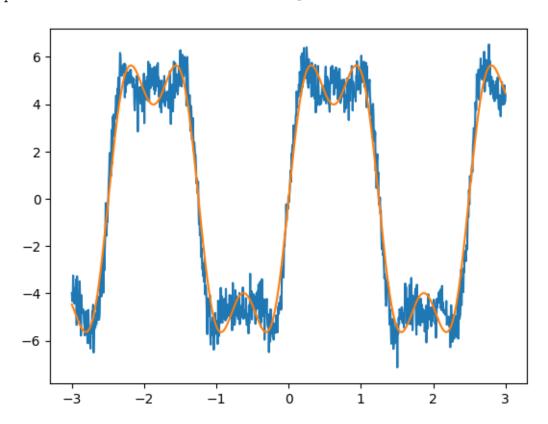
```
[100]: from scipy.optimize import curve_fit
  (zp1, zp2), pcov = curve_fit( fourier_1,x, y)
  print(f"Estimated function: exp(-{zp1}t) + {zp2}")
  zest = fourier_1(x, zp1, zp2)
  plt.plot(x, y, x, zest)
```

Estimated function: exp(-4.784329317633403t) + 1.2448266475990044



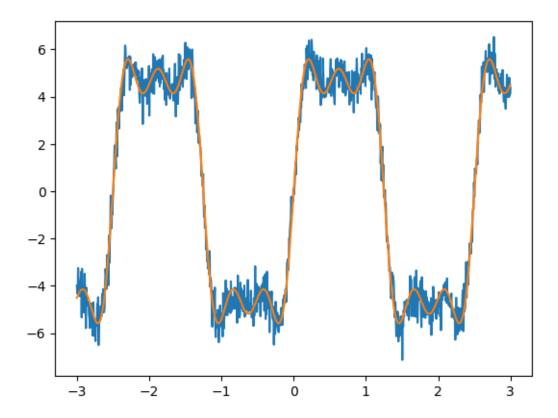
```
For n=3
[101]: from scipy.optimize import curve_fit
  (zp1, zp2), pcov = curve_fit( fourier_3,x, y)
  print(f"Estimated function: exp(-{zp1}t) + {zp2}")
  zest = fourier_3(x, zp1, zp2)
  plt.plot(x, y, x, zest)
```

Estimated function: exp(-4.695927291303469t) + 1.2473976512331715



```
For n=5
[102]: from scipy.optimize import curve_fit
  (zp1, zp2), pcov = curve_fit( fourier_5,x, y)
  print(f"Estimated function: exp(-{zp1}t) + {zp2}")
  zest = fourier_5(x, zp1, zp2)
  plt.plot(x, y, x, zest)
```

Estimated function: exp(-4.695620880486891t) + 1.2506520749990966



We see that at n=5, the fourier graph fits well with given data set. It now makes sense to use fourier_5 for curve_fit

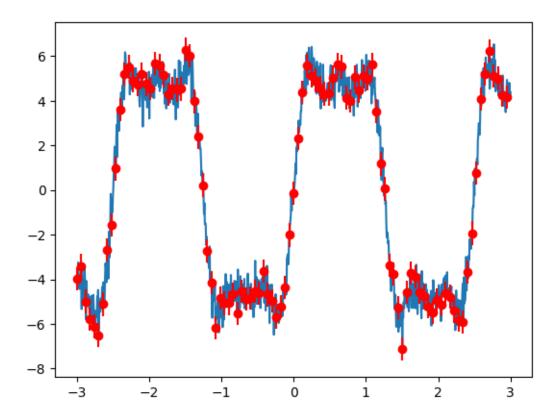
```
[103]: cuy_err=y-zest

plt.plot(x, y)

plt.errorbar(x[::10], y[::10], np.std(cuy_err), fmt='ro') #erroe bar for when_

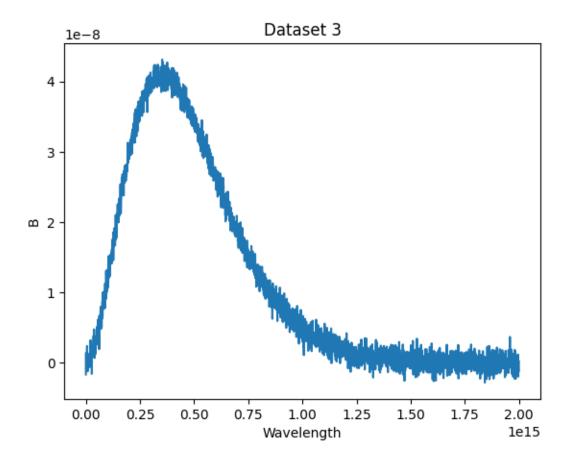
curvefit used
```

[103]: <ErrorbarContainer object of 3 artists>



1.1.3 For Dataset 3

[104]: Text(0.5, 1.0, 'Dataset 3')



The given dataset is said to follow Planck's law.

$$B(
u,T)=rac{2h
u^3}{c^2}rac{1}{rac{hv}{ek_BT}-1}$$

Hence, we try to define a function having frequency, temperature and planck's constant.

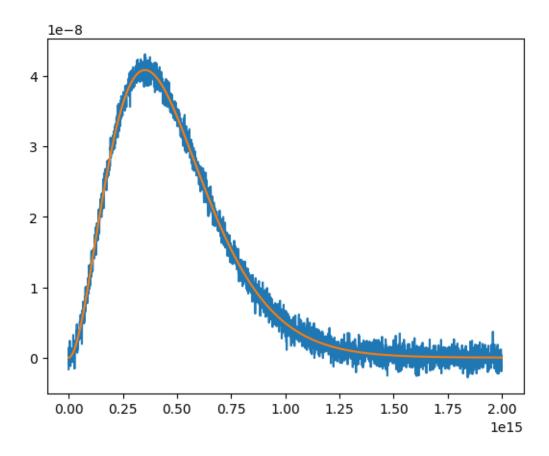
```
[105]: import math as m
def planck(f,h,T):
    c=3.0*(m.pow(10,8))
    kb=1.38*(m.pow(10,-23))

return ((2*h*(f*f*f))/(c*c)*(1/((np.exp((h*f)/(kb*T))-1))))
```

Now, you plot the curve using curve_fit.

```
[106]: from scipy.optimize import curve_fit
  (zp1, zp2), pcov = curve_fit( planck,x, y,p0=[6*m.pow(10,-34),300])
  print(f"Estimated function: exp(-{zp1}t) + {zp2}")
  zest = planck(x, zp1, zp2)
  plt.plot(x, y, x, zest)
```

Estimated function: $\exp(-6.643229758011344e-34t) + 6011.36152125128$



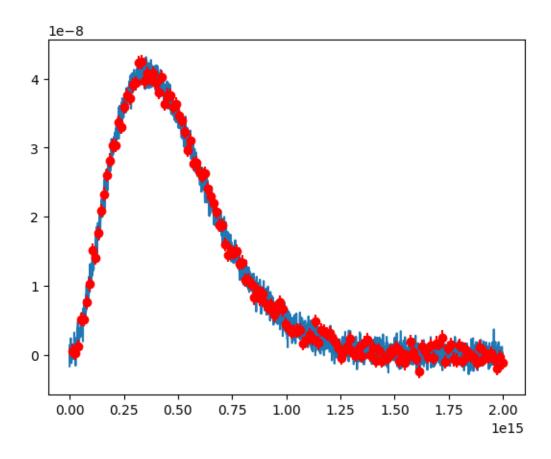
```
[107]: cuy_err=y-zest

plt.plot(x, y)

plt.errorbar(x[::20], y[::20], np.std(cuy_err), fmt='ro') #erroe bar for when_

curvefit used
```

[107]: <ErrorbarContainer object of 3 artists>

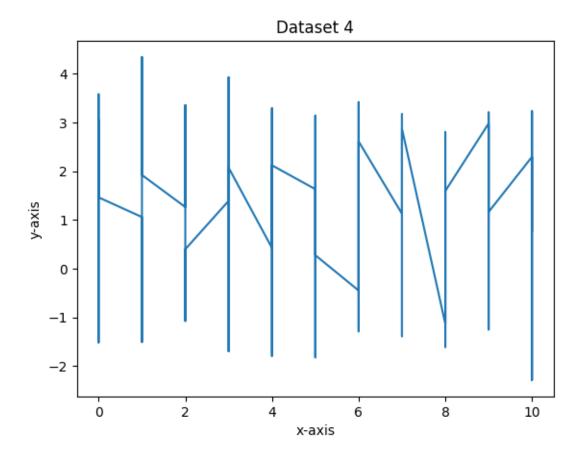


1.1.4 For Dataset 4

We do not know the nature of the the given dataset, hence we plot it using random methods to find a sequence.

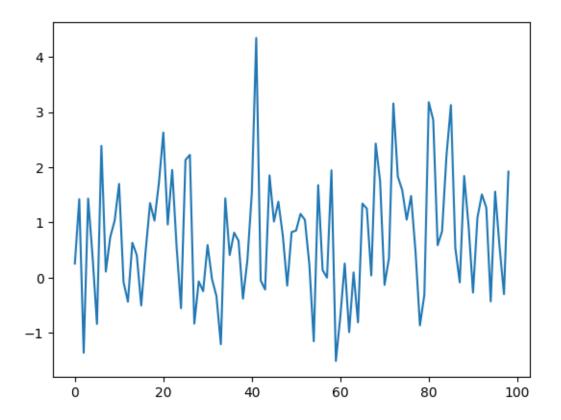
```
plt.title('Dataset 4')
```

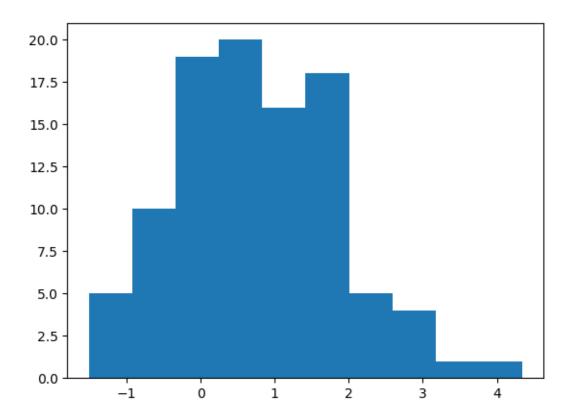
[108]: Text(0.5, 1.0, 'Dataset 4')

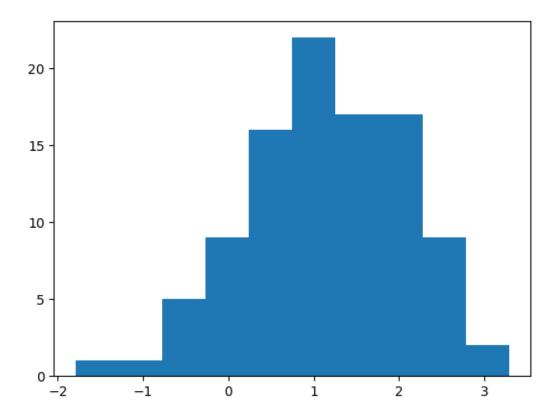


[109]: plt.plot(y[51:150])

[109]: [<matplotlib.lines.Line2D at 0x7f16a8b72af0>]

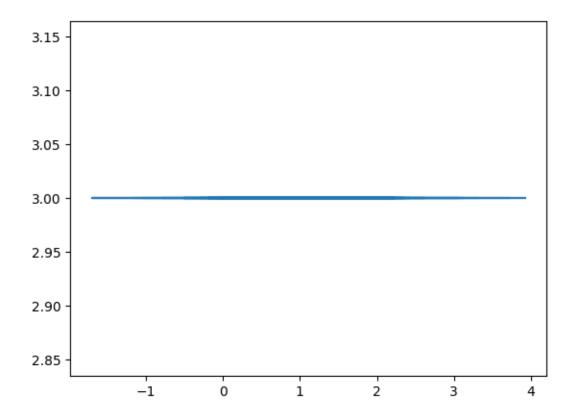






[112]: plt.plot(y[251:350],x[251:350])

[112]: [<matplotlib.lines.Line2D at 0x7f16a89fc5e0>]



After plotting many graphs, we see that the values of y are peaking at a value at a certain point and is almost symmetrical(not exactly).

This reminds us of 'Bell curve'. Now, we define a function to return the cdf of the datapoints. And also we define an inverse cdf fuction for the fitted curve, to get data points

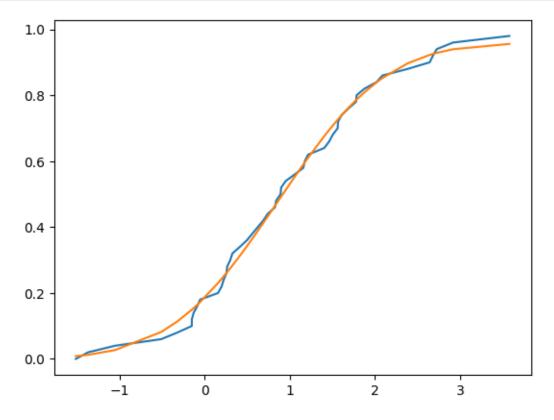
```
import math
def inverse_cdf(x, mean, stddev, amplitude):
    return (norm.ppf(x/amplitude)+mean)*stddev

from scipy.stats import norm

def f_cdf(x, mean, stddev, amplitude):
    return amplitude * norm.cdf((x - mean)/stddev)

inp = np.arange(0, 1, 0.01)
    x_pred = []
    y_mean = []
    y_pred = []
```

For x=0

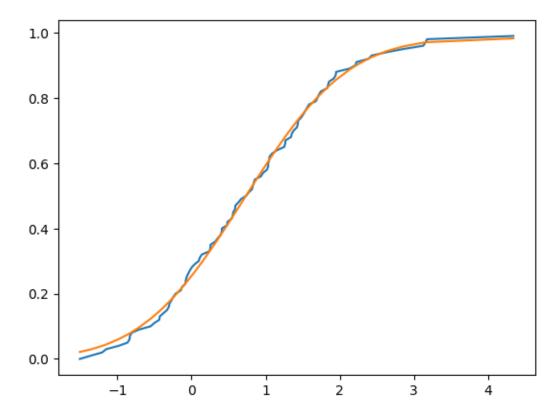


```
For x=1
[115]: y_sort = sorted(y[51:151])

(mean, stddev, amplitude), cov = curve_fit(f_cdf, y_sort, inp, p0 = [0.5, 1, 1])

plt.plot(y_sort, inp)
```

[0.867968285719736, 0.8028339635925559]



Similarly we plot it for eveyinteger value of x in the dataset

```
For x=2
[116]: y_sort = sorted(y[151:251])

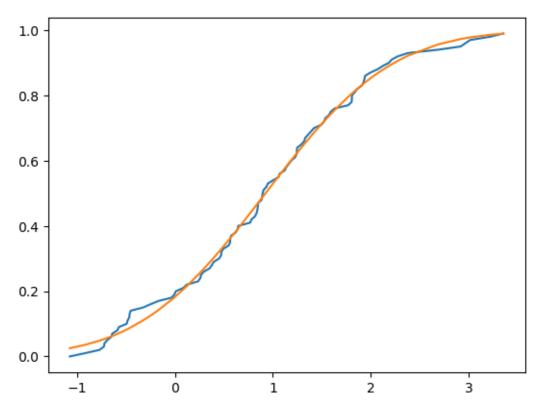
(mean, stddev, amplitude), cov = curve_fit(f_cdf, y_sort, inp, p0 = [0.5, 1, 1])

plt.plot(y_sort, inp)
plt.plot(y_sort, f_cdf(y_sort, mean, stddev, amplitude))
```

```
inverse_cdf_y = inverse_cdf(inp, mean, stddev, amplitude)
inverse_cdf_y = [i for i in inverse_cdf_y if not math.isnan(i) and not math.

isinf(i)]
y_mean.append(np.mean(inverse_cdf_y))

x_pred = x_pred + [2 for j in range(len(inverse_cdf_y))]
y_pred = y_pred + inverse_cdf_y
```



```
For x=3
[117]: y_sort = sorted(y[251:351])

(mean, stddev, amplitude), cov = curve_fit(f_cdf, y_sort, inp, p0 = [0.5, 1, 1])

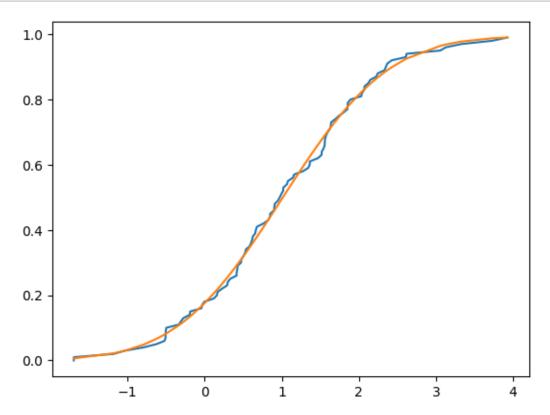
plt.plot(y_sort, inp)
plt.plot(y_sort, f_cdf(y_sort, mean, stddev, amplitude))

inverse_cdf_y = inverse_cdf(inp, mean, stddev, amplitude)
```

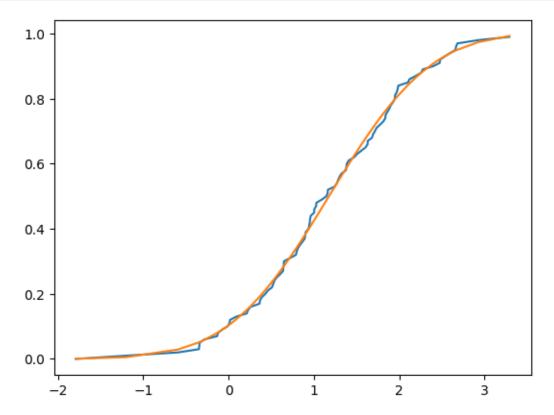
```
inverse_cdf_y = [i for i in inverse_cdf_y if not math.isnan(i) and not math.

isinf(i)]
y_mean.append(np.mean(inverse_cdf_y))

x_pred = x_pred + [3 for j in range(len(inverse_cdf_y))]
y_pred = y_pred + inverse_cdf_y
```



```
x_pred = x_pred + [4 for j in range(len(inverse_cdf_y))]
y_pred = y_pred + inverse_cdf_y
```



```
For x=5
[119]: y_sort = sorted(y[451:551])

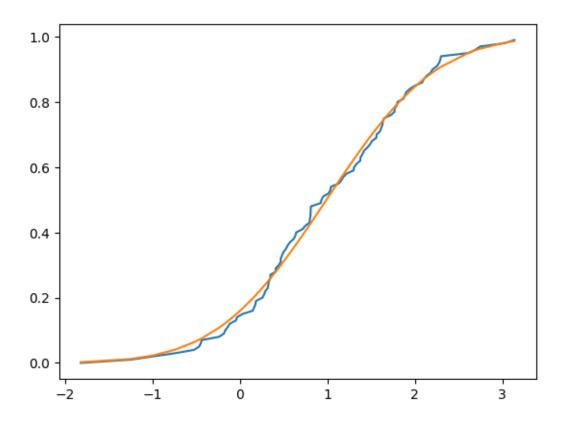
(mean, stddev, amplitude), cov = curve_fit(f_cdf, y_sort, inp, p0 = [0.5, 1, 1])

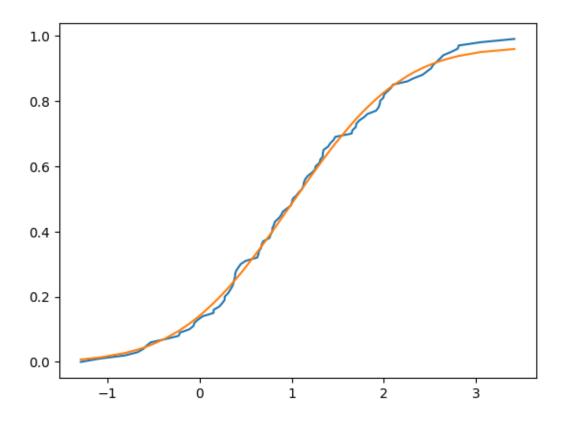
plt.plot(y_sort, inp)
plt.plot(y_sort, f_cdf(y_sort, mean, stddev, amplitude))

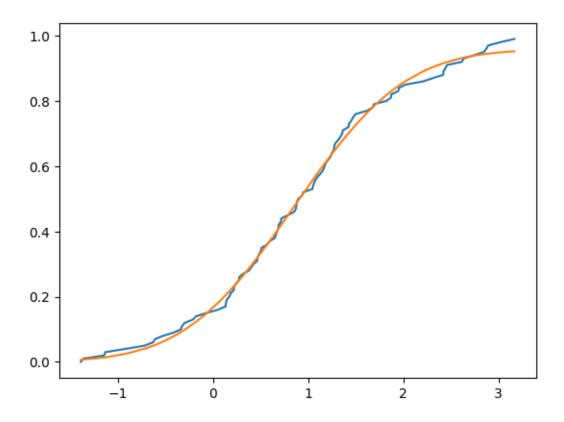
inverse_cdf_y = inverse_cdf(inp, mean, stddev, amplitude)
inverse_cdf_y = [i for i in inverse_cdf_y if not math.isnan(i) and not math.

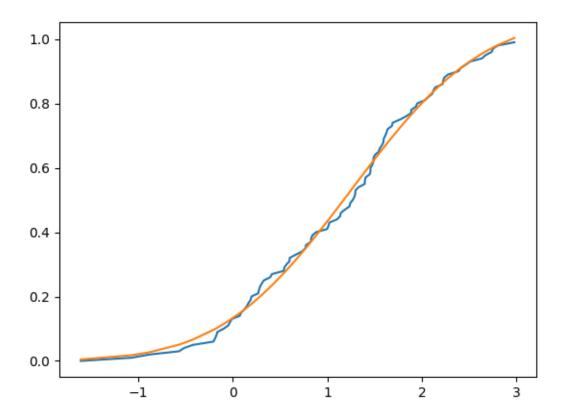
isinf(i)]
y_mean.append(np.mean(inverse_cdf_y))

x_pred = x_pred + [5 for j in range(len(inverse_cdf_y))]
y_pred = y_pred + inverse_cdf_y
```









```
For x=9
[123]: y_sort = sorted(y[851:951])

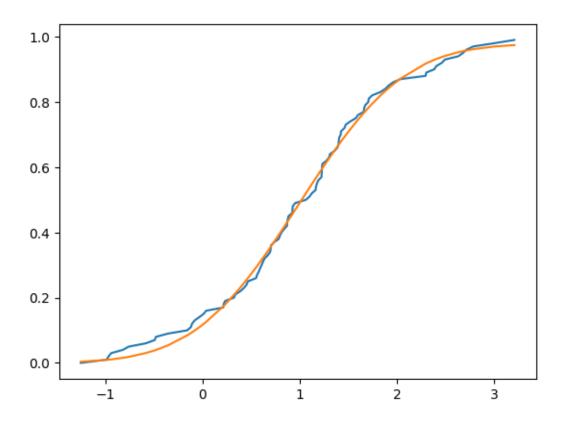
(mean, stddev, amplitude), cov = curve_fit(f_cdf, y_sort, inp, p0 = [0.5, 1, 1])

plt.plot(y_sort, inp)
plt.plot(y_sort, f_cdf(y_sort, mean, stddev, amplitude))

inverse_cdf_y = inverse_cdf(inp, mean, stddev, amplitude)
inverse_cdf_y = [i for i in inverse_cdf_y if not math.isnan(i) and not math.

isinf(i)]
y_mean.append(np.mean(inverse_cdf_y))

x_pred = x_pred + [9 for j in range(len(inverse_cdf_y))]
y_pred = y_pred + inverse_cdf_y
```



```
For x=10
y_sort = sorted(y[950:1000])

(mean, stddev, amplitude), cov = curve_fit(f_cdf, y_sort, inpo, p0 = [0.5, 1, 1])

plt.plot(y_sort, inpo)
plt.plot(y_sort, f_cdf(y_sort, mean, stddev, amplitude))

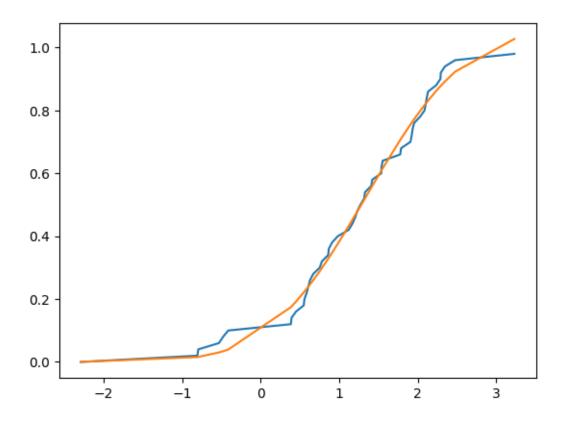
inverse_cdf_y = inverse_cdf(inpo, mean, stddev, amplitude)
inverse_cdf_y = [i for i in inverse_cdf_y if not math.isnan(i) and not math.

isinf(i)]

y_mean.append(np.mean(inverse_cdf_y))

x_pred = x_pred + [10 for j in range(len(inverse_cdf_y))]

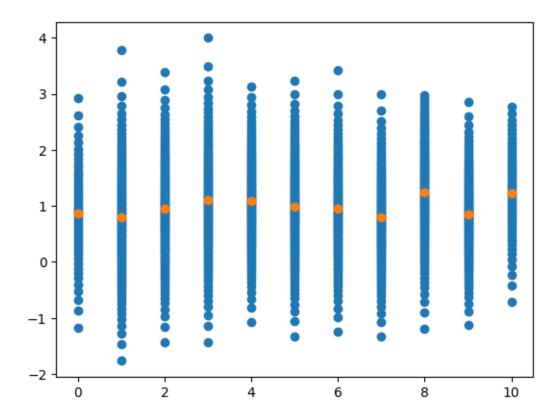
y_pred = y_pred + inverse_cdf_y
```



```
[125]: x_un=[i for i in range(11)]

plt.scatter(x_pred,y_pred)
plt.scatter(x_un,y_mean)
```

[125]: <matplotlib.collections.PathCollection at 0x7f16a898a640>



The orange highlighted datapoints are the mean points of the predicted y values for a given x from the Gaussian curve predicted from through curve_fit. Now I tried to fit them using a straight line and this is the acquired curve.

```
[126]: from scipy.optimize import curve_fit
    def stline(x, m, c): #defining a straight line function
        return m*x + c
    (zp1, zp2), pcov = curve_fit( stline,x_un, y_mean)
    print(f"Estimated function: exp(-{zp1}t) + {zp2}")
    z_est = stline(np.array(x_un), zp1, zp2)
    plt.plot(x_un, y_mean,x_un, z_est)
    plt.scatter(x_un,y_mean)
    plt.ylim(-2,4)
```

Estimated function: exp(-0.018704187577556874t) + 0.8929939862598517

[126]: (-2.0, 4.0)

