# EP20BTECH11015-Assignment-3

January 30, 2023

### 0.1 EP20BTECH11015 - ASSIGNMENT 3

[ ]:
```python
import numpy as np
import matplotlib.pyplot as plt
import scipy.stats as st
from scipy.optimize import curve_fit
from scipy import optimize as opt
```

1.

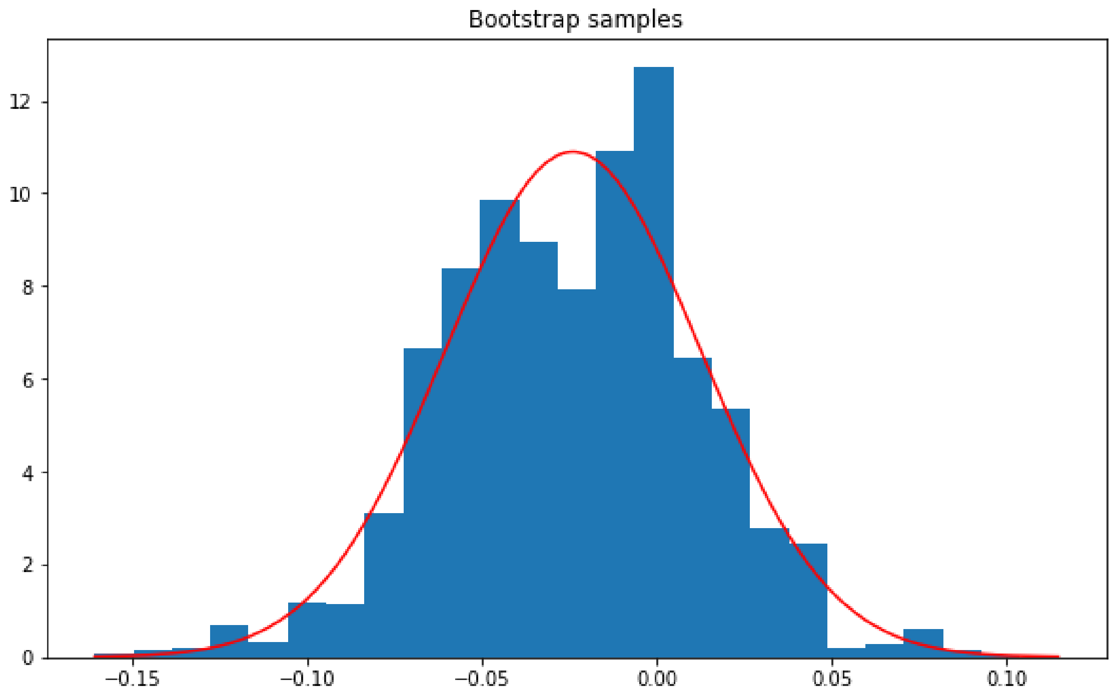
In class, we showed histograms of standard deviation and  G of bootstrap samples drawn from a Gaussian distribution with mean equal to 0 and standard deviation equal to 1.

Draw a similar histogram of median of 10,000 bootstrap samples drawn from the same Gaussian distribution. According to http://tinyurl.com/h6p43o8, the standard deviation of the sample median of a Gaussian distribution is equal to p √ /2n

Overlay a Gaussian distribution on top of the histogram with mean equal to the mean of the generated data sample and standard deviation equal to the standard deviation of the median (Hint: Look up astroML.stats.median sigmaG. Also note that you don't have to draw 10,000 histograms,

[ ]:
```python
# Bootstrap function
def bootstrap(data, n, func):
    """
    Parameters
    ----------
    data : array-like
        The data to bootstrap.
    n : int
        The number of bootstrap (re-)samples to generate.
    func : callable
        The function to apply to the bootstrap (re-)samples.

    Returns
    -------
    stats : array-like
        The bootstrap statistics.
    """
    stats = []
```

```
    for i in range(n):
        bootstrapped_sample = np.random.choice(data, size=len(data),␣
 ↪replace=True)
        stats.append(func(bootstrapped_sample))
    return np.array(stats)

#Genearating samples from a normal distribution
data = np.random.normal(0, 1, 1000)

# median of 10,000 bootstrap samples drawn from the same Gaussian distribution
bootstrap_medians = bootstrap(data, 10000, np.median)

#Plotting the histogram of the bootstrap samples
plt.figure(figsize=(10, 6))
plt.hist(bootstrap_medians, bins=25, density=True)

#Plotting the gaussian curve
bootstrap_medians.sort()    # sort the array to get a smooth gaussian curve
plt.plot(bootstrap_medians, st.norm.pdf(bootstrap_medians,␣
 ↪loc=bootstrap_medians.mean(), scale=bootstrap_medians.std()), color='red')
plt.title("Bootstrap samples")
plt.show()

#Comparing the standard deviation of the bootstrap samples with the theoretical␣
 ↪value
print("Std Dev of Bootstrapped median = {}".format(bootstrap_medians.std()))
print("Theoretical value = {}".format((np.pi/2000)**0.5))
```




```
Std Dev of Bootstrapped median = 0.03660389430390538
Theoretical value = 0.03963327297606011
```

2.

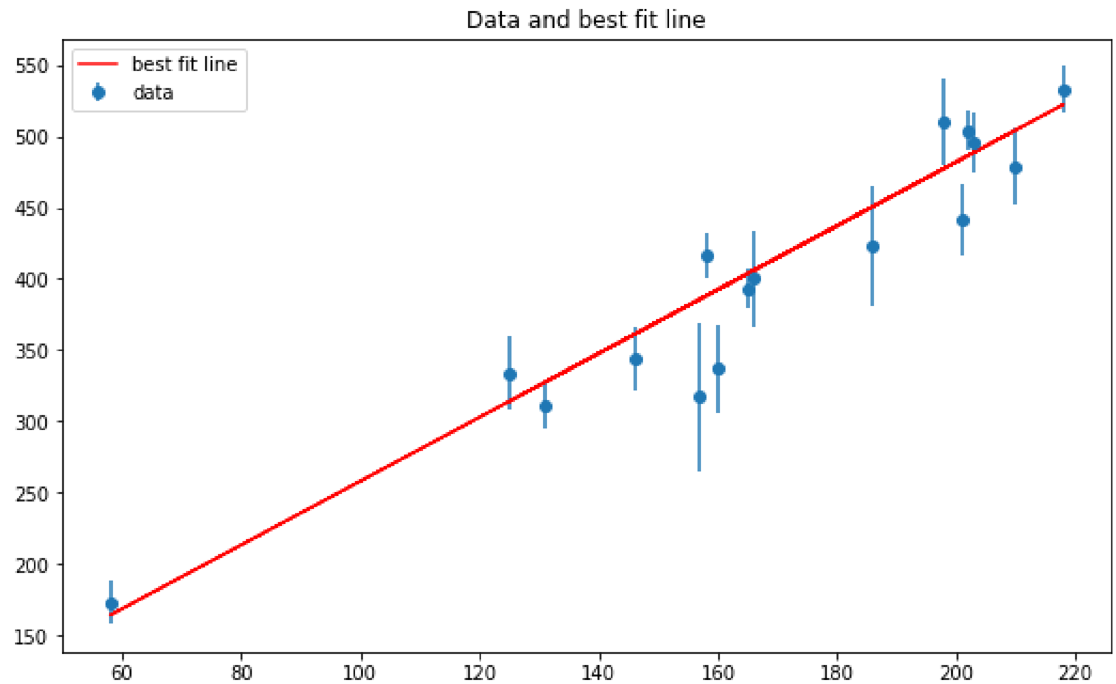
arXiv:1008.4686, Exercise 1 on Page 5, except the last sentence of the question related to 2 m. (Hint : Use

2 minimization to obtain best-fit values of b and m, instead of linear algebra. You can look up curve fit function in scipy.)

[ ]:
```
#Line function required for curve fitting
def line_fn(x, m, b):
    y = m*x + b
    return y

#Loading the data from the file
data = np.loadtxt('table.txt')
x = data[:, 1]  # x data
y = data[:, 2]  # y data
err_y = data[:, 3]  # error in y data

#Performing the chi2 minimization
chi2param = curve_fit(line_fn, xdata=x, ydata=y, sigma=err_y)

print(f"Best fit parameters = {np.round(chi2param[0], 4)}")
```

```
#Plotting the data and the best fit line
plt.figure(figsize=(10, 6))
plt.errorbar(x, y, yerr=err_y, fmt='o', label='data')
plt.plot(x, chi2param[0][1] + chi2param[0][0]*x, color='red', label='best fit␣
↪line')
plt.title("Data and best fit line")
plt.legend()
plt.show()
```

```
Best fit parameters = [ 2.2399 34.0477]
```




3.

Calculate the p-value for the four chi-square values for the plot shown in class from astroMl book which can be found at https://www.astroml.org/book_figures_1ed/chapter4/fig_chi2_eval.html. (Hint : You can read off the $\chi 2$ values from the graph by multiplying by D.O.F.)

[ ]:
```
# Generate Dataset
np.random.seed(1)

N = 50
L0 = 10
dL = 0.2
```

```
t = np.linspace(0, 1, N)
L_obs = np.random.normal(L0, dL, N)


y_vals = [L_obs, L_obs, L_obs, L_obs + 0.5 - t ** 2]
y_errs = [dL, dL * 2, dL / 2, dL]
titles = ['correct errors',
          'overestimated errors',
          'underestimated errors',
          'incorrect model']

for i in range(4):

    # compute the mean and the chi^2/dof
    mu = np.mean(y_vals[i])
    z = (y_vals[i] - mu) / y_errs[i]
    chi2 = np.sum(z ** 2)
    #chi2dof = chi2 / (N - 1)

    #Calculating and printing the p-value
    print('p-value for '+ titles[i] + ' =   %.5f' %st.chi2(N - 1).sf(chi2))
```

```
p-value for correct errors =   0.55435
p-value for overestimated errors =   1.00000
p-value for underestimated errors =   0.00000
p-value for incorrect model =   0.00000
```