es21btech11025-assign1

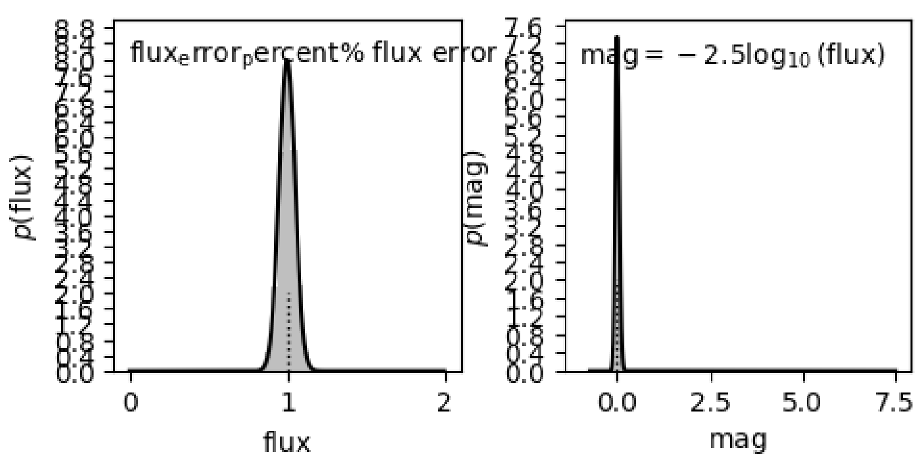
January 16, 2024

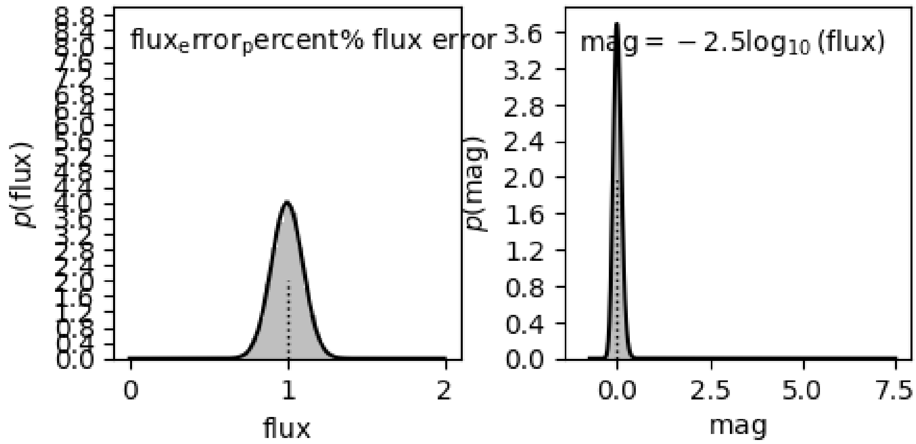
#Ranveer Sahu (es21btech11025) assignment 1

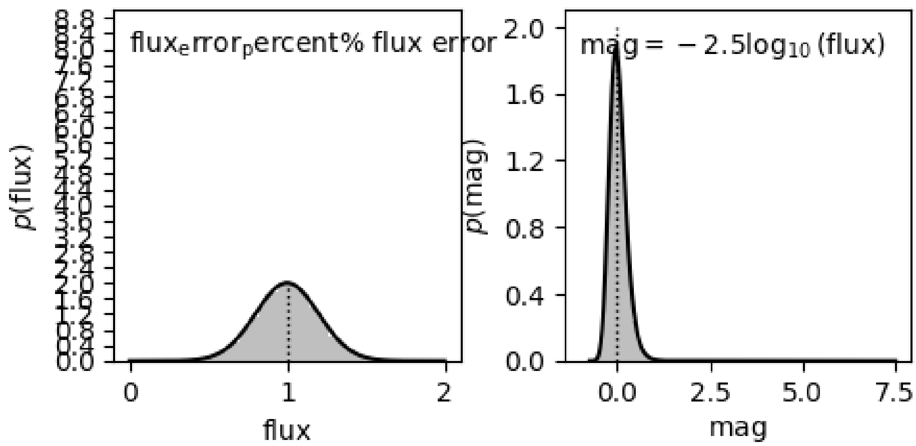
Q1. Redo figure 3.5 in astroml book https://www.astroml.org/book_figures/ chapter3/fig_flux_errors.html with 5%, 10% and 20% flux error. Com- ment on whether the magnitude distribution is assymetric in all the three cases.

[115]:
```
import numpy as np
from matplotlib import pyplot as plt
from scipy.stats import norm

def FluxError(flux_error_percent):
  np.random.seed(1)
  dist = norm(1, flux_error_percent/100)
  flux = dist.rvs(10000)
  flux_fit = np.linspace(0.001, 2, 1000)
  pdf_flux_fit = dist.pdf(flux_fit)

# transform this distribution into magnitude space
  mag = -2.5 * np.log10(flux)
  mag_fit = -2.5 * np.log10(flux_fit)
  pdf_mag_fit = pdf_flux_fit.copy()
  pdf_mag_fit[1:] /= abs(mag_fit[1:] - mag_fit[:-1])
  pdf_mag_fit /= np.dot(pdf_mag_fit[1:], abs(mag_fit[1:] - mag_fit[:-1]))

#------------------------------------------------------------
  # Plot the result
  fig = plt.figure(figsize=(5, 2.5))
  fig.subplots_adjust(bottom=0.17, top=0.9,
                      left=0.12, right=0.95, wspace=0.3)

  # first plot the flux distribution
  ax = fig.add_subplot(121)
  ax.hist(flux, bins=np.linspace(0, 2, 50),
          histtype='stepfilled', fc='gray', alpha=0.5, density=True)
  ax.plot(flux_fit, pdf_flux_fit, '-k')
  ax.plot([1, 1], [0, 2], ':k', lw=1)
  ax.set_xlim(-0.1, 2.1)
  ax.set_ylim(0, 9.0)
```

```
    ax.set_xlabel(r'${\rm flux}$')
    ax.set_ylabel(r'$p({\rm flux})$')
    ax.yaxis.set_major_locator(plt.MultipleLocator(0.4))
    ax.text(0.04, 0.95, r'${\rm flux_error_percent\%\ flux\ error}$',
            ha='left', va='top', transform=ax.transAxes)

    # next plot the magnitude distribution
    ax = fig.add_subplot(122)
    ax.hist(mag, bins=np.linspace(-1, 2, 50),
            histtype='stepfilled', fc='gray', alpha=0.5, density=True)
    ax.plot(mag_fit, pdf_mag_fit, '-k')
    ax.plot([0, 0], [0, 2], ':k', lw=1)

    ax.yaxis.set_major_locator(plt.MultipleLocator(0.4))
    ax.text(0.04, 0.95, r'${\rm mag} = -2.5\log_{10}({\rm flux})$',
            ha='left', va='top', transform=ax.transAxes)

    ax.set_xlabel(r'${\rm mag}$')
    ax.set_ylabel(r'$p({\rm mag})$')

    plt.show()


flux_errors = [5, 10, 20] # flux array with given error which we have to estimate by using for loop
for i in flux_errors:
    FluxError(i)
    plt.show()
```



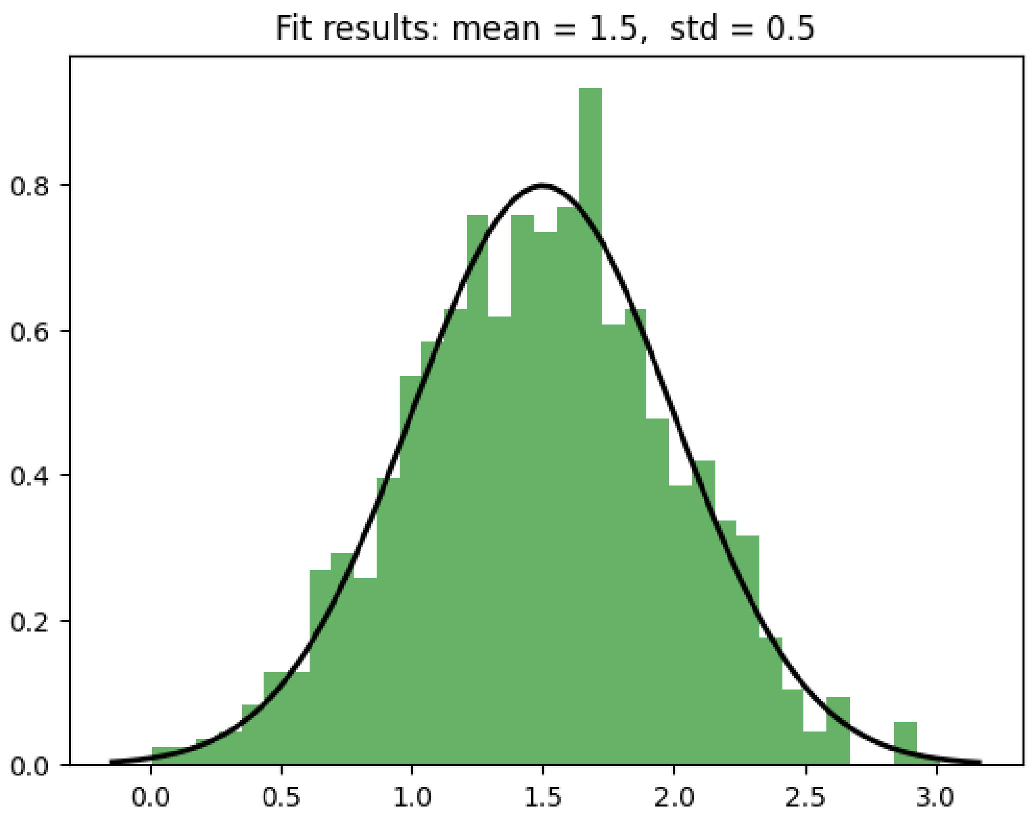




Q2. Create 1000 draws from a normal distribution of mean of 1.5 and standard deviation of 0.5. Plot the pdf. Calculate the sample mean, variance, skewness, kurtosis as well as standard deviation using MAD and G of these samples.

[56]:
```
import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm, skew, kurtosis

# point 1: sample data generators using normal distributions
samples = np.random.normal(1.5, 0.5, 1000)

# point 2: find and plot pdf and hist
plt.hist(samples, bins=35, density=True, alpha=0.6, color='g')
xmin, xmax = plt.xlim()
x = np.linspace(xmin, xmax, 100)
```

```python
p = norm.pdf(x, 1.5, 0.5)
plt.plot(x, p, 'k', linewidth=2)
plt.title('Fit results: mean = 1.5,  std = 0.5')
plt.show()

# point  3: Calculate sample statistics using inbuild functions␣
 ↪mean,var,skewness,kurtosis,mad and sigma_g
nmean = np.mean(samples)
nvar = np.var(samples)
skness = skew(samples)
kurtosis = kurtosis(samples)
mad = np.mean(np.abs(samples - np.mean(samples)))
sigma_g = 1.4826 * np.median(np.abs(samples - np.median(samples)))
```



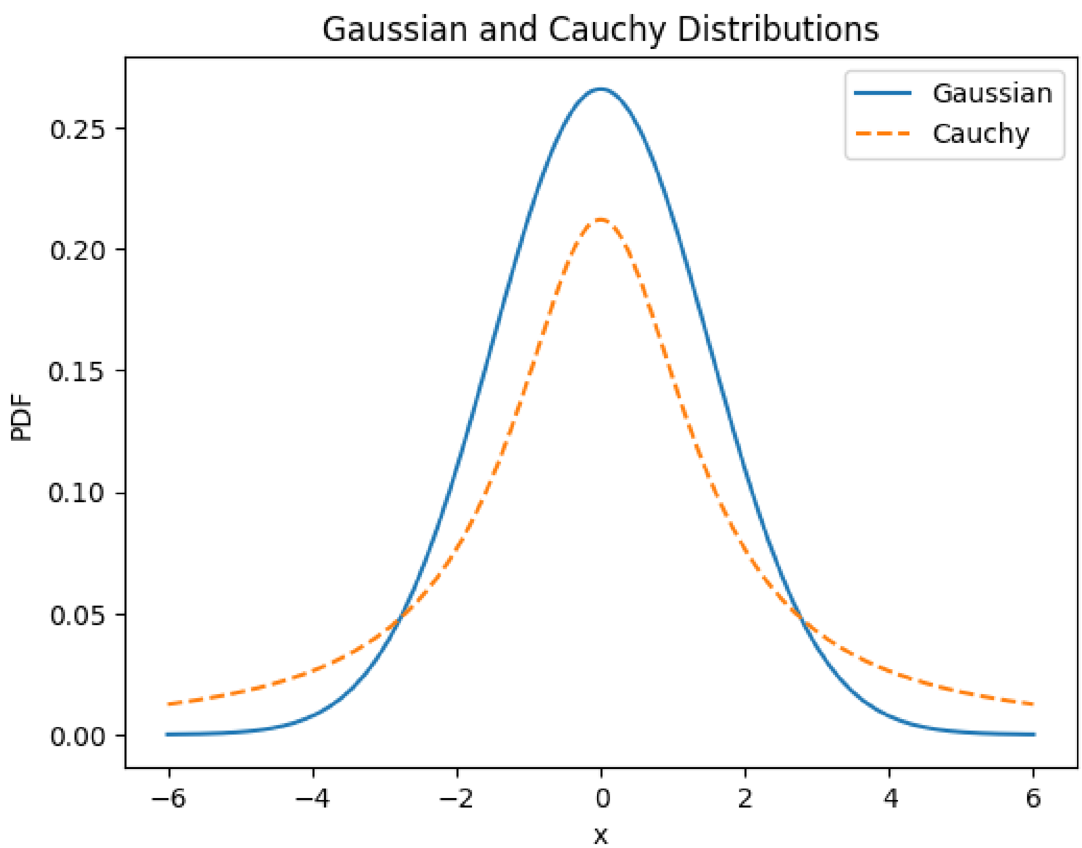
[57]:
```python
# point 4: prints all statisticals results of sample data
print(f"Sample Mean = {nmean}" )
print(f"Sample Variance = {nvar}" )
print(f"Sample Skewness = {skness}" )
print(f"Sample Kurtosis = {kurtosis}" )
print(f"Std_deviation (MAD): = {mad}")
print(f"Std_deviation ( G) = {sigma_g}" )
```

```
Sample Mean = 1.4885568848738844
Sample Variance = 0.25383515561832154
Sample Skewness = -0.015364832098242048
Sample Kurtosis = -0.16556819623736896
Std_deviation (MAD): = 0.4052164122077202
Std_deviation ( G) = 0.5004938334229624
```

Q3. Plot a Cauchy distribution with =0 and =1.5 superposed on the top of a Gaussian distribution with =0 and =1.5. Use two different line styles to distinguish between the Gaussan and Cauchy distribution on the plot and also indicate these in the legends.

[58]:
```
import numpy as np
import matplotlib.pyplot as plt
from scipy import stats

np.random.seed(42)

#  point 1: Generate random samples of both distributions
g_dist = stats.norm(0,1.5)
c_dist = stats.cauchy(0, 1.5)

x = np.linspace(-6, 6, 1000)
```

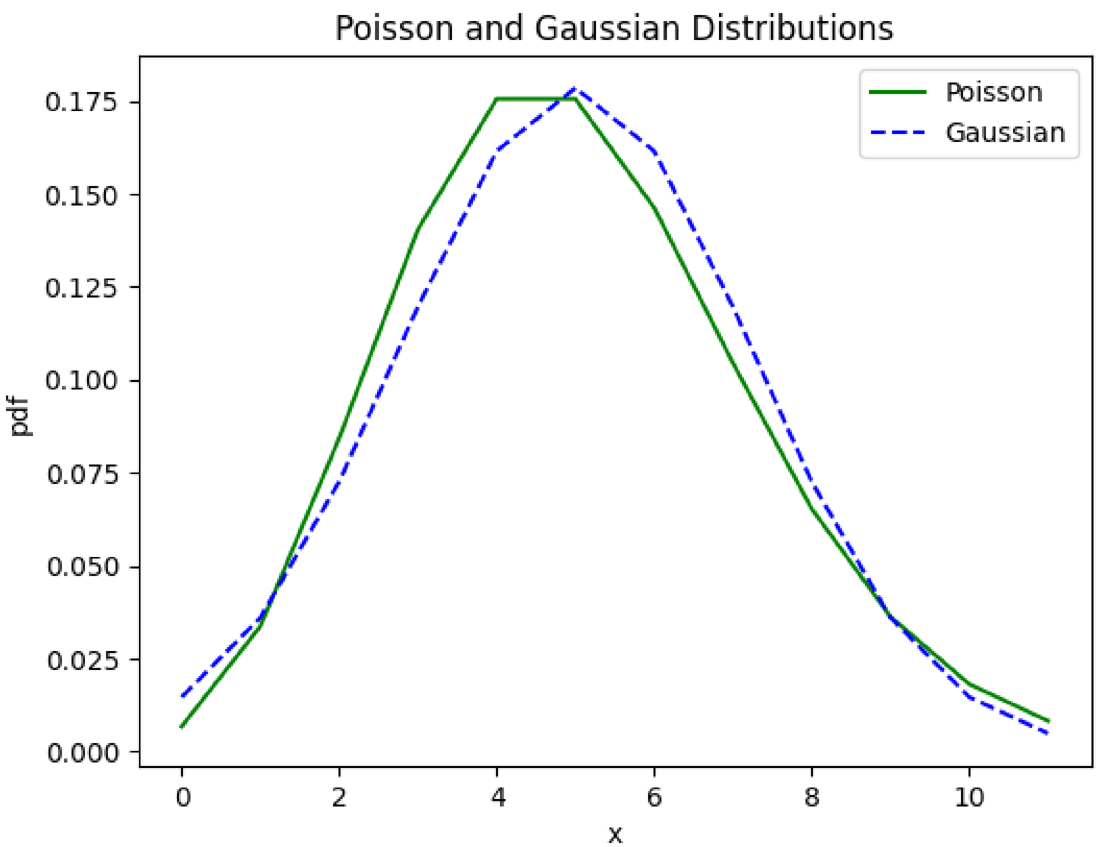
[59]:
```
# point 2:  plot pdf of Gaussian and cauchy distributions
gaus_pdf = g_dist.pdf(x)
cauchy_pdf = c_dist.pdf(x)

#plot gaussian nd cauchy in single graph
plt.plot(x, gaus_pdf, linestyle='solid', label='Gaussian')
plt.plot(x, cauchy_pdf, linestyle='dashed', label='Cauchy')
plt.title('Gaussian and Cauchy Distributions')
plt.xlabel('x')
plt.ylabel('PDF')

plt.legend()
plt.show()
```



Q4. Plot Poisson distribution with mean of 5, superposed on top of a Gaussian distribution with mean of 5 and standard deviation of square root of 5. Use two different line styles for the two distributions and make sure the plot contains legends for both of them.

[83]:
```
from scipy.stats import poisson as ps, norm

x = np.arange(0, 12)



ps_pmf = ps.pmf(x, 5)
gs_pdf = norm.pdf(x, loc=5, scale=np.sqrt(5))



plt.plot(x, ps_pmf, label='Poisson',color='green',linestyle='solid')
plt.plot(x, gs_pdf, label='Gaussian',color='blue', linestyle='dashed')

plt.xlabel('x')
plt.ylabel('pdf')
plt.title('Poisson and Gaussian Distributions')
plt.legend()
```

```
plt.show()
```



Q5 The following were the measurements of mean lifetime of K meson (as of 1990) (in units of 10−10 s) : 0.8920±0.00044; 0.881±0.009; 0.8913±0.00032; 0.9837±0.00048; 0.8958± 0.00045. Calculate the weighted mean lifetime and uncertainty of the mean.

[89]:
```
x=[ 0.8920, 0.881, 0.8913, 0.9837,0.8958]
delta_change=[0.00044,0.009,0.00032,0.00048,0.00045]

# intially weight mean and uncertainity of mean =0

p=0
q=0
for i in range(len(x)):
    p+=(x[i]/delta_change[i]**2)
    q+=(1/delta_change[i]**2)

print("weighted mean: ",p/q)
print("uncertainity of the mean ",np.sqrt(1/q))
```

```
weighted mean:  0.9089185199574897
uncertainity of the mean  0.00020318737026848627
```

Q6. Download the eccentricity distribution of exoplanets from the exoplanet catalog http://exoplanet.eu/catalog/. Look for the column titled e, which denotes the eccentricity. Draw the histogram of this distribution. Then redraw the same histogram after Gaussianizing the distribution using

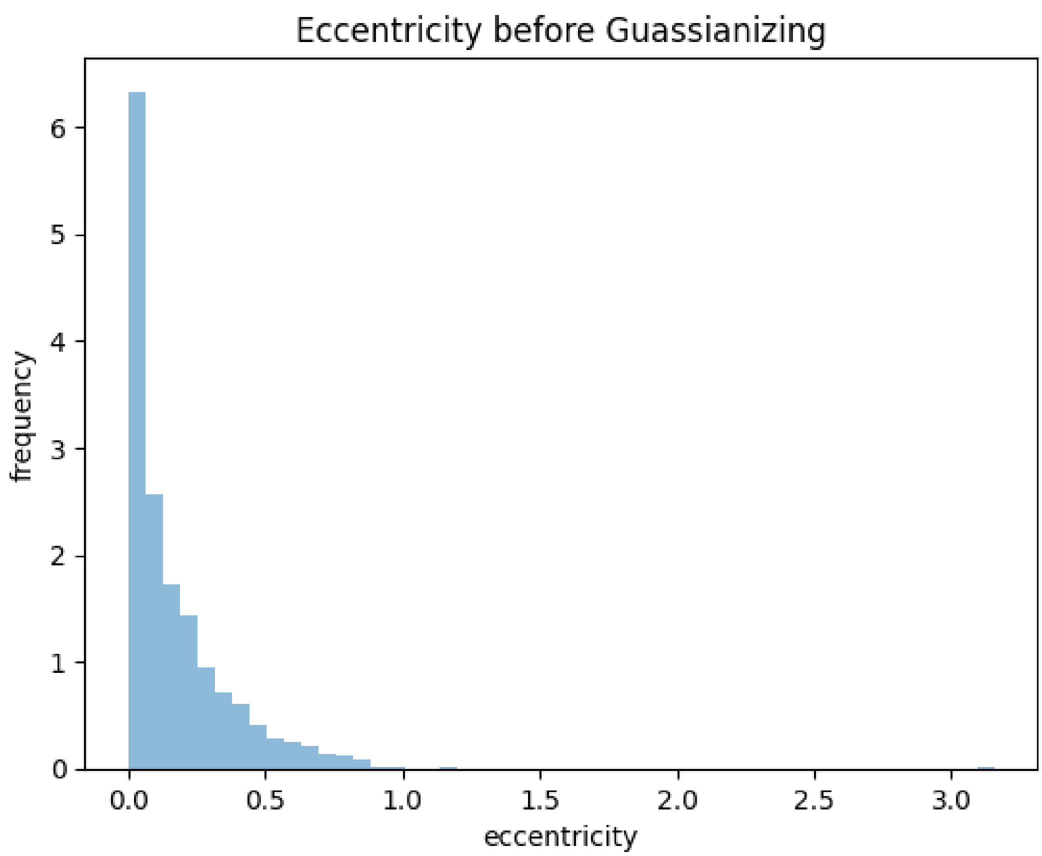
Box-transformation either using scipy.stats.boxcox or from first prin- ciples using the equations shown in class or in arXiv:1508.00931. Note

that exoplanets without eccentricity data can be ignored.

[98]:
```python
import pandas as pd
df=pd.read_csv('exoplanet.csv')
```

[99]:
```python
y=df['eccentricity']
y.dropna(inplace=True)
```

[100]:
```python
plt.hist(y,bins=50,histtype='stepfilled',alpha=0.5,density=True)
plt.xlabel('eccentricity')
plt.ylabel('frequency')
plt.title('Eccentricity before Guassianizing')
plt.show()
```



[101]:

```
y_1=[i for i in y if i>0]
updated_data,lambda_value= stats.boxcox(y_1)
#plotting the histogram of eccentricity after Gaussianizing
plt.hist(updated_data,bins=50,histtype='stepfilled',alpha=0.5,density=True)
plt.xlabel('eccentricity')
plt.ylabel('frequency')
plt.title('Eccentricity after Gaussianizing')
plt.show()
```