In [ ]:

```
!pip install emcee
!pip install nestle
!pip install astroML
```

In [2]:

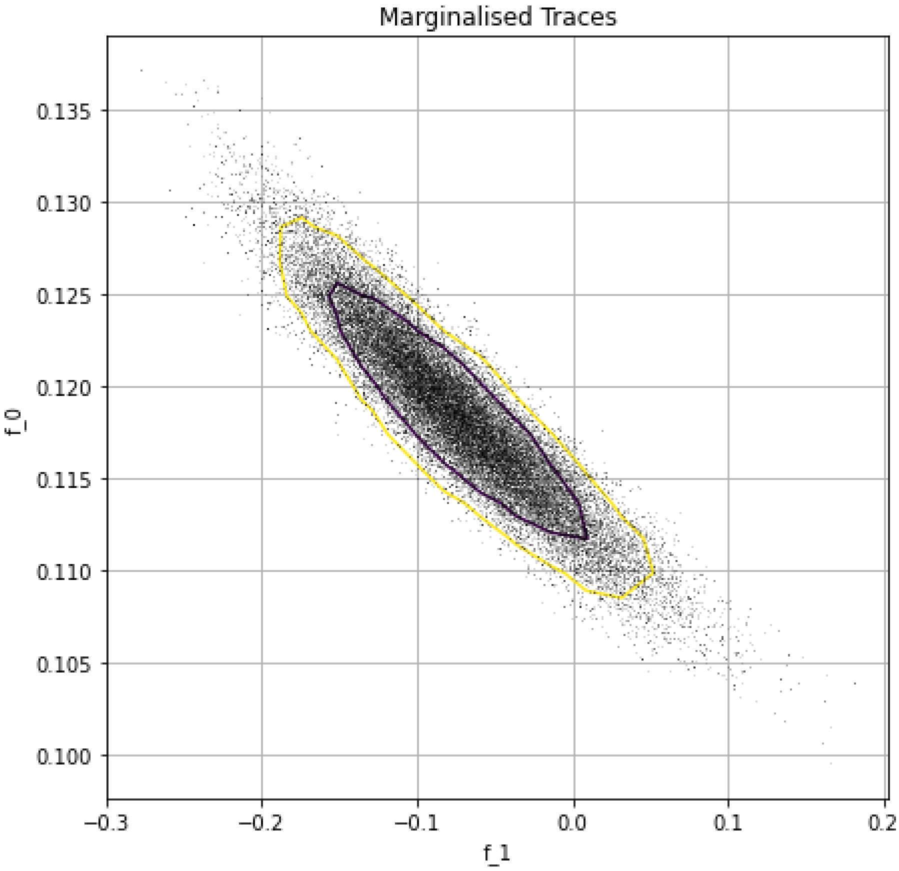
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import emcee
from scipy import optimize, stats
from sklearn.neighbors import KernelDensity
import nestle
from astropy import stats as stats_astropy
from astroML import stats as stats_astroML
```

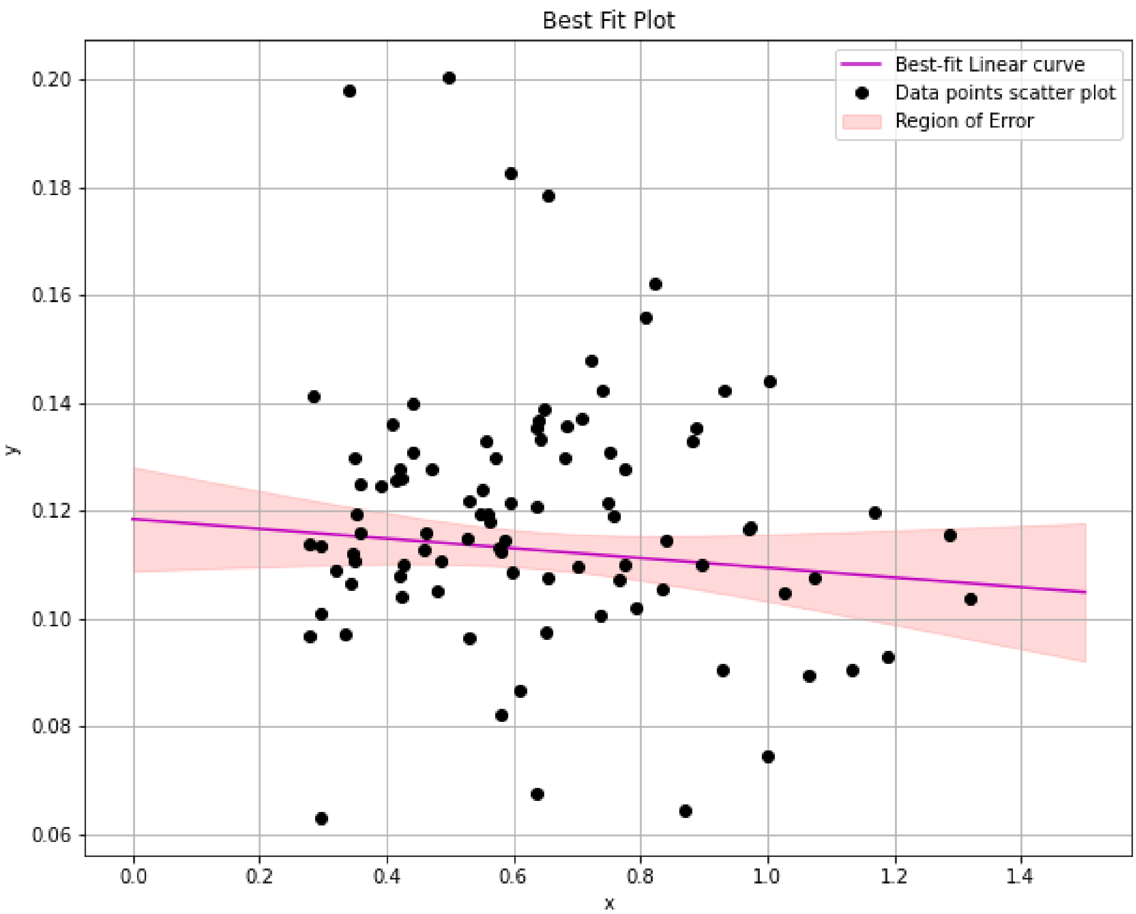
Question 1

In [3]:

```
# extracting data from the website
data = np.loadtxt('https://iith.ac.in/~shantanud/fgas_spt.txt')
z = data[:, 0]
fgas = data[:, 1]
fgas_error = data[:, 2]

# utility function for log prior
def log_prior(theta):
    m, b = theta
    if -0.5 < m < 0.5 and 0 < b < 0.5:
        return 0.0
    return -np.inf

# utility function for log likelihood
def log_llihood(theta, x, y, y_error):
    m, b = theta
    y_model = b*(1+m*x)
    return -0.5 * np.sum(((y_model - y)/y_error)**2)

# function for log posterior
def log_posterior(theta, x, y, y_error):
    log_pr = log_prior(theta)
    if not np.isfinite(log_pr):
        return -np.inf
    return log_pr + log_llihood(theta, x, y, y_error)

# MCMC walkers
nwalkers = 50
# number of final posterior samples
nsamples = 1000
# burn period
nburn = 1000
# number of MCMC nsteps
nsteps = nburn + nsamples

# initial guesses
guesses = np.array([np.random.uniform(-0.5, 0.5, nwalkers), np.random.uniform(0.0, 0.5,
nwalkers)]).T
# number of dimensions
ndims = guesses.shape[1]

sampler = emcee.EnsembleSampler(nwalkers, ndims, log_posterior, args=[z,fgas,fgas_error
])
sampler.run_mcmc(guesses, nsteps)
samples = sampler.chain[:, nburn:, :].reshape((-1, ndims))

# function for calculating sigma level
def sigma_level(t1, t2, nbins=20):
    L, xbins, ybins = np.histogram2d(t1, t2, nbins)
    L[L == 0] = 1E-16

    shape = L.shape
    L = L.ravel()

    i_sort = np.argsort(L)[::-1]
    i_unsort = np.argsort(i_sort)
    # cumulative sum
    L_cumsum = L[i_sort].cumsum()
    L_cumsum /= L_cumsum[-1]
```

```
    sigma = L_cumsum[i_unsort].reshape(shape)

    xbins = 0.5 * (xbins[1:] + xbins[:-1])
    ybins = 0.5 * (ybins[1:] + ybins[:-1])
    return xbins, ybins, sigma

# plotting marginalised traces
trace = samples.T
xbins, ybins, sigma = sigma_level(trace[0],trace[1])

plt.figure(figsize=(7,7))
plt.contour(xbins, ybins, sigma.T, levels=[0.68,0.90])
plt.plot(trace[0], trace[1], ',k', alpha=0.15)

plt.title("Marginalised Traces")
plt.xlabel('f_1')
plt.ylabel('f_0')
plt.grid()
plt.show()

# plotting best fit curves
x1 = np.linspace(0, 1.5, 2000)
m, b = trace[:2]
y1 = b[:,None]*(1+m[:,None]*x1)
# for error region bounds
bound1 = y1.mean(0)-2*y1.std(0)
bound2 = y1.mean(0)+2*y1.std(0)

plt.figure(figsize=(10,8))
plt.plot(x1, y1.mean(0),'-m', label='Best-fit Linear curve')
plt.plot(z, fgas, 'ok', label='Data points scatter plot')
plt.fill_between(x1, bound1, bound2, alpha=0.15, color = 'r', label='Region of Error')

plt.xlabel('x')
plt.ylabel('y')
plt.title("Best Fit Plot")
plt.grid()
plt.legend()
plt.show()
```


Marginalised Traces
f_0
f_1
0.135
0.130
0.125
0.120
0.115
0.110
0.105
0.100
−0.3
−0.2
−0.1
0.0
0.1
0.2


Best Fit Plot
Best-fit Linear curve
Data points scatter plot
Region of Error
y
x
0.20
0.18
0.16
0.14
0.12
0.10
0.08
0.06
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4

Question 2

In [4]:

```
data = np.array([[0.42,  0.72,  0.,  0.3,  0.15,0.09,  0.19,  0.35,  0.4,  0.54,
                  0.42,  0.69,  0.2,  0.88,  0.03,0.67,  0.42,  0.56,  0.14,  0.2],
                 [0.33,  0.41, -0.22,  0.01, -0.05, -0.05, -0.12,  0.26,  0.29,  0.39,
                  0.31,  0.42, -0.01,  0.58, -0.2, 0.52,  0.15,  0.32, -0.13, -0.09],
                 [0.1,  0.1,  0.1,  0.1,  0.1, 0.1,  0.1,  0.1,  0.1,  0.1,
                  0.1,  0.1,  0.1,  0.1,  0.1, 0.1,  0.1,  0.1,  0.1,  0.1]])

# function for polynomial fit
def polynomial_fit(theta, x):
    return sum(t * x ** n for (n, t) in enumerate(theta))

# function for log likelihood
def log_llihood(theta, data=data):
    x, y, sigma_y = data
    yM = polynomial_fit(theta, x)
    return -0.5 * np.sum(np.log(2 * np.pi * sigma_y ** 2) + (y - yM) ** 2 / sigma_y **
2)

# function for prior
def prior(theta):
    return 200*theta - 100

# printing required things
x, y, sigma_y = data
result_lin = nestle.sample(log_llihood, prior, 2)
print(result_lin.summary())
result_quad = nestle.sample(log_llihood, prior, 3)
print()
print(result_quad.summary())
```

```
niter: 1557
ncall: 2711
nsamples: 1657
logz:  7.310 +/-  0.371
h: 13.785

niter: 2117
ncall: 3797
nsamples: 2217
logz:  2.520 +/-  0.434
h: 18.803
```

The above values don't agree with the blog

Question 3

In [5]:

```
# importing the input data
dataframe = pd.read_csv('SDSS_quasar.dat',sep = '\s+')
data2 = dataframe['z']
data = data2.to_numpy()

# points on x-axis
x_1 = np.linspace(-0.5, 5, 1000)

# input pdf
normal_dist = stats.norm(np.mean(data),np.std(data))
pdf_input = normal_dist.pdf(x_1)

# KDE estimate using gaussian kernel
log_pdf_gaus = KernelDensity(kernel='gaussian', bandwidth=0.2).fit(data[:,np.newaxis]).
score_samples(x_1[:,np.newaxis])
pdf_g = np.exp(log_pdf_gaus)

# KDE estimate using exponential kernel
log_pdf_exp = KernelDensity(kernel='exponential', bandwidth=0.2).fit(data[:,np.newaxis
]).score_samples(x_1[:,np.newaxis])
pdf_exp = np.exp(log_pdf_exp)

# plot
plt.plot(x_1 , pdf_input, 'black', label = 'Input')
plt.plot(x_1, pdf_g, 'r', label = 'Gaussian')
plt.plot(x_1, pdf_exp, 'g', label = 'Exponential')
plt.title('KDE for Gaussian and Exponential kernels')
plt.xlabel('x')
plt.ylabel('y')
plt.legend()
plt.grid()
plt.show()
```