es21btech11025-assign7

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EP4130: Data Science Analysis

Assignment 7

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[70]:
```
pip install emcee
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: emcee in /home/coder/.local/lib/python3.10/site-
packages (3.1.4)
Requirement already satisfied: numpy in /home/coder/.local/lib/python3.10/site-
packages (from emcee) (1.24.3)
Note: you may need to restart the kernel to use updated packages.
```

[71]:
```
pip install corner
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: corner in /home/coder/.local/lib/python3.10/site-
packages (2.2.2)
Requirement already satisfied: matplotlib>=2.1 in
/home/coder/.local/lib/python3.10/site-packages (from corner) (3.7.1)
Requirement already satisfied: packaging>=20.0 in
/home/coder/.local/lib/python3.10/site-packages (from matplotlib>=2.1->corner)
(23.0)
Requirement already satisfied: python-dateutil>=2.7 in
/home/coder/.local/lib/python3.10/site-packages (from matplotlib>=2.1->corner)
(2.8.2)
Requirement already satisfied: contourpy>=1.0.1 in
/home/coder/.local/lib/python3.10/site-packages (from matplotlib>=2.1->corner)
(1.0.7)
Requirement already satisfied: pillow>=6.2.0 in /usr/lib/python3/dist-packages
(from matplotlib>=2.1->corner) (9.0.1)
Requirement already satisfied: fonttools>=4.22.0 in
/home/coder/.local/lib/python3.10/site-packages (from matplotlib>=2.1->corner)
(4.39.3)
Requirement already satisfied: cycler>=0.10 in
```

```
/home/coder/.local/lib/python3.10/site-packages (from matplotlib>=2.1->corner)
(0.11.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/lib/python3/dist-
packages (from matplotlib>=2.1->corner) (2.4.7)
Requirement already satisfied: numpy>=1.20 in
/home/coder/.local/lib/python3.10/site-packages (from matplotlib>=2.1->corner)
(1.24.3)
Requirement already satisfied: kiwisolver>=1.0.1 in
/home/coder/.local/lib/python3.10/site-packages (from matplotlib>=2.1->corner)
(1.4.4)
Requirement already satisfied: six>=1.5 in /usr/lib/python3/dist-packages (from
python-dateutil>=2.7->matplotlib>=2.1->corner) (1.16.0)
Note: you may need to restart the kernel to use updated packages.
```

[72]:
```
pip install dynesty
```

```
Defaulting to user installation because normal site-packages is not writeable
Requirement already satisfied: dynesty in
/home/coder/.local/lib/python3.10/site-packages (2.1.3)
Note: you may need to restart the kernel to use updated packages.
```

[73]:
```
import numpy as np
import scipy as sp
import pandas as pd
import matplotlib.pyplot as plt
import emcee
import corner
import dynesty
from dynesty import NestedSampler
from sklearn.neighbors import KernelDensity as kde
```

Question 1

Download the SPT fgas data from http://iith.ac.in/~shantanud/fgas_ spt.txt. Fit the data to f0 (1 + f1 z) where f0 and f1 are unknown constants. Determine the best fit values of f0 and f1 including 68% and 90% credible intervals using emcee and corner.py . The priors on f0 and f1 should be $0 <$ f0 < 0.5 and $-0.5 <$ f1 < 0.5.

[74]:
```
data = pd.read_csv("fgas_spt.txt")
z = data["z"]
f_gas = data["fgas"]
fgas_err = data["fgas_error"]
```

defining log_prior:

[75]:
```
def log_prior(theta):
    f0 , f1 = theta
```

```
    if 0 < f0 < 0.5 and -0.5 < f1 < 0.5:
        return 0.0
    return -np.inf
```

defining the log likelihood:

[76]:
```
def log_likelihood(theta, z, f_gas, fgas_err):
    f0, f1 = theta
    model = f0 + f1 * z
    return -0.5 * np.sum(((f_gas - model) / fgas_err)**2)
```

definign the log posterior:

[77]:
```
def log_posterior(theta, z, f_gas, fgas_err):
    return log_prior(theta) + log_likelihood(theta, z, f_gas, fgas_err)
```

running MCMC:

[78]:
```
nwalkers = 50
nsteps = 2000
ndim = 2
nburn = 1000
```

initial guess for parameters:

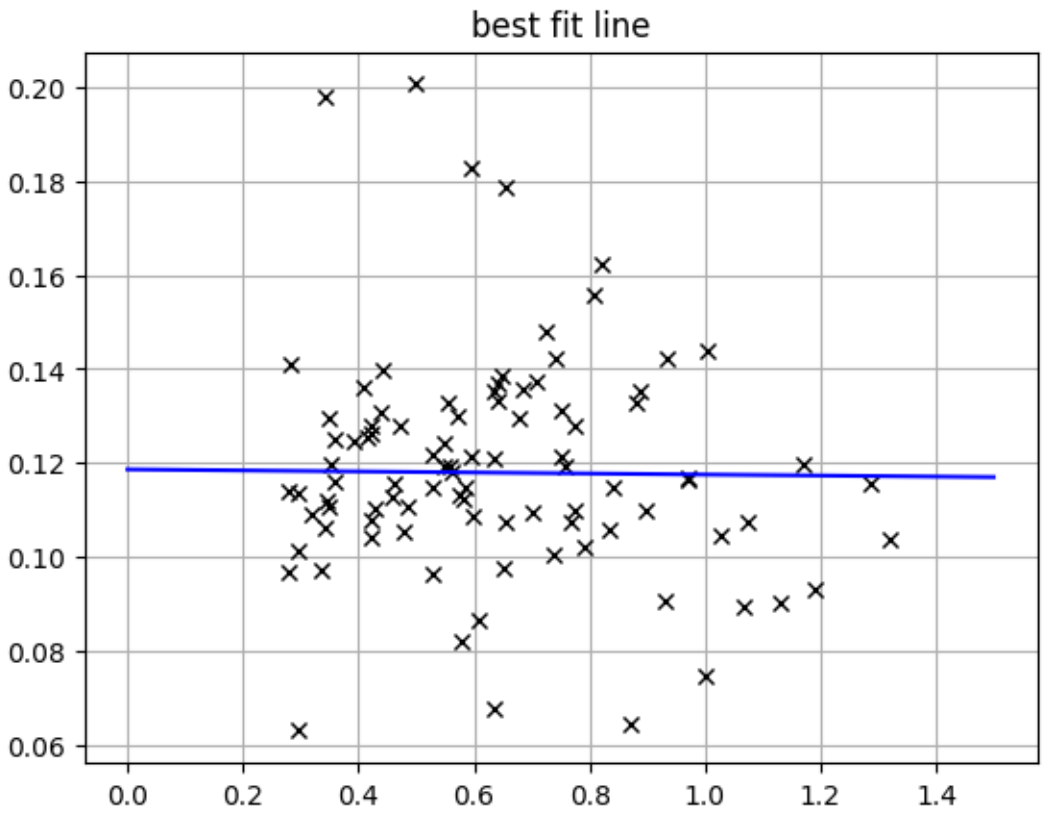
[79]:
```
f0_guess = np.random.uniform(0 , 0.5 , nwalkers)
f1_guess = np.random.uniform(-0.5 , 0.5 , nwalkers)
initial = np.vstack((f0_guess , f1_guess)).T
```

defining the sampler:

[80]:
```
sampler = emcee.EnsembleSampler(nwalkers , ndim , log_posterior , args = (z ,␣
 ↪f_gas , fgas_err))
sampler.run_mcmc(initial , nsteps)
samples = sampler.chain[: , nburn: , :].reshape(-1 , ndim)
```

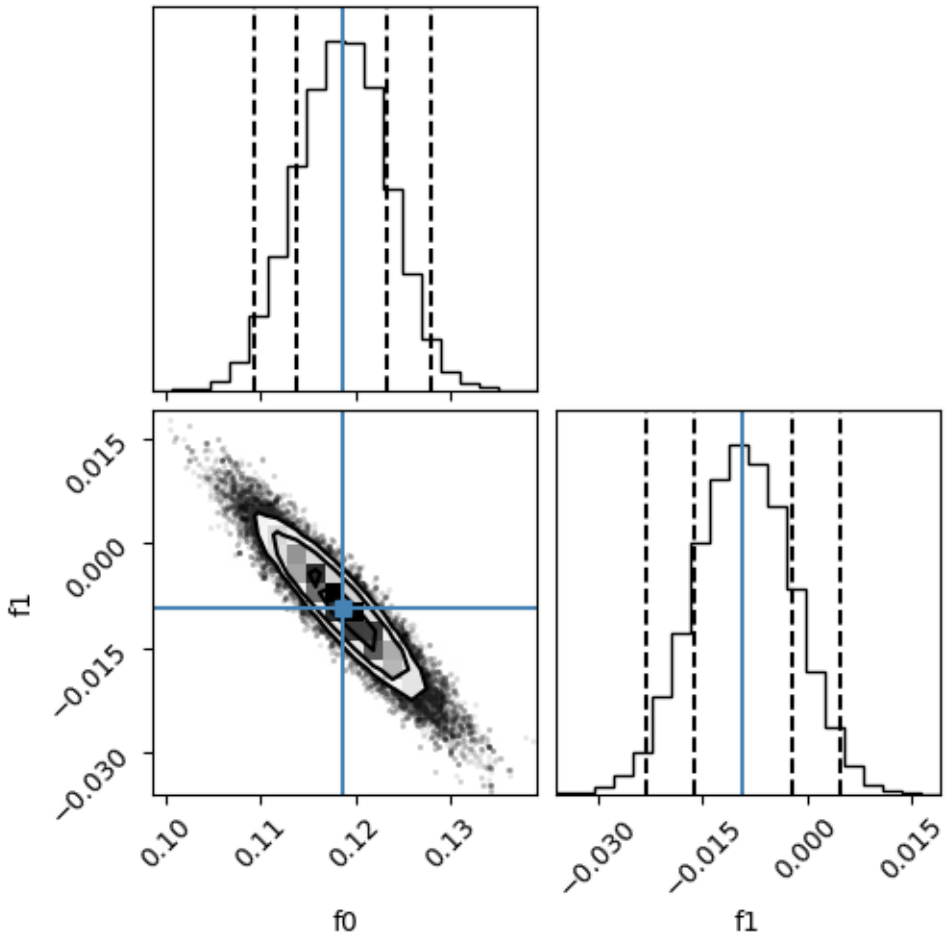
Plots:

[81]:
```
f0 = samples[:,0].mean()
f1 = samples[:,1].mean()
x = np.linspace(0,1.5,100)
plt.plot(z , f_gas , 'kx')
plt.title("best fit line")
plt.plot(x , f0 * (1 + f1*x) , 'b-')
plt.grid(True)
plt.show()
```



[82]:
```
print("68% and 95% joint confidence intervals for f_0 and f_1")
corner.corner(samples , labels = ["f0" , "f1"] , truths = [f0 , f1] , quantiles␣
 ↪= (0.16 , 0.84 , 0.025 , 0.975))
plt.show()
```

```
68% and 95% joint confidence intervals for f_0 and f_1
```



Question 2

Calculate the Bayes factor for the linear and quadratic model for the example given on fifth blog article of the Pythonic Perambulations Series using dynesty or Nestle. Do the values agree with what's on the blog(obtained by integrating the emcee samples).?

[83]:
```
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]])
```

```
x , y , sigma_y = data
```

polynomial fit function:

[84]:
```
def polynomial_fit(theta):
    sum = 0
    for idx , coeff in enumerate(theta):
        sum += coeff * x ** idx
    return sum
```

log likelihood function:

[85]:
```
def log_likelyhood(theta, data=data):
    pred = polynomial_fit(theta)
    return -0.5 * np.sum(np.log(2 * np.pi * sigma_y ** 2) + (y - pred) ** 2 /␣
 ↪sigma_y ** 2)
```

prior function:

[86]:
```
def prior(theta):
    return 200*theta - 100
```

[87]:
```
# Taking reference from
# http://mattpitkin.github.io/samplers-demo/pages/samplers-samplers-everywhere/
 ↪#dynesty

nlive = 1024       # number of live points
bound = 'multi'    # use MutliNest algorithm for bounds
ndims = 2          # two parameters
sample = 'unif'    # uniform sampling
tol = 0.1          # the stopping criterion
```

[88]:
```
sampler = NestedSampler(log_likelyhood, prior, ndims,
                        bound=bound, sample=sample, nlive=nlive)

sampler.run_nested(dlogz=tol, print_progress=False) # don't output progress bar

res = sampler.results # get results dictionary from sampler

logZdynesty_linear = res.logz[-1]        # value of logZ
logZerrdynesty_linear = res.logzerr[-1]  # estimate of the statistcal␣
 ↪uncertainty on logZ
```

[89]:
```
print("log(Z) for the Linear Model = {} ± {}".format(logZdynesty_linear,␣
 ↪logZerrdynesty_linear))
```

```
log(Z) for the Linear Model = 7.027910396437706 ± 0.14782896065052578
```

[90]:
```
# Taking reference from
# http://mattpitkin.github.io/samplers-demo/pages/samplers-samplers-everywhere/
  ↪#dynesty

nlive = 1024       # number of live points
bound = 'multi'    # use MutliNest algorithm for bounds
ndims = 3          # three parameters
sample = 'unif'    # uniform sampling
tol = 0.1          # the stopping criterion
```

[91]:
```
sampler = NestedSampler(log_likelyhood, prior, ndims,
                        bound=bound, sample=sample, nlive=nlive)

sampler.run_nested(dlogz=tol, print_progress=False) # don't output progress bar

res = sampler.results # get results dictionary from sampler

logZdynesty_quadratic = res.logz[-1]        # value of logZ
logZerrdynesty_quadratic = res.logzerr[-1]  # estimate of the statistcal␣
  ↪uncertainty on logZ
```

[92]:
```
print("log(Z) for the Quad. Model = {} ± {}".format(logZdynesty_quadratic,␣
  ↪logZerrdynesty_quadratic))
```

```
log(Z) for the Quad. Model = 2.5350348388325794 ± 0.17156736844087703
```

[93]:
```
print("Bayes factor(quad. model):",format(np.exp(logZdynesty_quadratic) / np.
  ↪exp(logZdynesty_linear)))
```

```
Bayes factor(quad. model): 0.01118842454832019
```

Question 3

Download the SDSS quasar dataset from http://astrostatistics.psu.edu/datasets/SDSS_quasar.dat. Plot the KDE estimate of the quasar redshift distribution (the column with the title z) using a Gaussian and also an exponential kernel (with bandwidth=0.2) from -0.5 to 5.5. (20 points)(Hint: Look at the KDE help page in scikit-learn or use the corresponding functions in astroML module by looking at source code of astroML figures 6.3 and 6.4)

[94]:
```
data = pd.read_csv("SDSS_quasar.txt" , sep = " ")
data
```

[94]:

	SDSS_J	R.A.	Dec.	z	u_mag	sig_u	\
0	000009.26+151754.5	0.038605	15.298476	1.1986	19.921	0.042	\
1	000009.38+135618.4	0.039088	13.938447	2.2400	19.218	0.026	
2	000009.42-102751.9	0.039269	-10.464428	1.8442	19.249	0.036	
3	000011.41+145545.6	0.047547	14.929353	0.4596	19.637	0.030	

```
4       000011.96+000225.3    0.049842   0.040372  0.4790  18.237  0.028
…                      …         …         …      …     …     …
46415  235949.46+150430.6  359.956093  15.075185  0.2977  19.094  0.025
46416  235953.44-093655.6  359.972672  -9.615454  0.3585  19.509  0.045
46417  235956.72+135131.7  359.986358  13.858825  2.3826  20.010  0.040
46418  235958.21+005139.8  359.992546   0.861062  2.0382  19.256  0.034
46419  235959.06-090944.0  359.996089  -9.162229  1.2845  18.403  0.021

        g_mag  sig_g   r_mag  sig_r  …  sig_z  Radio  X-ray   J_mag  sig_J
0      19.811  0.036  19.386  0.017  …  0.069   -1.0 -9.000   0.000  0.000  \
1      18.893  0.022  18.445  0.018  …  0.033   -1.0 -9.000   0.000  0.000
2      19.029  0.027  18.980  0.021  …  0.047    0.0 -9.000   0.000  0.000
3      19.466  0.024  19.362  0.022  …  0.047   -1.0 -9.000   0.000  0.000
4      17.971  0.020  18.025  0.019  …  0.029    0.0 -1.660  16.651  0.136
…        …     …      …      …   …    …      …     …      …      …
46415  18.966  0.023  18.668  0.016  …  0.033   -1.0 -1.429  16.676  0.180
46416  19.276  0.022  18.895  0.018  …  0.039    0.0 -9.000  16.976  0.173
46417  19.427  0.027  19.217  0.018  …  0.048   -1.0 -9.000   0.000  0.000
46418  19.004  0.021  18.794  0.017  …  0.036    0.0 -9.000   0.000  0.000
46419  18.373  0.015  18.139  0.024  …  0.036    0.0 -9.000   0.000  0.000

        H_mag  sig_H   K_mag  sig_K     M_i
0       0.000  0.000   0.000  0.000 -25.085
1       0.000  0.000   0.000  0.000 -27.419
2       0.000  0.000   0.000  0.000 -26.459
3       0.000  0.000   0.000  0.000 -22.728
4      15.820  0.149  14.821  0.111 -24.046
…        …     …      …      …      …
46415  15.661  0.176  15.187  0.130 -22.286
46416  16.188  0.164  15.502  0.238 -22.549
46417   0.000  0.000   0.000  0.000 -26.665
46418   0.000  0.000   0.000  0.000 -26.900
46419   0.000  0.000   0.000  0.000 -26.297

[46420 rows x 23 columns]
```

[95]:
```
quasar = data["z"]
quasar = quasar.to_numpy().reshape(-1,1)
x = np.linspace(-0.5 , 5.5 , 1000)

gaussian_kde = kde(kernel = "gaussian" , bandwidth = 0.2).fit(quasar)
exponential_kde = kde(kernel = "exponential" , bandwidth = 0.2).fit(quasar)
```

[97]:
```
plt.plot(x , np.exp(gaussian_kde.score_samples(x.reshape(-1,1))) , 'g-' , label␣
↪= "Gaussian KDE")
plt.plot(x , np.exp(exponential_kde.score_samples(x.reshape(-1,1))) , 'b-' ,␣
↪label = "Exponential KDE")
```

```
plt.grid(True)
plt.legend()
plt.title("KDE using Gaus. and Exp. Kernels with bandwidth = 0.2")
plt.show()
```