

```
In [85]: import numpy as np
import matplotlib.pyplot as plt
from scipy.stats import norm, laplace, bernoulli
import scipy.optimize as optimize
import math
```

Defining constant and writing the function for generating measured data without the noise

```
In [87]: N = 201
magnitude = 1.2
mu = 0 # loc
sigma = 1 # beta
alpha = 0
gamma = 0.1
x = np.linspace(-3, 3, N)
params = [1, -8, 4]

def create_y_model(params):
    def y(x): return sum([p*(x**i) for i, p in enumerate(params)])
    return y
```

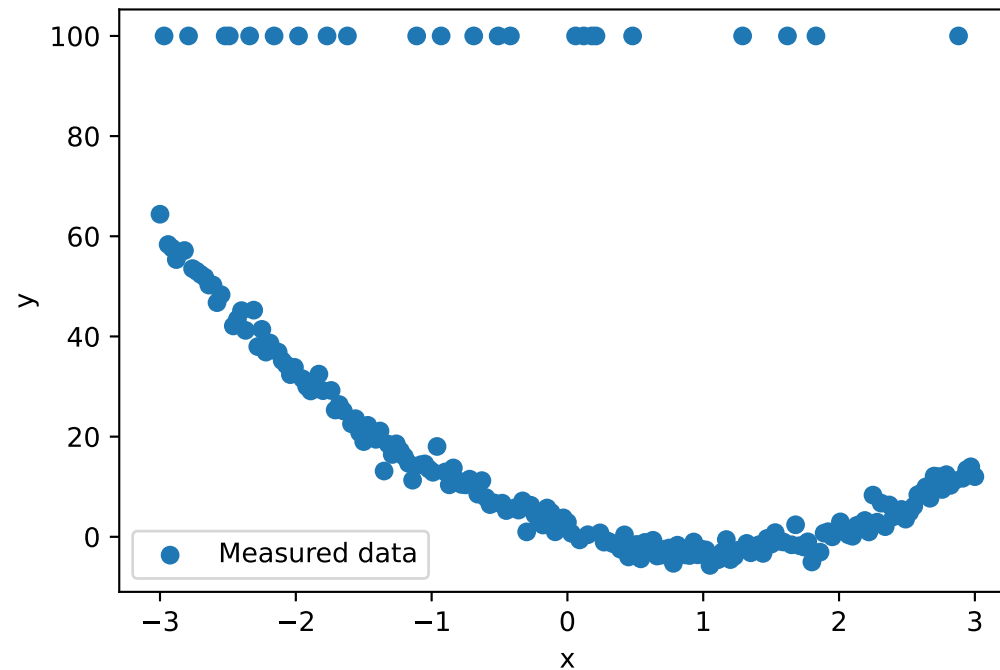
The Laplacian noise function

```
In [89]: def add_noise_to_true_model(x, N, params, magnitude, alpha, mu, sigma):
y = create_y_model(params)
y_true = y(x)
y_added_noise = y_true + magnitude * \
    (alpha*np.random.normal(mu, sigma, N) +
    (1-alpha)*np.random.laplace(mu, sigma, N))
return y_added_noise
```

Adding the outlier noise function

```
In [91]: def add_outlier(params, N, magnitude, alpha, mu, sigma, gamma):
y_added_noise = add_noise_to_true_model(x,
N, params, magnitude, alpha, mu, sigma)
data = bernoulli.rvs(size=N, p=gamma)
for i in range(N):
    if data[i] == 1:
        y_added_noise[i] = 100
return y_added_noise

y_measured_data = add_outlier(params, N, magnitude, alpha, mu, sigma, gamma)
plt.figure()
plt.scatter(x, y_measured_data, label="Measured data")
plt.legend()
plt.xlabel("x")
plt.ylabel("y")
plt.show()
```



Splitting the measured data into training, testing and validation

```
In [93]: y_training_set = y_measured_data[0:math.floor(len(y_measured_data)/3)]
x_training_set = x[0:math.floor(len(x)/3)]

y_testing_set = y_measured_data[math.floor(len(y_measured_data)/3):math
.floor(len(y_measured_data)*2/3)]
x_testing_set = x[math.floor(len(x)/3):math.floor(len(x)*2/3)]

y_validation_set = y_measured_data[math.floor(len(y_measured_data)*2/3
):]
x_validation_set = x[math.floor(len(x)*2/3):]
```

Estimating the LS estimator for each mode

```
In [95]: def LS_estimator_given_mode(mode, x, y):
u_tensor_0 = np.reshape(x, (len(x), 1))

ones_vec = np.ones((len(x), 1))
u_tensor = np.append(ones_vec, u_tensor_0, axis=1)

for i in range(2, mode):
    u_tensor = np.append(u_tensor, np.power(u_tensor_0, i), axis=1)

u_transpose_dot_u = np.dot(u_tensor.T, u_tensor) # calculating dot
product
u_transpose_dot_u_inv = np.linalg.inv(
    u_transpose_dot_u) # calculating inverse
u_transpose_dot_y = np.dot(u_tensor.T, y) # calculating dot product

LS_params = np.dot(u_transpose_dot_u_inv, u_transpose_dot_y)
# Recreate model based on LS estimate:
LS_params = LS_params.tolist()
return LS_params

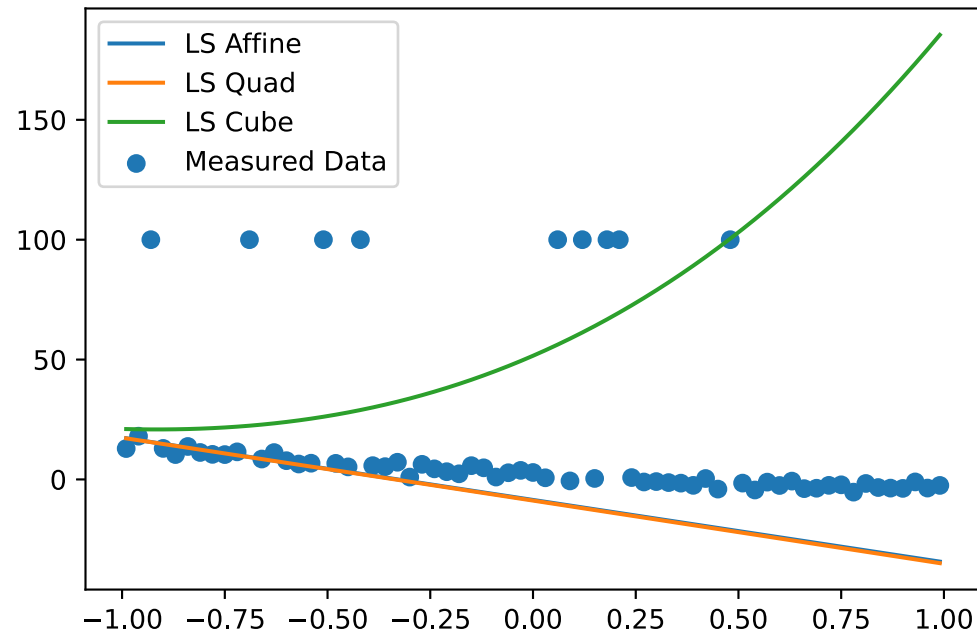
LS_params_affine = LS_estimator_given_mode(2,x_training_set, y_training_s
```

```
et)
LS_params_quad = LS_estimator_given_mode(3,x_training_set,y_training_set)
LS_params_cube = LS_estimator_given_mode(4,x_training_set,y_training_set)

y_hat_LS_affine = create_y_model(LS_params_affine)
y_hat_LS_quad = create_y_model(LS_params_quad)
y_hat_LS_cube = create_y_model(LS_params_cube)
```

When plotting the different LS estimator modes for the training set, we can clearly see that the affine and quadratic estimator is performing the best, while the cubic estimator has terrible performance

```
In [97]: plt.figure()
plt.scatter(x_testing_set,y_testing_set, label= "Measured Data")
plt.plot(x_testing_set,y_hat_LS_affine(x_testing_set), label= "LS Affine")
plt.plot(x_testing_set,y_hat_LS_quad(x_testing_set), label="LS Quad")
plt.plot(x_testing_set,y_hat_LS_cube(x_testing_set),label= "LS Cube")
plt.legend()
plt.show()
```



The code for estimating the ML estimator for each mode

```
In [99]: def log_lik(par_vec,x,y):
    pdf = laplace.pdf
    # If the standard deviation parameter is negative, return a large value:
    if par_vec[-1] < 0:
        return(1e8)
    # The likelihood function values:
    lik = pdf(y,
        loc=sum([p*(x**i) for i, p in enumerate(par_vec[:-1])]),
        scale=par_vec[-1])

    if all(v == 0 for v in lik):
        return(1e8)
    # Logarithm of zero = -Inf
    return(-sum(np.log(lik[np.nonzero(lik)])))
```

```

def ML_estimator_given_mode(mode, N, x,y):
    init_guess = np.zeros(mode+1)
    init_guess[-1] = len(x)

    opt_res = optimize.minimize(fun=log_lik,
                                x0=init_guess,
                                options={'disp': True},
                                args=(x,y))

    MLE_params = opt_res.x[:-1]
    MLE_params = MLE_params.tolist()
    return MLE_params

ML_params_affine = ML_estimator_given_mode(2,N,x_traning_set,y_traning_set)
ML_params_quad = ML_estimator_given_mode(3,N,x_traning_set,y_traning_set)
ML_params_cube = ML_estimator_given_mode(4,N,x_traning_set,y_traning_set)

y_hat_ML_affine = create_y_model(ML_params_affine)
y_hat_ML_quad = create_y_model(ML_params_quad)
y_hat_ML_cube = create_y_model(ML_params_cube)

```

```

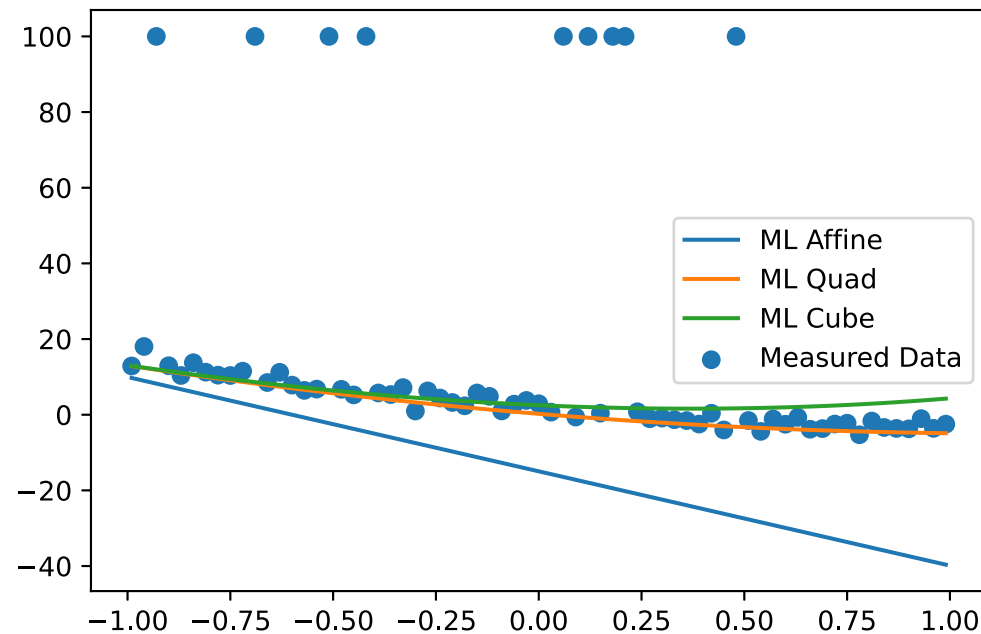
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 270.900525
Iterations: 17
Function evaluations: 336
Gradient evaluations: 81
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 269.065481
Iterations: 35
Function evaluations: 623
Gradient evaluations: 123
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 269.015023
Iterations: 23
Function evaluations: 596
Gradient evaluations: 98

```

Plotting the different ML estimators we can see that the quadratic and cubic estimators performed really well. Although the affine estimator was not yielding good result it was still performing reasonably well compared to the ML estimators

```
In [100]: plt.figure()
plt.scatter(x_testing_set,y_testing_set, label= "Measured Data")
plt.plot(x_testing_set,y_hat_ML_affine(x_testing_set), label= "ML Affine")
plt.plot(x_testing_set,y_hat_ML_quad(x_testing_set), label="ML Quad")
plt.plot(x_testing_set,y_hat_ML_cube(x_testing_set),label= "ML Cube")
plt.legend()
```

```
Out[100]: <matplotlib.legend.Legend at 0x2b3d403bd00>
```



Renning the performance index on the testing data for alle the different estimators, we can clearly observe that the best estimator is the quadratic ML estimator as was evident in the plots

we did earlier. The second best estimator is the cubic ML estimator. The worst performances came from the LS estimators.

```
In [101]: def performance_index(x_data,y_data,params):
            y_hat_model = create_y_model(params)
            y_hat = y_hat_model(x_data)

            performance = 0
            for i in range(len(y_data)):
                performance += abs(y_data[i] - y_hat[i])
            return performance

            performance_LS_affine = performance_index(x_testing_set,y_testing_set,
            LS_params_affine)
            performance_LS_quad = performance_index(x_testing_set,y_testing_set, LS
            _params_quad)
            performance_LS_cube = performance_index(x_testing_set,y_testing_set, LS
            _params_cube)
            performance_ML_affine = performance_index(x_testing_set,y_testing_set,
            ML_params_affine)
            performance_ML_quad = performance_index(x_testing_set,y_testing_set, ML
            _params_quad)
            performance_ML_cube = performance_index(x_testing_set,y_testing_set, ML
            _params_cube)

            print("LS Affine: ", performance_LS_affine)
            print("LS Quad: ", performance_LS_quad)
            print("LS Cube: ", performance_LS_cube)
            print("ML Affine: ", performance_ML_affine)
            print("ML Quad: ", performance_ML_quad)
            print("ML Cube: ", performance_ML_cube)

            LS Affine: 1662.5771103211305
            LS Quad: 1681.5744939718413
            LS Cube: 4475.585107256561
            ML Affine: 2066.210291534851
            ML Quad: 973.7625424503735
            ML Cube: 1021.0821063426866
```



In the final part of our assignment i have plotted all the estimators as a function of gamma. If one scrolls past all the warnings one can see the plot at the end. I have choose to exclude the LS cubic estimator from the plots because it was too large and so streched out the graph too much and made it too difficult to compare the performamance index of the other estimators. The most robust estimators seems to be the LS affine estimator which has the least amount and least rapid spikes in it's performance. However it is clear that the LS affine estimator is not the best estimator if gamma is less than 0.2. The ML quadratic estimator have really good performance in the range gamma = 0 to 0.15, after that it spikes and, but then for gamma > 0.25, the spike ends and it becomes a relatively good estimator. To me it becomes clear that the ML estimators have the best performances on average when gamma is either < 0.2 or > 0.4. In between there the LS affine estimator is sometimes good. For gamma > 0.5 all the estimators becomes equally good. At least from what i can see in my plots. To answer the quesiton a) The LS affine estimator degrades least and b) the ML quadratic estimator performs the best

```
In [102]: def plot_LS_ML_func_of_gamma(x,params, N, magnitude, alpha, mu, sigma):
    gamma = np.linspace(0,1,30)
    LS_affine_performance_vector = [0]*len(gamma)
    LS_quad_performance_vector = [0]*len(gamma)
    LS_cube_performance_vector = [0]*len(gamma)
    ML_affine_performance_vector = [0]*len(gamma)
    ML_quad_performance_vector = [0]*len(gamma)
    ML_cube_performance_vector = [0]*len(gamma)

    y = create_y_model(params)
    y_true = y(x)
    y_added_noise = y_true + magnitude * \
        (alpha*np.random.normal(mu, sigma, N) +
         (1-alpha)*np.random.laplace(mu, sigma, N))

    x_traning_set = x[0:math.floor(len(x)/3)]
    x_testing_set = x[math.floor(len(x)/3):math.floor(len(x)*2/3)]
    x_validation_set = x[math.floor(len(x)*2/3):]

    for j in range(len(gamma)):
        data = bernoulli.rvs(size=N, p=gamma[j])
        for i in range(N):
```

```

        if data[i] == 1:
            y_added_noise[i] = 100

        y_measured_data = y_added_noise
        y_training_set = y_measured_data[0:math.floor(len(y_measured_data)/3)]
        y_testing_set = y_measured_data[math.floor(len(y_measured_data)/3):math.floor(len(y_measured_data)*2/3)]
        y_validation_set = y_measured_data[math.floor(len(y_measured_data)*2/3):]

        LS_params_affine = LS_estimator_given_mode(2,x_training_set, y_training_set)
        LS_params_quad = LS_estimator_given_mode(3,x_training_set,y_training_set)
        LS_params_cube = LS_estimator_given_mode(4,x_training_set,y_training_set)

        ML_params_affine = ML_estimator_given_mode(2,N,x_training_set,y_training_set)
        ML_params_quad = ML_estimator_given_mode(3,N,x_training_set,y_training_set)
        ML_params_cube = ML_estimator_given_mode(4,N,x_training_set,y_training_set)

        LS_affine_performance_vector[j] = performance_index(x_validation_set,y_validation_set, LS_params_affine)
        LS_quad_performance_vector[j] = performance_index(x_validation_set,y_validation_set, LS_params_quad)
        LS_cube_performance_vector[j] = performance_index(x_validation_set,y_validation_set, LS_params_cube)
        ML_affine_performance_vector[j] = performance_index(x_validation_set,y_validation_set, ML_params_affine)
        ML_quad_performance_vector[j] = performance_index(x_validation_set,y_validation_set, ML_params_quad)
        ML_cube_performance_vector[j] = performance_index(x_validation_set,y_validation_set, ML_params_cube)

```

```

plt.figure()
plt.plot(gamma, LS_affine_performance_vector, label="LS Affine")
plt.plot(gamma, LS_quad_performance_vector, label="LS Quad")
#plt.plot(gamma, LS_cube_performance_vector, label="LS Cube")
plt.plot(gamma, ML_affine_performance_vector, label="ML Affine")
plt.plot(gamma, ML_quad_performance_vector, label="ML Quad")
plt.plot(gamma, ML_cube_performance_vector, label="ML Cube")
plt.legend()
plt.xlabel('gamma')
plt.ylabel('Performance index')
plt.show()

plot_LS_ML_func_of_gamma(x,params, N, magnitude, alpha, mu, sigma)

```

```

Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 142.102576
Iterations: 23
Function evaluations: 420
Gradient evaluations: 102
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 115.435949
Iterations: 28
Function evaluations: 626
Gradient evaluations: 123
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 115.008290
Iterations: 53
Function evaluations: 1037
Gradient evaluations: 172
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 201.454826
Iterations: 25
Function evaluations: 415
Gradient evaluations: 101
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 191.707810
Iterations: 35
Function evaluations: 672
Gradient evaluations: 133
Warning: Desired error not necessarily achieved due to precision loss.

```

```
Current function value: 191.776975
Iterations: 20
Function evaluations: 601
Gradient evaluations: 99
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 221.214440
Iterations: 22
Function evaluations: 480
Gradient evaluations: 117
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 214.093968
Iterations: 52
Function evaluations: 1025
Gradient evaluations: 203
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 214.144882
Iterations: 22
Function evaluations: 672
Gradient evaluations: 110
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 257.719842
Iterations: 17
Function evaluations: 288
Gradient evaluations: 71
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 253.871864
Iterations: 16
Function evaluations: 400
Gradient evaluations: 79
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 253.835530
Iterations: 25
Function evaluations: 726
Gradient evaluations: 119
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 303.302256
Iterations: 22
Function evaluations: 484
Gradient evaluations: 117
Warning: Desired error not necessarily achieved due to precision loss.
```

```
Current function value: 301.725019
Iterations: 32
Function evaluations: 676
Gradient evaluations: 134
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 301.718902
Iterations: 27
Function evaluations: 1074
Gradient evaluations: 177
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 323.996536
Iterations: 20
Function evaluations: 327
Gradient evaluations: 80
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 323.210440
Iterations: 17
Function evaluations: 325
Gradient evaluations: 64
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 323.195353
Iterations: 28
Function evaluations: 585
Gradient evaluations: 97
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 340.657697
Iterations: 29
Function evaluations: 580
Gradient evaluations: 142
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 340.404941
Iterations: 11
Function evaluations: 377
Gradient evaluations: 73
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 340.300297
Iterations: 57
Function evaluations: 2059
Gradient evaluations: 342
Warning: Desired error not necessarily achieved due to precision loss.
```

```
Current function value: 338.894398
Iterations: 20
Function evaluations: 462
Gradient evaluations: 113
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 335.435681
Iterations: 24
Function evaluations: 397
Gradient evaluations: 78
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 334.645775
Iterations: 16
Function evaluations: 438
Gradient evaluations: 72
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 314.566871
Iterations: 45
Function evaluations: 608
Gradient evaluations: 149
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 314.566875
Iterations: 53
Function evaluations: 674
Gradient evaluations: 133
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 314.613445
Iterations: 33
Function evaluations: 611
Gradient evaluations: 101
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 298.584614
Iterations: 46
Function evaluations: 536
Gradient evaluations: 131
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 298.584615
Iterations: 52
Function evaluations: 752
Gradient evaluations: 148
Warning: Desired error not necessarily achieved due to precision loss.
```

```
Current function value: 298.584622
Iterations: 77
Function evaluations: 1068
Gradient evaluations: 176
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 265.509467
Iterations: 48
Function evaluations: 608
Gradient evaluations: 149
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 265.509471
Iterations: 50
Function evaluations: 566
Gradient evaluations: 111
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 265.509501
Iterations: 67
Function evaluations: 960
Gradient evaluations: 158
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 248.038481
Iterations: 39
Function evaluations: 411
Gradient evaluations: 100
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 248.038481
Iterations: 55
Function evaluations: 913
Gradient evaluations: 180
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 248.038503
Iterations: 55
Function evaluations: 780
Gradient evaluations: 128
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 208.632371
Iterations: 51
Function evaluations: 531
Gradient evaluations: 130
Warning: Desired error not necessarily achieved due to precision loss.
```

```
Current function value: 208.632384
Iterations: 53
Function evaluations: 664
Gradient evaluations: 131
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 208.632381
Iterations: 69
Function evaluations: 1092
Gradient evaluations: 180
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 153.704912
Iterations: 50
Function evaluations: 600
Gradient evaluations: 147
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 153.704915
Iterations: 46
Function evaluations: 766
Gradient evaluations: 151
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 153.704964
Iterations: 71
Function evaluations: 990
Gradient evaluations: 163
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 153.704912
Iterations: 50
Function evaluations: 600
Gradient evaluations: 147
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 153.704915
Iterations: 46
Function evaluations: 766
Gradient evaluations: 151
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: 153.704964
Iterations: 71
Function evaluations: 990
Gradient evaluations: 163
Warning: Desired error not necessarily achieved due to precision loss.
```



```
Current function value: -843.811314
Iterations: 53
Function evaluations: 910
Gradient evaluations: 225
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: -747.379070
Iterations: 74
Function evaluations: 1026
Gradient evaluations: 203
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: -250.957523
Iterations: 59
Function evaluations: 1086
Gradient evaluations: 179
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: -843.811314
Iterations: 53
Function evaluations: 910
Gradient evaluations: 225
Warning: Desired error not necessarily achieved due to precision loss.
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Warning: Desired error not necessarily achieved due to precision loss.
Current function value: -747.379070
Iterations: 74
Function evaluations: 1026
Gradient evaluations: 203
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: -250.957523
Iterations: 59
Function evaluations: 1086
Gradient evaluations: 179
Warning: Desired error not necessarily achieved due to precision loss.
Current function value: -843.811314
Iterations: 53
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