

HW1

b)

```
In [1]: import numpy
import random
```

```
import matplotlib.pyplot as plt

from typing import Union
from scipy.optimize import minimize
```

```
In [2]: seed = numpy.loadtxt("Seed.txt").item()
random.seed(seed)
```

```
In [3]: EPS = 1e-12
```

```
def neg_log_likelihood(thetas: tuple[int, int], input: Union[numpy.ndarray, list]):
    mapping = {
        (0, 0): thetas[0],
        (0, 1): 1 - thetas[0],
        (1, 1): thetas[1],
        (1, 0): 1 - thetas[1]
    }

    neg_log_lik = 0

    for i in range(len(input)-1):
        neg_log_lik -= numpy.log(mapping[(input[i], input[i+1])] + EPS)

    return neg_log_lik
```

```
In [4]: input = numpy.loadtxt("Input.txt")
```

```
emp_null_theta_1 = []
emp_null_theta_2 = []
bounds = ((0, 1), (0, 1))

for i in range(1000):
    resampled = random.choices(input, k=len(input))
    theta_1_mle, theta_2_mle = minimize(fun=lambda thetas: neg_log_likelihood(thetas, resampled), x0 = [0.2, 0.2], bounds = bounds).x
    emp_null_theta_1.append(theta_1_mle)
    emp_null_theta_2.append(theta_2_mle)

obs_theta_1_mle, obs_theta_2_mle = minimize(fun=lambda thetas: neg_log_likelihood(thetas, input), x0 = [0.5, 0.5], bounds = bounds).x
```

```
In [5]: # null distribution for theta 1 ( $p_{\theta 0}$ )
```

```
plt.hist(emp_null_theta_1)
plt.title(r"Empirical null distribution for $p_{\theta 0}^{*}$")
plt.axvline(x = obs_theta_1_mle, color = "red", label=r"$p_{\theta 0}^{*}$")
```

```

plt.xlabel(r"$p_{\theta_0}^{*}$")
plt.legend()
plt.show()

# null distribution for theta 2 (p_11)
plt.hist(emp_null_theta_2)
plt.axvline(x = obs_theta_2_mle, color = "red", label=r"$p^{*}_{\theta_1}$")
plt.title(r"Empirical null distribution for $p^{*}_{\theta_1}$")
plt.xlabel(r"$p_{\theta_1}^{*}$")
plt.legend()
plt.show()

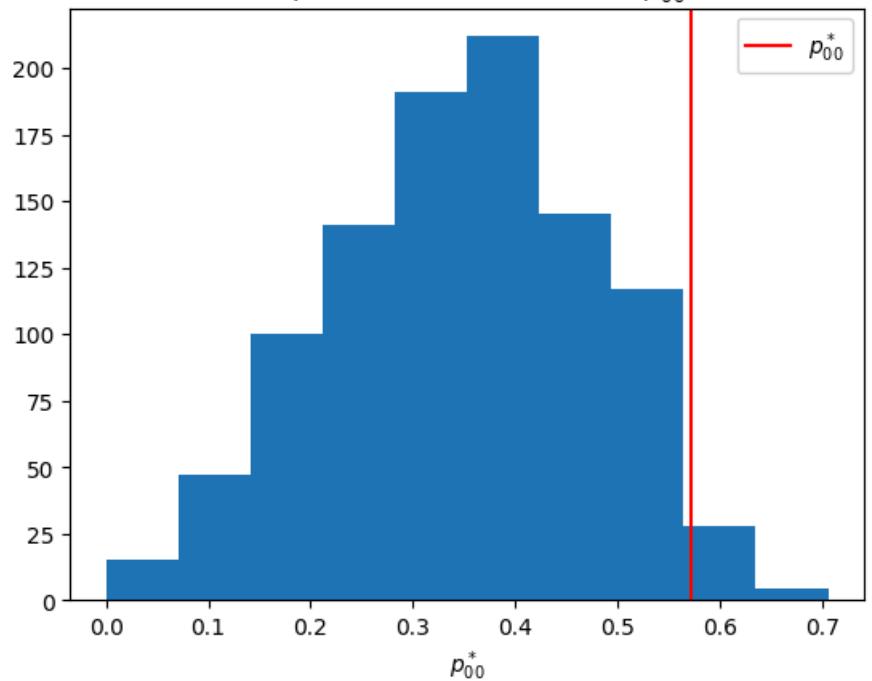
def ecdf(x):
    x = numpy.sort(x)
    y = numpy.arange(1, len(x) + 1) / len(x)
    return x, y

# empirical cdf for theta 1 (p_00)
x, y = ecdf(emp_null_theta_1)
plt.plot(x, y)
plt.title(r"Empirical cdf distribution for $p^{*}_{\theta_0}$")
plt.axvline(obs_theta_1_mle, color="red", label=r"$p^{*}_{\theta_0}$")
plt.xlabel(r"$p^{*}_{\theta_0}$")
plt.ylabel("ECDF")
plt.legend()
plt.show()

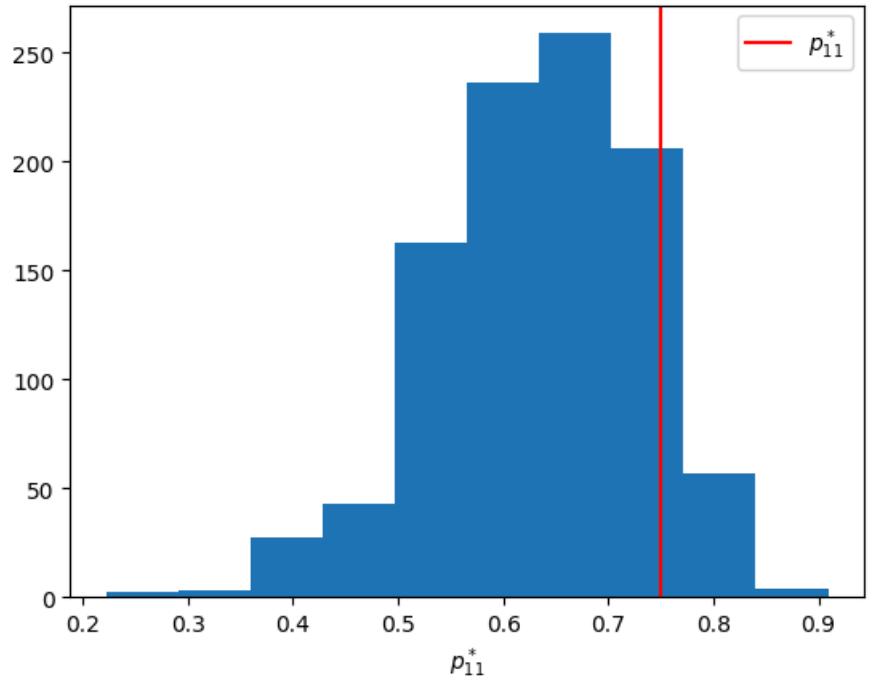
# empirical cdf for theta 2 (p_11)
x, y = ecdf(emp_null_theta_2)
plt.plot(x, y)
plt.title(r"Empirical cdf distribution for $p^{*}_{\theta_1}$")
plt.axvline(obs_theta_2_mle, color="red", label=r"$p^{*}_{\theta_1}$")
plt.xlabel(r"$p^{*}_{\theta_1}$")
plt.ylabel("ECDF")
plt.legend()
plt.show()

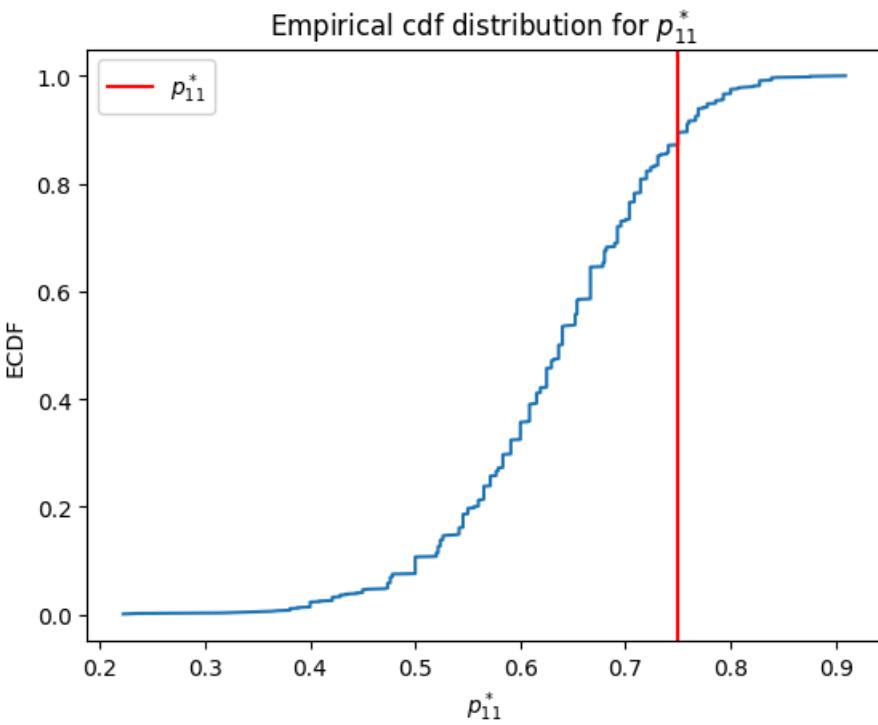
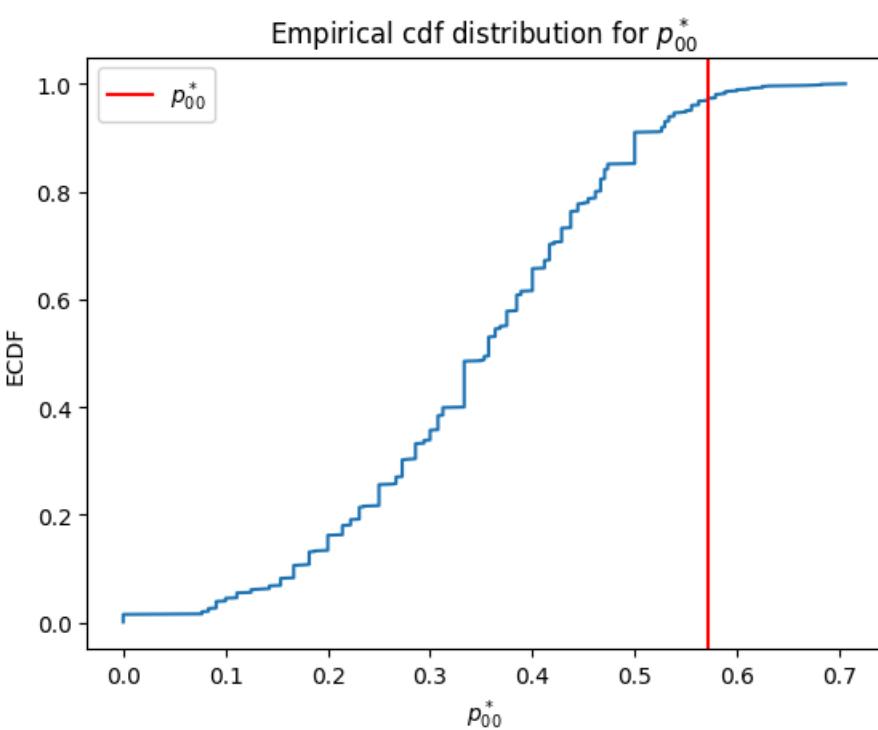
```

Empirical null distribution for p_{00}^*



Empirical null distribution for p_{11}^*





In [6]: # p-value for our test of the hypothesis applied to p_{00}
p_val_p00 = sum(1 for b in emp_null_theta_1 if b > obs_theta_1_mle) / 1000

```

# p-value for our test of the hypothesis applied to p_11
p_val_p11 = sum(1 for b in emp_null_theta_2 if b > obs_theta_2_mle) / 1000

speil = f"""For p_00, the empirical p-value of {p_val_p00} indicates that the observed transition probability is unlikely to arise from an i.i.d. sequence, providing evidence for a first-order Markov model. Assuming an alpha of 0.05 we reject our null of a simple coin flip model.

For p_11, the empirical p-value of {p_val_p11} indicates that we do not have statistical significance, assuming an alpha of 0.05, to reject the null hypothesis that the data was generated via a simple coin flip model.

print(speil)

```

For p_00, the empirical p-value of 0.027 indicates that the observed transition probability is unlikely to arise from an i.i.d. sequence, providing evidence for a first-order Markov model. Assuming an alpha of 0.05 we reject our null of a simple coin flip model.

For p_11, the empirical p-value of 0.108 indicates that we do not have statistical significance, assuming an alpha of 0.05, to reject the null hypothesis that the data was generated via a simple coin flip model.

HW2

b)

```

In [7]: import matplotlib.pyplot as plt
import numpy as np

In [8]: def g(t, y, theta, x0=2):
    x = np.sin(theta * t) + x0
    return ((y - x)**2).sum()

def first_deriv_g(t, y, theta, x0=2):
    return (- 2 * (y - np.sin(theta * t) - x0) * np.cos(theta * t) * t).sum()

def second_deriv_g(t, y, theta, x0=2):
    return ( 2 * (y - np.sin(theta * t) - x0) * np.sin(theta * t) * (t**2) + 2 * (np.cos(theta * t)**2) * (t ** 2)).sum()

def theta_step(t, y, theta, x0=2):
    delta_theta = - first_deriv_g(t, y, theta, x0=x0)/second_deriv_g(t, y, theta, x0=x0)
    theta += delta_theta
    return theta

def run_newton_method(t, y, theta, x0=2, n_max=30, eps=10**(-8), is_save=False):
    if is_save:
        save(theta, how='w')
    for i in range(n_max):
        theta_new = theta_step(t, y, theta, x0=x0)
        if abs(theta_new - theta) < eps:
            theta = theta_new
            break
    else:
        theta = theta_new
    if is_save:
        save(theta, how='a')
    return theta

```

```
def save(x, how='a', name='Exc7Task2a.txt'):
    with open(name, how) as f:
        f.write('%.3f\n' % x)
```

In [9]:

```
data = np.loadtxt('Data.txt', ndmin=2, converters = float, delimiter=",")
thetas = np.linspace(0, 20, 100)
```

In [10]:

```
val = [g(data[:, 0], data[:, 1], theta, x0=2).item() for theta in thetas]
der1 = [first_deriv_g(data[:, 0], data[:, 1], theta, x0=2).item() for theta in thetas]
der2 = [second_deriv_g(data[:, 0], data[:, 1], theta, x0=2).item() for theta in thetas]
```

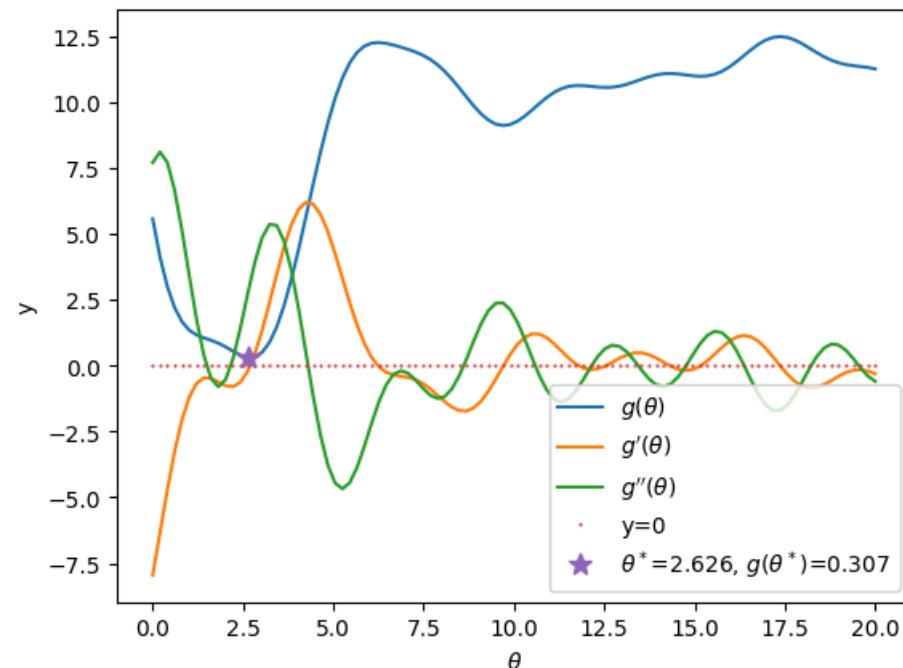
In [11]:

```
index = np.argmin(val)
```

In [12]:

```
plt.plot(thetas, val, label=r'$g(\theta)$')
plt.plot(thetas, der1, label=r'$g^{\prime}(\theta)$')
plt.plot(thetas, der2, label=r'$g^{\prime\prime}(\theta)$')
plt.plot(thetas, [0]*len(thetas), '.', label='y=0', markersize=1)
plt.plot(thetas[index], val[index], '*', label=r'$\theta^*=2.626, g(\theta^*)=0.307$', markersize=10)
plt.xlabel(r'$\theta$')
plt.ylabel('y')
plt.legend()
```

Out[12]:



c)

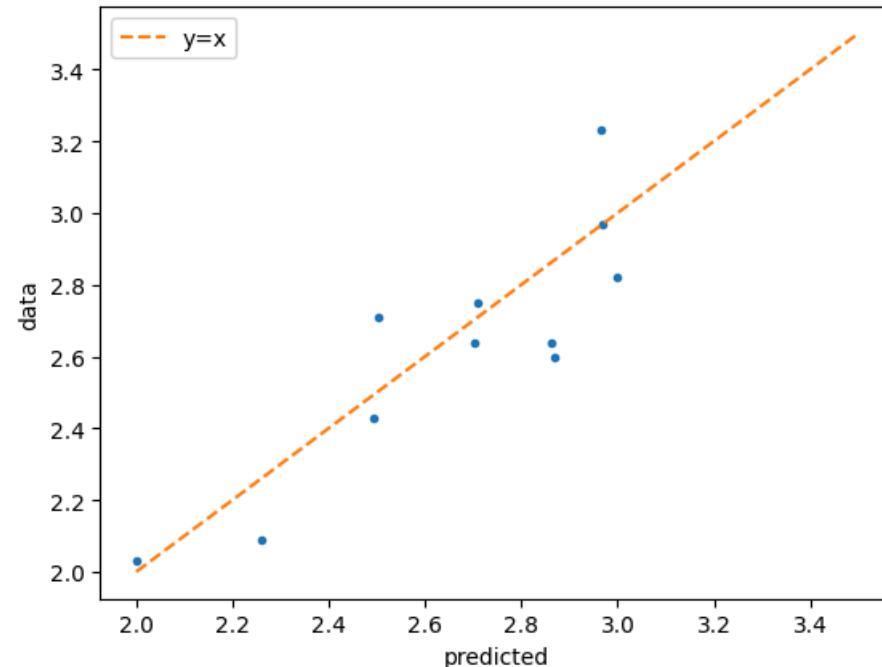
In [13]:

```
def model(t, theta, x0=2):
    return np.sin(theta * t) + x0
```

```
In [14]: pred = model(data[:, 0], thetas[index])
```

```
In [15]: plt.plot(pred, data[:, 1], '.')
plt.plot(np.linspace(2, 3.5, 10), np.linspace(2, 3.5, 10), '--', label='y=x')
plt.xlabel('predicted')
plt.ylabel('data')
plt.legend()
```

```
Out[15]: <matplotlib.legend.Legend at 0x1250e7b50>
```



According to the comparison, it seems that the Newton method is not guaranteed to provide the global optimal parameter as the result from the Newton method function differ from the parameter corresponding to the global minimum value:

```
In [16]: n_max = 30
eps = 10**(-8)
theta = 3

result = run_newton_method(data[:, 0], data[:, 1], theta, x0=2, n_max=n_max, eps=eps).item()
```

```
In [17]: print('Newton method: %f\nGlobal minimum value parameter for the objective function: %f' % (result, thetas[index]))
```

Newton method: 2.702120

Global minimum value parameter for the objective function: 2.626263

Additionally, it is important to correctly initialize the Newton method function, otherwise it would give the parameter associated with the local, not global minimum.

```
In [18]: theta_start = 10
run_newton_method(data[:, 0], data[:, 1], theta_start, x0=2, n_max=n_max, eps=eps).item()
```

```
Out[18]: 9.711984372034813
```

HW3

$y_i = x_{i|\theta} + \eta_i$ and $\eta_i \sim Norm(0, \sigma_i^2)$

$$L(y_i|\theta) = \prod_{i=1}^n p(y_i|\theta)$$

where $p(y_i|\theta) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(y_i - x_{i|\theta})^2}{2\sigma_i^2}\right)$

$$L(y_i|\theta) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left(-\frac{(y_i - x_{i|\theta})^2}{2\sigma_i^2}\right) = \frac{1}{(2\pi)^{\frac{n}{2}} \sigma_1 \dots \sigma_n} \exp\left(-\sum_{i=1}^n \frac{(y_i - x_{i|\theta})^2}{2\sigma_i^2}\right)$$

$$l(y_i|\theta) = \log L(y_i|\theta) = \underbrace{\frac{n}{2} \log(\frac{1}{2\pi})}_{\text{constant}} - \sum_{i=1}^n \log(\sigma_i) - \sum_{i=1}^n \frac{(y_i - x_{i|\theta})^2}{2\sigma_i^2}$$

no θ

2 is a constant

$$\text{As } \theta^* = \arg \min_{\theta} (-l(y_i|\theta))$$

Therefore

$$\text{As } \theta^* = \arg \min_{\theta} \left(\sum_{i=1}^n \frac{(y_i - x_{i|\theta})^2}{\sigma_i^2} \right)$$

$$\text{The objective function is } g(\theta) = \sum_{i=1}^n \frac{(y_i - x_{i|\theta})^2}{\sigma_i^2}$$

HW4

$$N = 2$$

$$t = (1, 3)$$

$$y = (6, 7)$$

$$(\theta_1, \theta_2)^\top = (1, 1)$$

$$x_i = \theta_1 e^{\theta_2 t_i}$$

$$g(\theta) = \sum_{i=1}^N (x_{i|\theta} - y_i)^2 = \sum_{i=1}^N (\theta_1 e^{\theta_2 t_i} - y_i)^2$$

$$\frac{dg(\theta)}{d\theta_1} = 2 \sum_{i=1}^N (\theta_1 e^{\theta_2 t_i} - y_i) e^{\theta_2 t_i} = 2 \sum_{i=1}^N (1 e^{1 t_i} - y_i) e^{t_i} = 2(e - 6)e + 2(e^3 - 7)e^3$$

$$\frac{dg(\theta)}{d\theta_2} = 2 \sum_{i=1}^N (\theta_1 e^{\theta_2 t_i} - y_i) e^{\theta_2 t_i} \theta_1 t_i = 2 \sum_{i=1}^N (e^{t_i} - y_i) e^{t_i} t_i = 2e(e - 6) + 6e^3(e^3 - 7)$$

$$\frac{d^2g(\theta)}{d\theta_1^2} = 2 \sum_{i=1}^N e^{\theta_2 t_i} = 2e^2 + 2e^{2 \cdot 3} = 2(e^2 + e^6)$$

$$\frac{d^2g(\theta)}{d\theta_1 d\theta_2} = 2 \sum_{i=1}^N (\theta_1 e^{2\theta_2 t_i} 2t_i - y_i e^{\theta_2 t_i} t_i) = 2 \sum_{i=1}^N (1e^{2t_i} 2t_i - y_i e^{1t_i} t_i) = 2(2e^2 - 6e) + 2(6e^6 - 7 \cdot 3e^3) = 2(2e^2 - 6e) + 2(6e^6 - 21e^3)$$

$$\frac{d^2g(\theta)}{d\theta_2^2} = 2 \sum_{i=1}^N (\theta_2^2 e^{2\theta_2 t_i} 2t_i^2 - y_i \theta_1 e^{\theta_2 t_i} t_i^2) = 2(1e^2 2 - 6e) + 2(e^{2 \cdot 3} 2 \cdot 9 - 7e^3 9) = 2(2e^2 - 6e + 18e^6 - 63e^3)$$

In [19]:

```
import numpy as np

print(f'''
d g(theta)/ d theta1: {2 * (np.exp(1) - 6) * np.exp(1) + 2 * (np.exp(1)**3 - 7) * np.exp(1)**3}
d g(theta)/ d theta2: {2 * np.exp(1) * (np.exp(1) - 6) + 6 * np.exp(1)**3 * (np.exp(1)**3 - 7)}

d^2 g(theta)/ d theta1^2: {2 * (np.exp(1)**2 + np.exp(1)**6)}
d^2 g(theta)/ d theta1 dtheta2: {2 * (np.exp(1)**2 * 2 - 6 * np.exp(1) + 6 * np.exp(1)**6 - 21 * np.exp(1)**3)}
d^2 g(theta)/ d theta1^2: {2 * (np.exp(1)**2 * 2 - 6 * np.exp(1) + 18 * np.exp(1)**6 - 63 * np.exp(1)**3)}
'''')
```

d g(theta)/ d theta1: 507.8188003171955
d g(theta)/ d theta2: 1559.1389404388808

d^2 g(theta)/ d theta1^2: 821.6356991833313
d^2 g(theta)/ d theta1 dtheta2: 3994.4898135931526
d^2 g(theta)/ d theta1^2: 11989.595755871029

$$H = \begin{bmatrix} \frac{d^2g(\theta)}{d\theta_1^2} & \frac{d^2g(\theta)}{d\theta_1 d\theta_2} \\ \frac{d^2g(\theta)}{d\theta_1 d\theta_2} & \frac{d^2g(\theta)}{d\theta_2^2} \end{bmatrix} = \begin{bmatrix} 821.6 & 3994.5 \\ 3994.5 & 11989.6 \end{bmatrix}$$

If we consider H as: $\begin{bmatrix} a & b \\ b & c \end{bmatrix}$

$$H^{-1} = \frac{1}{a \cdot c - b^2} \begin{bmatrix} c & -b \\ -b & a \end{bmatrix} = \frac{1}{821.6 \cdot 11989.6 - 3994.5^2} \begin{bmatrix} 11989.6 & -3994.5 \\ -3994.5 & 821.6 \end{bmatrix} = \frac{1}{-6105374.8} \begin{bmatrix} 11989.6 & -3994.5 \\ -3994.5 & 821.6 \end{bmatrix} = \begin{bmatrix} -0.001964 & 0.00065426 \\ 0.00065426 & -0.0001346 \end{bmatrix}$$

$$\theta^{s+1} = \theta^s + \Delta\theta = \theta^s - H^{-1} \cdot \nabla g(\theta^s) = \begin{bmatrix} 1 \\ 1 \end{bmatrix} - \begin{bmatrix} -0.001964 & 0.00065426 \\ 0.00065426 & -0.0001346 \end{bmatrix} \begin{bmatrix} 507.82 \\ 1559.14 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} - \begin{bmatrix} 0.0228 \\ 0.1224 \end{bmatrix} = \begin{bmatrix} 0.9772 \\ 0.8776 \end{bmatrix}$$