Linear Regression

import library

```
import numpy as np
import matplotlib.image as img
import matplotlib.pyplot as plt
import matplotlib.colors as colors
from mpl_toolkits.mplot3d import Axes3D
```

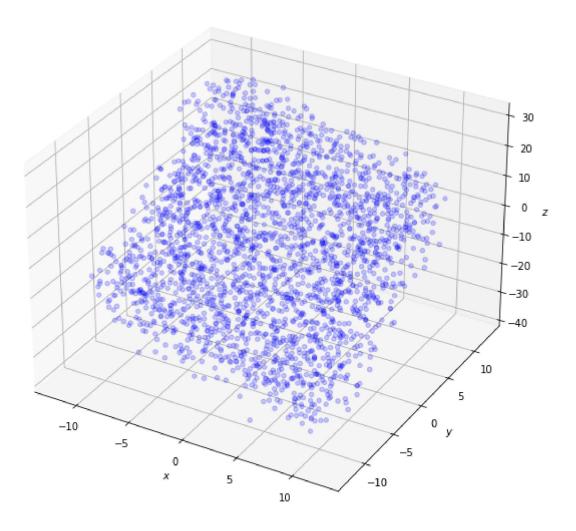
load point data for training and testing

plot the data in the three dimensional space

In [3]: ▶

```
fig = plt.figure(figsize=(12, 8))
ax1 = plt.subplot(111, projection='3d')
plt.title('data')
ax1.set_xlabel('$x$')
ax1.set_ylabel('$y$')
ax1.set_zlabel('$z$')
ax1.scatter(xx, yy, zz, marker='o', color='blue', alpha=0.2)
plt.tight_layout()
plt.show()
```

data



In [4]:

return loss

compute the loss function

```
def compute_residual(theta, x, y, z):
    num_data = x.shape[0]
    first = np.ones(num_data)
    X = np.column_stack([first, x, y])
    residual = z - X.dot(theta)
    return residual, num_data

In [5]:

def compute_loss(theta, x, y, z):
    residual, num_data = compute_residual(theta, x, y, z)
```

```
compute the gradient for each model parameter (DO NOT COMPUTE THE GRADIENT FOR EACH MODEL PARAMETER, BUT DO COMPUTE THE GRADIENT OF THE MODEL PARAMTER VECTOR)
```

```
In [6]:

def compute_gradient(theta, x, y, z):
    one = np.ones(num_data)
    X = np.column_stack([one,x,y])
    f = np.dot(X.T,(X.dot(theta) - z))
    grad = f / num_data
    return grad
```

gradient descent for each model parameter

loss = np.sum(np.square(residual))/(2*num_data)

H

```
In [7]:
num_iteration = 1000
learning_rate = 0.01
               = np.array((0, 0, 0))
theta
theta_iteration = np.zeros((num_iteration, theta.size))
loss_iteration = np.zeros(num_iteration)
for i in range(num_iteration):
   theta = theta - learning_rate * compute_gradient(theta, xx, yy, zz)
   loss = compute_loss(theta, xx, yy, zz)
   theta_iteration[i] = theta
   loss_iteration[i] = loss
   print("iteration = %4d, loss = %5.5f" % (i, loss))
iteration = 150, loss = /.338/4
iteration = 151, loss = 7.33442
iteration = 152, loss = 7.33018
iteration = 153, loss = 7.32603
iteration = 154, loss = 7.32195
iteration = 155, loss = 7.31796
iteration = 156, loss = 7.31405
iteration = 157, loss = 7.31022
iteration = 158, loss = 7.30646
iteration = 159, loss = 7.30278
iteration = 160, loss = 7.29917
iteration = 161, loss = 7.29564
iteration = 162, loss = 7.29217
iteration = 163, loss = 7.28877
iteration = 164, loss = 7.28544
iteration = 165, loss = 7.28218
iteration = 166, loss = 7.27898
iteration = 167, loss = 7.27585
iteration = 168, loss = 7.27277
itaration - 160 | 1000 - 7 96076
In [8]:
f = theta[0] + theta[1] * xx + theta[2] * yy
```

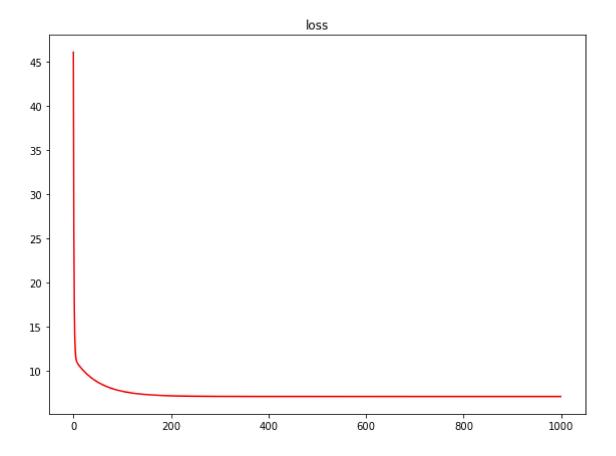
plot the results

In [10]: ▶

```
In [11]: ▶
```

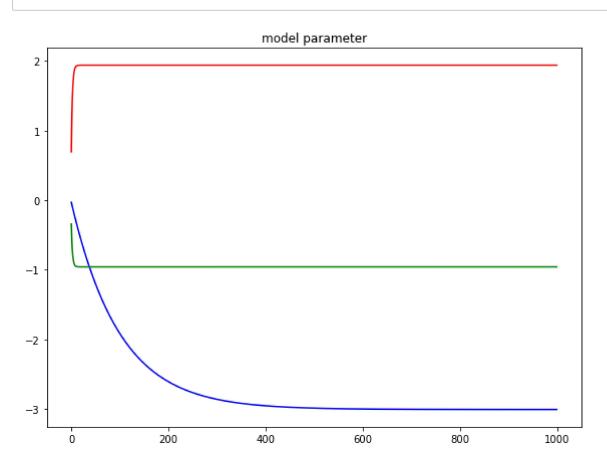
In [12]: ▶

plot_loss_curve(loss_iteration)



In [13]: ▶

plot_model_parameter(theta_iteration)

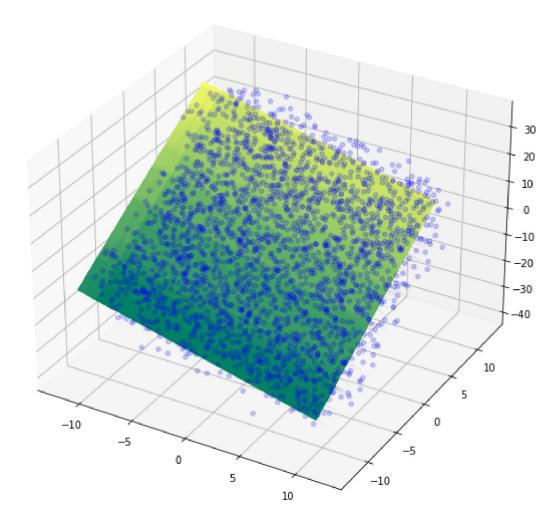


In [14]:

In [15]: ▶

```
plot_surface(XX, YY, ZZ, xx, yy, zz)
```

regression surface



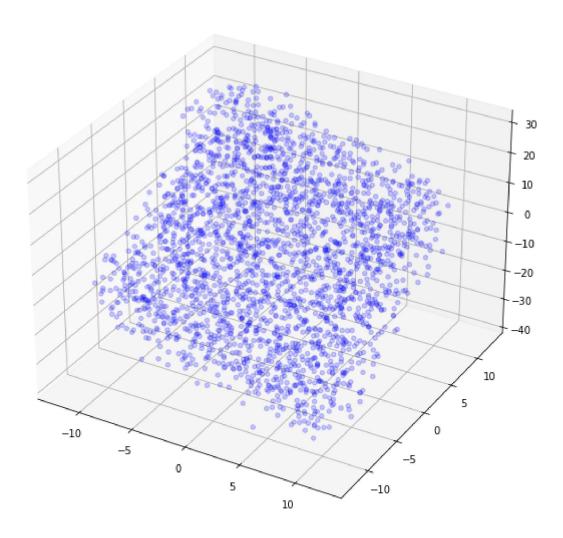
* results

01. plot the input data in blue point in 3-dimensional space

In [16]:

plot_data(xx, yy, zz)

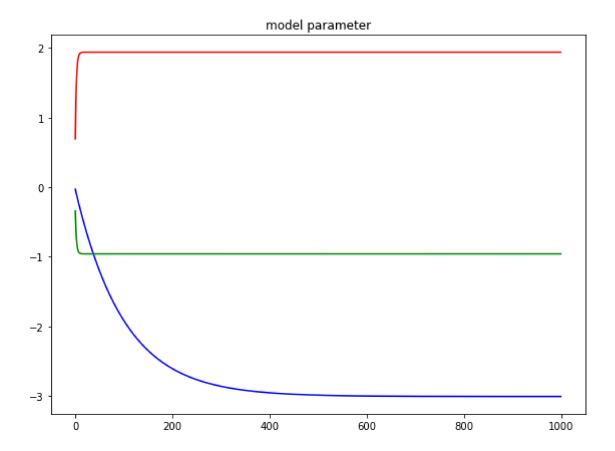
data



02. plot the values of the model parameters θ_0 in red curve, θ_1 in green curve, and θ_2 in blue curve over the gradient descent iterations

In [17]: ▶

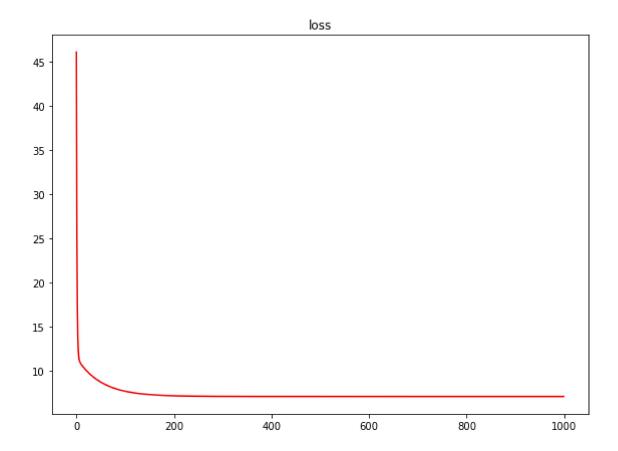
plot_model_parameter(theta_iteration)



03. plot the loss values $\mathcal{L}(\theta)$ in red curve over the gradient descent iterations

In [18]: ▶

plot_loss_curve(loss_iteration)



04. plot the optimal regression surface $\hat{f}(\theta^*)$ in 3-dimensional space with a given set of data points superimposed

In [19]: ▶

plot_surface(XX, YY, ZZ, xx, yy, zz)

regression surface

