Regression

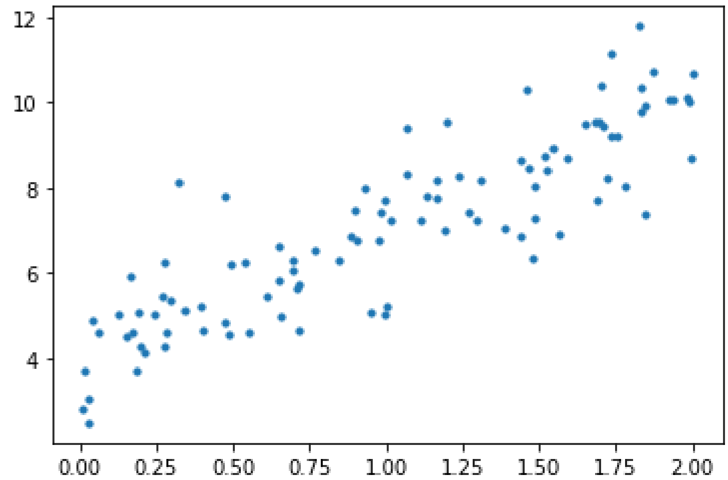
Data creation

```
import pandas as pd
import os
import numpy as np
import matplotlib.pyplot as plt
import torch
```

```
m = 100
X = 2 * torch.rand(m, 1)
y = 4 + 3 * X + torch.randn(m, 1)
```

```
plt.scatter(X, y, s=10)
```

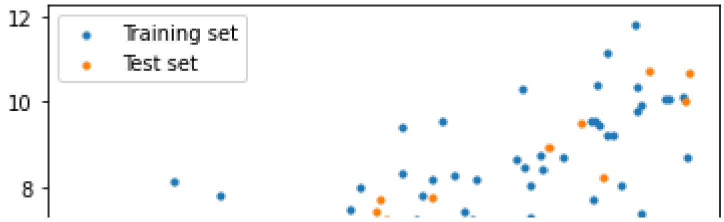
```
<matplotlib.collections.PathCollection at 0x7f947ace9590>
```




```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
plt.scatter(X_train, y_train, s=10)
plt.scatter(X_test, y_test, s=10)
plt.legend(['Training set', 'Test set'])
```

```
<matplotlib.legend.Legend at 0x7f946b656210>
```



Regression model

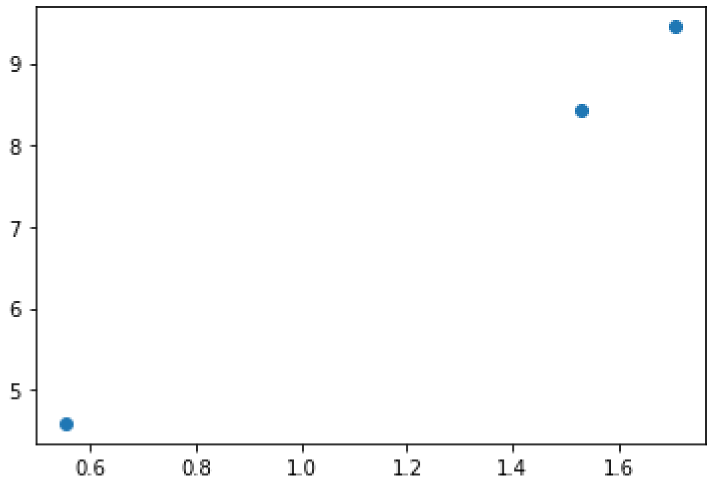
```
X_train_3 = X_train[:3]
y_train_3 = y_train[:3]
```

```
X_train_3, y_train_3
```

```
(tensor([[1.7067],
         [1.5265],
         [0.5538]]), tensor([[9.4494],
         [8.4113],
         [4.5896]]))
```

```
plt.scatter(X_train_3, y_train_3)
```

```
<matplotlib.collections.PathCollection at 0x7f946b5ee590>
```



Hypothesis

H(x) = Wx+b

```
W = torch.zeros(1, requires_grad=True)
b = torch.zeros(1, requires_grad=True)
hypothesis = X_train_3 * W + b
```

```
hypothesis
```

```
tensor([[0.],
```

```
        [0.],
        [0.]], grad_fn=<AddBackward0>)
```

Compute loss

cost(W, b) = mean((H(x) - y)^2)

```
cost = torch.mean((hypothesis - y_train_3) ** 2)
```

```
cost
```

```
tensor(60.3686, grad_fn=<MeanBackward0>)
```

Gradient descent

미분으로 계산

```
y_train_3
```

```
tensor([[9.4494],
        [8.4113],
        [4.5896]])
```

```
## dC/dW
sum((2/3) * ((W * X_train_3 + b) - y_train_3) * X_train_3)
```

```
tensor([-21.0059], grad_fn=<AddBackward0>)
```

```
## dC/db
sum((2/3) * ((W * X_train_3 + b) - y_train_3))
```

```
tensor([-14.9669], grad_fn=<AddBackward0>)
```

torch.optim 라이브러리 활용

```
import torch.optim as optim
```

Optimizer 설정 - Stochastic gradient descent 를 활용하여 W와 b를 최적화.
learning rate=0.01

```
optimizer = optim.SGD([W, b], lr=0.01)
```

최적화 과정 - 3가지가 항상 붙어다님.

```
hypothesis = X_train_3 * W + b
cost = torch.mean((hypothesis - y_train_3) ** 2)
```

```
optimizer.zero_grad() # 모든 gradient를 0으로 초기화
cost.backward(retain_graph=True) # gradient 계산하여 (parameters).grad를 저장
optimizer.step() # step으로 parameter를 개선
```

gradient 확인

```
W.grad, b.grad
```

```
(tensor([-21.0059]), tensor([-14.9669]))
```

```
print(W, b)
```

```
tensor([0.2101], requires_grad=True) tensor([0.1497], requires_grad=True)
```

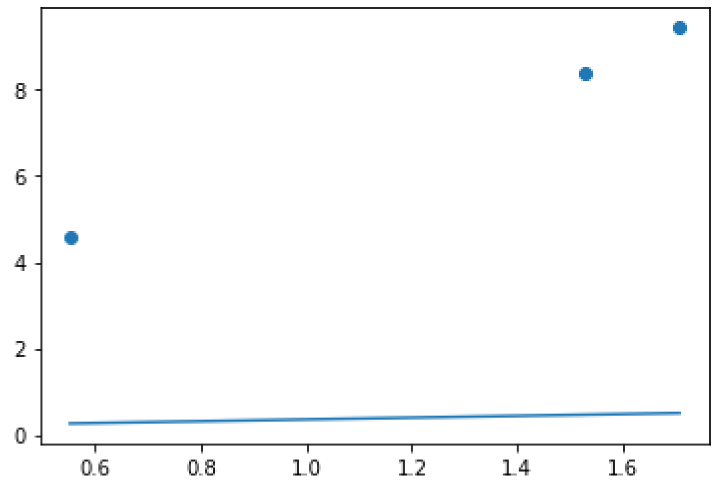
1 step이후 확인

```
hypothesis = X_train_3 * W + b
hypothesis
```

```
tensor([[0.5082],
        [0.4703],
        [0.2660]], grad_fn=<AddBackward0>)
```

```
plt.scatter(X_train_3, y_train_3)
plt.plot(X_train_3, hypothesis.detach().numpy())
```

```
[<matplotlib.lines.Line2D at 0x7f946b4f87d0>]
```



Training with Full code

```
# Data setup
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Model initialize
W = torch.zeros(1, requires_grad=True)
b = torch.zeros(1, requires_grad=True)

# Set optimizer
optimizer = optim.SGD([W, b], lr=0.01)

nb_epochs = 1000
for epoch in range(nb_epochs + 1):
    # Calculate H(X)
    hypothesis = X_train * W + b
#     hypothesis = X_train_3 * W + b

    # Calculate cost
    cost = torch.mean((hypothesis - y_train) ** 2)
#     cost = torch.mean((hypothesis - y_train_3) ** 2)

    # Parameter gradient descent
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

    if epoch % 20 == 0:
        print('Epoch {:4d}/{} W: {:.3f}, b: {:.3f} Cost: {:.6f}'.format(
            epoch, nb_epochs, W.item(), b.item(), cost.item()
        ))
```

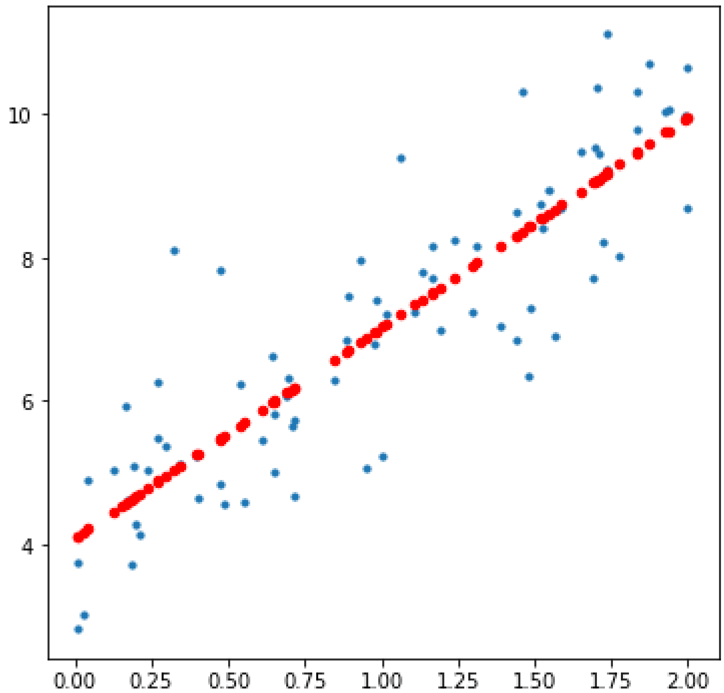
```
Epoch    0/1000 W: 0.160, b: 0.140 Cost: 53.038891
Epoch   20/1000 W: 2.212, b: 1.972 Cost: 9.947540
Epoch   40/1000 W: 3.026, b: 2.758 Cost: 2.665808
Epoch   60/1000 W: 3.333, b: 3.112 Cost: 1.417548
Epoch   80/1000 W: 3.434, b: 3.287 Cost: 1.188125
Epoch  100/1000 W: 3.453, b: 3.386 Cost: 1.132732
Epoch  120/1000 W: 3.439, b: 3.452 Cost: 1.108790
Epoch  140/1000 W: 3.413, b: 3.504 Cost: 1.092014
Epoch  160/1000 W: 3.383, b: 3.547 Cost: 1.078076
Epoch  180/1000 W: 3.354, b: 3.586 Cost: 1.066038
Epoch  200/1000 W: 3.325, b: 3.622 Cost: 1.055560
Epoch  220/1000 W: 3.298, b: 3.655 Cost: 1.046426
Epoch  240/1000 W: 3.272, b: 3.685 Cost: 1.038461
Epoch  260/1000 W: 3.249, b: 3.714 Cost: 1.031516
Epoch  280/1000 W: 3.226, b: 3.740 Cost: 1.025460
Epoch  300/1000 W: 3.205, b: 3.765 Cost: 1.020178
Epoch  320/1000 W: 3.186, b: 3.788 Cost: 1.015573
Epoch  340/1000 W: 3.168, b: 3.810 Cost: 1.011556
Epoch  360/1000 W: 3.151, b: 3.830 Cost: 1.008054
Epoch  380/1000 W: 3.135, b: 3.849 Cost: 1.005000
Epoch  400/1000 W: 3.120, b: 3.867 Cost: 1.002337
Epoch  420/1000 W: 3.106, b: 3.883 Cost: 1.000015
Epoch  440/1000 W: 3.093, b: 3.899 Cost: 0.997989
Epoch  460/1000 W: 3.081, b: 3.913 Cost: 0.996223
Epoch  480/1000 W: 3.070, b: 3.926 Cost: 0.994683
```

```
Epoch  500/1000 W: 3.060, b: 3.939 Cost: 0.993340
Epoch  520/1000 W: 3.050, b: 3.951 Cost: 0.992169
Epoch  540/1000 W: 3.041, b: 3.962 Cost: 0.991148
Epoch  560/1000 W: 3.032, b: 3.972 Cost: 0.990258
Epoch  580/1000 W: 3.024, b: 3.981 Cost: 0.989481
Epoch  600/1000 W: 3.017, b: 3.990 Cost: 0.988804
Epoch  620/1000 W: 3.010, b: 3.998 Cost: 0.988213
Epoch  640/1000 W: 3.003, b: 4.006 Cost: 0.987698
Epoch  660/1000 W: 2.997, b: 4.013 Cost: 0.987249
Epoch  680/1000 W: 2.991, b: 4.020 Cost: 0.986858
Epoch  700/1000 W: 2.986, b: 4.027 Cost: 0.986516
Epoch  720/1000 W: 2.981, b: 4.032 Cost: 0.986218
Epoch  740/1000 W: 2.977, b: 4.038 Cost: 0.985959
Epoch  760/1000 W: 2.972, b: 4.043 Cost: 0.985732
Epoch  780/1000 W: 2.968, b: 4.048 Cost: 0.985535
Epoch  800/1000 W: 2.965, b: 4.052 Cost: 0.985362
Epoch  820/1000 W: 2.961, b: 4.057 Cost: 0.985212
Epoch  840/1000 W: 2.958, b: 4.060 Cost: 0.985081
Epoch  860/1000 W: 2.955, b: 4.064 Cost: 0.984967
Epoch  880/1000 W: 2.952, b: 4.067 Cost: 0.984868
Epoch  900/1000 W: 2.949, b: 4.071 Cost: 0.984781
Epoch  920/1000 W: 2.947, b: 4.074 Cost: 0.984705
Epoch  940/1000 W: 2.944, b: 4.076 Cost: 0.984639
Epoch  960/1000 W: 2.942, b: 4.079 Cost: 0.984581
Epoch  980/1000 W: 2.940, b: 4.081 Cost: 0.984531
Epoch 1000/1000 W: 2.938, b: 4.084 Cost: 0.984487
```

```
1 hx = (X_train * W + b).detach().numpy()
```

```
1 plt.figure(figsize=[6, 6])
2 plt.scatter(X_train, y_train, s=10)
3 plt.scatter(X_train, hx, s=20, c='r')
```

<matplotlib.collections.PathCollection at 0x7f946b4d6e10>



High level implementation with nn.Module

`nn.module`을 활용하여 모델 구축

`nn.module`: 신경망 모듈. 각종 레이어(linear, conv, ...)를 지원하며 output을 return하는 forward(input) 메서드를 포함함

```
from torch import nn as nn
from torch.nn import functional as F
```

nn.Linear 레이어의 활용

```
class my_LinearRegression(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = nn.Linear(1, 1)

    def forward(self, x):
        return self.linear(x)
```

```
model = my_LinearRegression()
```

```
model
```

```
my_LinearRegression(
  (linear): Linear(in_features=1, out_features=1, bias=True)
)
```

```
hypothesis = model(X_train[:3])
```

```
hypothesis
```

```
tensor([[ 0.4109],
        [-0.4739],
        [-0.2649]], grad_fn=<AddmmBackward>)
```

```
hypothesis = model(X_train)
cost = F.mse_loss(hypothesis, y_train)
```

```
cost
```

```
tensor(55.6750, grad_fn=<MseLossBackward>)
```

```
optimizer = optim.SGD(model.parameters(), lr=0.01)
```

```
optimizer.zero_grad()
cost.backward()
```

```
optimizer.step()
```

Training with Full code

```
# Data setup
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

# Model initialize
model = my_LinearRegression()

# Set optimizer
optimizer = optim.SGD(model.parameters(), lr=0.01)

nb_epochs = 1000
for epoch in range(nb_epochs + 1):
    # Calculate H(X)
    hypothesis = model(X_train)

    # Calculate cost
    cost = F.mse_loss(hypothesis, y_train)

    # Parameter gradient descent
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

    if epoch % 20 == 0:
        params = list(model.parameters())
        W = params[0].item()
        b = params[1].item()
        print('Epoch {:4d}/{} W: {:.3f}, b: {:.3f} Cost: {:.6f}'.format(
            epoch, nb_epochs, W, b, cost.item()
        ))
```

```
Epoch    0/1000 W: 0.946, b: 0.348 Cost: 37.520115
Epoch   20/1000 W: 2.637, b: 1.902 Cost: 7.496470
Epoch   40/1000 W: 3.293, b: 2.581 Cost: 2.423627
Epoch   60/1000 W: 3.528, b: 2.899 Cost: 1.537814
Epoch   80/1000 W: 3.592, b: 3.067 Cost: 1.358345
Epoch  100/1000 W: 3.589, b: 3.171 Cost: 1.301265
Epoch  120/1000 W: 3.561, b: 3.246 Cost: 1.268185
Epoch  140/1000 W: 3.523, b: 3.308 Cost: 1.242164
Epoch  160/1000 W: 3.484, b: 3.361 Cost: 1.219972
Epoch  180/1000 W: 3.446, b: 3.410 Cost: 1.200723
Epoch  200/1000 W: 3.410, b: 3.455 Cost: 1.183975
Epoch  220/1000 W: 3.375, b: 3.496 Cost: 1.169392
Epoch  240/1000 W: 3.343, b: 3.535 Cost: 1.156693
Epoch  260/1000 W: 3.313, b: 3.571 Cost: 1.145634
Epoch  280/1000 W: 3.285, b: 3.605 Cost: 1.136003
Epoch  300/1000 W: 3.259, b: 3.636 Cost: 1.127617
Epoch  320/1000 W: 3.234, b: 3.665 Cost: 1.120313
Epoch  340/1000 W: 3.212, b: 3.692 Cost: 1.113953
Epoch  360/1000 W: 3.190, b: 3.718 Cost: 1.108415
```

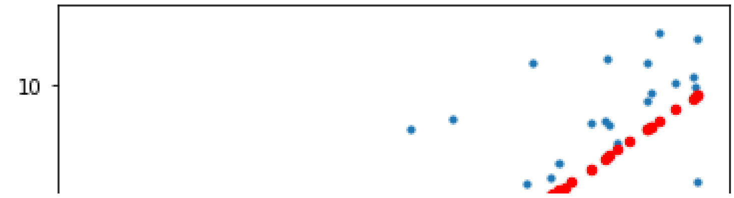
```
Epoch  380/1000 W: 3.170, b: 3.742 Cost: 1.103592
Epoch  400/1000 W: 3.152, b: 3.764 Cost: 1.099392
Epoch  420/1000 W: 3.135, b: 3.784 Cost: 1.095734
Epoch  440/1000 W: 3.118, b: 3.804 Cost: 1.092549
Epoch  460/1000 W: 3.103, b: 3.822 Cost: 1.089775
Epoch  480/1000 W: 3.089, b: 3.839 Cost: 1.087359
Epoch  500/1000 W: 3.076, b: 3.854 Cost: 1.085256
Epoch  520/1000 W: 3.064, b: 3.869 Cost: 1.083424
Epoch  540/1000 W: 3.053, b: 3.883 Cost: 1.081829
Epoch  560/1000 W: 3.042, b: 3.895 Cost: 1.080440
Epoch  580/1000 W: 3.032, b: 3.907 Cost: 1.079230
Epoch  600/1000 W: 3.023, b: 3.918 Cost: 1.078177
Epoch  620/1000 W: 3.014, b: 3.929 Cost: 1.077259
Epoch  640/1000 W: 3.006, b: 3.938 Cost: 1.076460
Epoch  660/1000 W: 2.998, b: 3.947 Cost: 1.075765
Epoch  680/1000 W: 2.991, b: 3.956 Cost: 1.075159
Epoch  700/1000 W: 2.985, b: 3.964 Cost: 1.074631
Epoch  720/1000 W: 2.979, b: 3.971 Cost: 1.074172
Epoch  740/1000 W: 2.973, b: 3.978 Cost: 1.073772
Epoch  760/1000 W: 2.968, b: 3.984 Cost: 1.073423
Epoch  780/1000 W: 2.963, b: 3.990 Cost: 1.073120
Epoch  800/1000 W: 2.958, b: 3.996 Cost: 1.072855
Epoch  820/1000 W: 2.954, b: 4.001 Cost: 1.072625
Epoch  840/1000 W: 2.950, b: 4.006 Cost: 1.072425
Epoch  860/1000 W: 2.946, b: 4.010 Cost: 1.072251
Epoch  880/1000 W: 2.942, b: 4.015 Cost: 1.072098
Epoch  900/1000 W: 2.939, b: 4.019 Cost: 1.071966
Epoch  920/1000 W: 2.936, b: 4.022 Cost: 1.071851
Epoch  940/1000 W: 2.933, b: 4.026 Cost: 1.071751
Epoch  960/1000 W: 2.930, b: 4.029 Cost: 1.071663
Epoch  980/1000 W: 2.928, b: 4.032 Cost: 1.071587
Epoch 1000/1000 W: 2.926, b: 4.035 Cost: 1.071521
```

결과 확인

```
hx = (model(X_train)).detach().numpy()
```

```
plt.figure(figsize=[6, 6])
plt.scatter(X_train, y_train, s=10)
plt.scatter(X_train, hx, s=20, c='r')
```

```
<matplotlib.collections.PathCollection at 0x7f946b4ad890>
```



Multivariate Linear Regression

```
m = 100
x1 = torch.rand(m, 1)
x2 = 2 * torch.rand(m, 1)
x3 = 3 * torch.rand(m, 1)
X = torch.cat((x1, x2, x3), axis=1)
y = 4 + 3 * x1 + 2 * x2 + 5 * x3 + torch.randn(m, 1)
```

```
X.shape, y.shape
```

```
(torch.Size([100, 3]), torch.Size([100, 1]))
```

```
class MultivariateLinearRegressionModel(nn.Module):
    def __init__(self):
        super().__init__()
        self.linear = nn.Linear(3, 1)

    def forward(self, x):
        return self.linear(x)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)

model = MultivariateLinearRegressionModel()

# Set optimizer
optimizer = optim.SGD(model.parameters(), lr=0.01)

nb_epochs = 2000
for epoch in range(nb_epochs + 1):
    # Calculate H(X)
    hypothesis = model(X_train)

    # Calculate cost
    cost = F.mse_loss(hypothesis, y_train)

    # Parameter gradient descent
    optimizer.zero_grad()
    cost.backward()
    optimizer.step()

    if epoch % 20 == 0:
```

```
        params = list(model.parameters())

        print('Epoch {:4d}/{} {} Cost: {:.6f}'.format(
            epoch, nb_epochs, list(model.parameters()), cost.item()
        ))
```

```
Epoch    0/2000 [Parameter containing:
tensor([[-0.0884,  0.0534,  0.0660]], requires_grad=True), Parameter containing:
tensor([0.6565], requires_grad=True)] Cost: 289.553070
Epoch   20/2000 [Parameter containing:
tensor([[1.1863, 2.4604, 4.7005]], requires_grad=True), Parameter containing:
tensor([3.1468], requires_grad=True)] Cost: 5.294409
Epoch   40/2000 [Parameter containing:
tensor([[1.3738, 2.6122, 5.2532]], requires_grad=True), Parameter containing:
tensor([3.4503], requires_grad=True)] Cost: 1.672374
Epoch   60/2000 [Parameter containing:
tensor([[1.4377, 2.5288, 5.3444]], requires_grad=True), Parameter containing:
tensor([3.5116], requires_grad=True)] Cost: 1.539234
Epoch   80/2000 [Parameter containing:
tensor([[1.4851, 2.4322, 5.3775]], requires_grad=True), Parameter containing:
tensor([3.5463], requires_grad=True)] Cost: 1.468914
Epoch  100/2000 [Parameter containing:
tensor([[1.5282, 2.3454, 5.3987]], requires_grad=True), Parameter containing:
tensor([3.5780], requires_grad=True)] Cost: 1.414102
Epoch  120/2000 [Parameter containing:
tensor([[1.5685, 2.2693, 5.4139]], requires_grad=True), Parameter containing:
tensor([3.6092], requires_grad=True)] Cost: 1.370545
Epoch  140/2000 [Parameter containing:
tensor([[1.6062, 2.2025, 5.4247]], requires_grad=True), Parameter containing:
tensor([3.6399], requires_grad=True)] Cost: 1.335511
Epoch  160/2000 [Parameter containing:
tensor([[1.6416, 2.1438, 5.4320]], requires_grad=True), Parameter containing:
tensor([3.6700], requires_grad=True)] Cost: 1.307000
Epoch  180/2000 [Parameter containing:
tensor([[1.6749, 2.0921, 5.4363]], requires_grad=True), Parameter containing:
tensor([3.6993], requires_grad=True)] Cost: 1.283536
Epoch  200/2000 [Parameter containing:
tensor([[1.7061, 2.0464, 5.4383]], requires_grad=True), Parameter containing:
tensor([3.7277], requires_grad=True)] Cost: 1.264021
Epoch  220/2000 [Parameter containing:
tensor([[1.7354, 2.0059, 5.4383]], requires_grad=True), Parameter containing:
tensor([3.7552], requires_grad=True)] Cost: 1.247635
Epoch  240/2000 [Parameter containing:
tensor([[1.7629, 1.9699, 5.4369]], requires_grad=True), Parameter containing:
tensor([3.7816], requires_grad=True)] Cost: 1.233756
Epoch  260/2000 [Parameter containing:
tensor([[1.7888, 1.9377, 5.4343]], requires_grad=True), Parameter containing:
tensor([3.8071], requires_grad=True)] Cost: 1.221911
Epoch  280/2000 [Parameter containing:
tensor([[1.8130, 1.9090, 5.4308]], requires_grad=True), Parameter containing:
tensor([3.8315], requires_grad=True)] Cost: 1.211734
Epoch  300/2000 [Parameter containing:
tensor([[1.8358, 1.8832, 5.4266]], requires_grad=True), Parameter containing:
tensor([3.8548], requires_grad=True)] Cost: 1.202940
Epoch  320/2000 [Parameter containing:
tensor([[1.8573, 1.8600, 5.4218]], requires_grad=True), Parameter containing:
tensor([3.8772], requires_grad=True)] Cost: 1.195304
Epoch  340/2000 [Parameter containing:
tensor([[1.8774, 1.8391, 5.4167]], requires_grad=True), Parameter containing:
tensor([3.8985], requires_grad=True)] Cost: 1.188647
```

```
Epoch  360/2000 [Parameter containing:
tensor([[1.8963, 1.8202, 5.4114]], requires_grad=True), Parameter containing:
tensor([3.9188], requires_grad=True)] Cost: 1.182823
Epoch  380/2000 [Parameter containing:
tensor([[1.9141, 1.8030, 5.4058]], requires_grad=True), Parameter containing:
```

결과 확인

```
from sklearn.decomposition import PCA
```

```
pca = PCA(n_components=1)
X_pca = pca.fit_transform(X_train)
```

```
hx = model(X_train).detach().numpy()
```

```
plt.scatter(X_pca, y_train, s=20)
plt.scatter(X_pca, hx, s=20)
```

```
<matplotlib.collections.PathCollection at 0x7f946984bbd0>
```