1　Section1_入力層~中間層

重みとバイアス

```python
import numpy as np

x = np.array([0,1])
w = np.array([0.5,0.5])
b = -0.7
print(w*x)
c=np.sum(w*x)
d=np.sum(w*x) + b
print(c)
print(d)
```

入力

重み

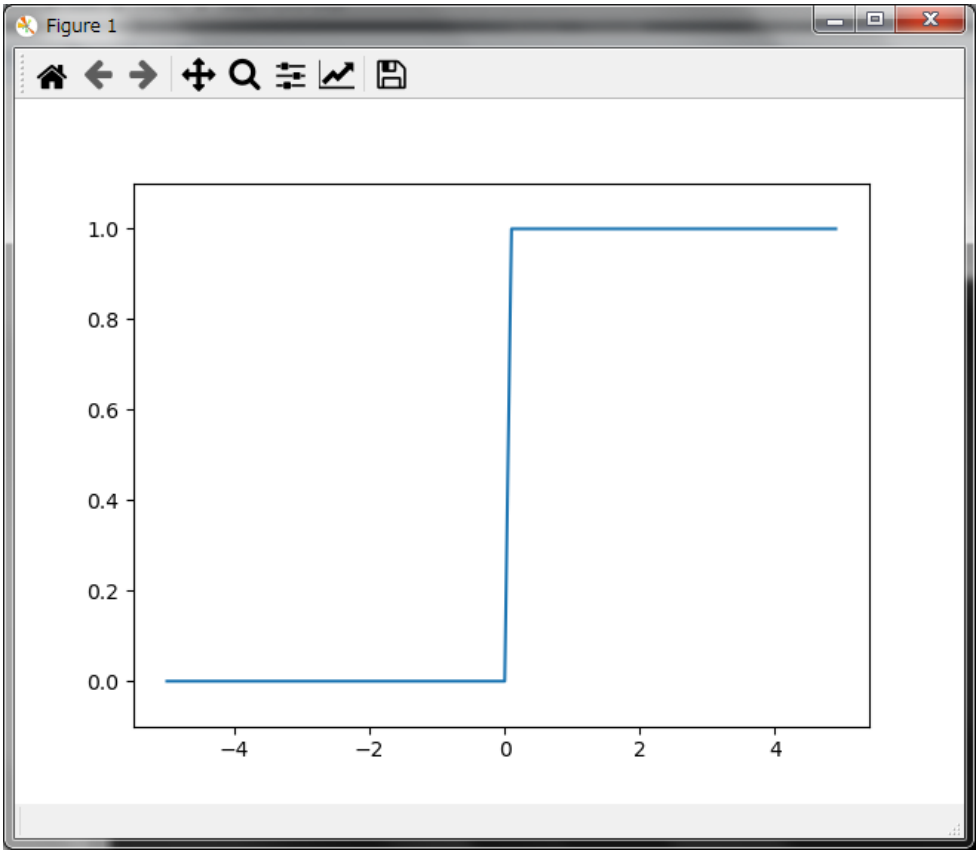
バイアス

```
[0.  0.5]
0.5
-0.19999999999999996
```

2　Section2_活性化関数

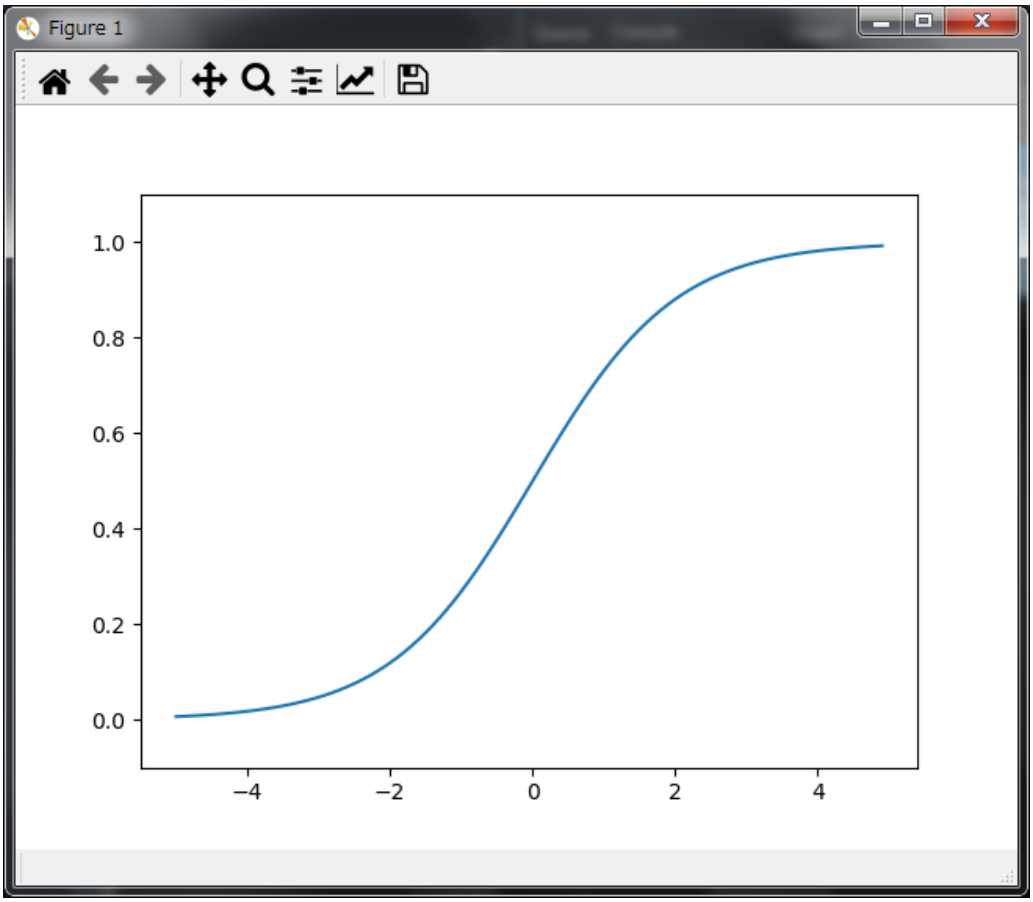
（1）ステップ関数

```python
import numpy as np
import matplotlib.pylab as plt

def step_function(x):
    return np.array(x > 0, dtype=np.int)
x = np.arange(-5.0, 5.0, 0.1)
y = step_function(x)
plt.plot(x,y)
plt.ylim(-0.1, 1.1)
plt.show()
```



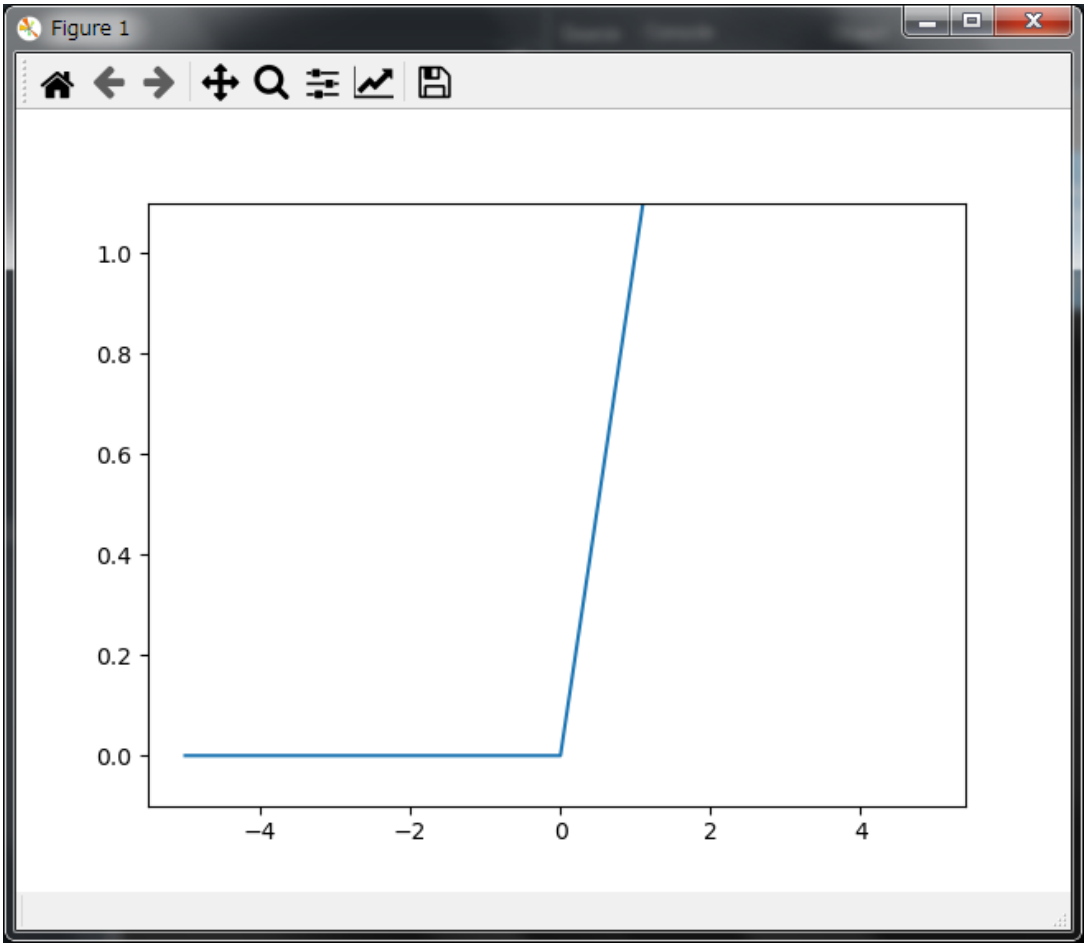
（2）シグモイド関数

```python
import numpy as np
import matplotlib.pylab as plt

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

x = np.arange(-5.0, 5.0, 0.1)
y = sigmoid(x)
plt.plot(x,y)
plt.ylim(-0.1, 1.1)
plt.show()
```



（3）ReLU 関数

```python
import numpy as np
import matplotlib.pylab as plt

def relu(x):
    return np.maximum(0,x)

x = np.arange(-5.0, 5.0, 0.1)
y = relu(x)
plt.plot(x,y)
plt.ylim(-0.1, 1.1)
plt.show()

```



3　Section3_出力層

（1）ソフトマックス関数

```python
import numpy as np

a = np.array([0.3, 2.9, 4.0])
exp_a = np.exp(a)
print(exp_a)
sum_exp_a = np.sum(exp_a)
print(sum_exp_a)
y = exp_a / sum_exp_a
print(y)
```

```
[ 1.34985881 18.17414537 54.59815003]
74.1221542101633
[0.01821127 0.24519181 0.73659691]
```

```python
import numpy as np

def softmax(a):
    c = np.max(a)
    exp_a = np.exp(a - c)
    sum_exp_a = np.sum(exp_a)
    y = exp_a / sum_exp_a
    return y
a = np.array([0.3, 2.9, 4.0])
y = softmax(a)
print(y)
out = np.sum(y)
print(out)
```

```
[0.01821127 0.24519181 0.73659691]
1.0
```

（2） 3層ニューラルネットワーク

```python
import numpy as np

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def identity_function(x):
    return x

def init_network():
    network = {}
    network['w1'] = np.array([[0.1, 0.3, 0.5],[0.2, 0.4, 0.6]])
    network['b1'] = np.array([0.1, 0.2, 0.3])
    network['w2'] = np.array([[0.1, 0.4],[0.2, 0.5],[0.3, 0.6]])
    network['b2'] = np.array([0.1, 0.2])
    network['w3'] = np.array([[0.1, 0.3],[0.2, 0.4]])
    network['b3'] = np.array([0.1, 0.2])

    return network

def forward(network, x):
    w1, w2, w3 = network['w1'], network['w2'], network['w3']
    b1, b2, b3 = network['b1'], network['b2'], network['b3']

    a1 = np.dot(x, w1) + b1
    z1 = sigmoid(a1)
    a2 = np.dot(z1, w2) + b2
    z2 = sigmoid(a2)
    a3 = np.dot(z2, w3) + b3
    y = identity_function(a3)

    return y

network = init_network()
x = np.array([1.0, 0.5])
y = forward(network, x)
print(y)


```

```
[0.31682708 0.69627909]
```

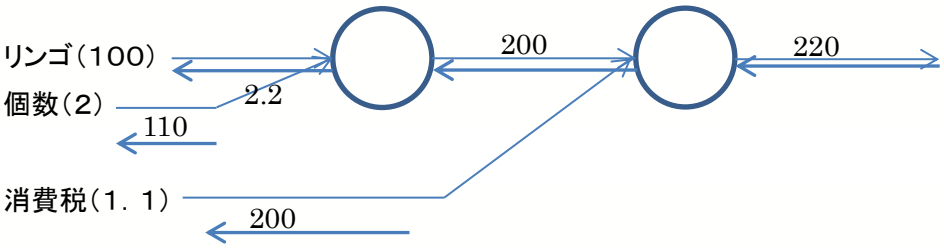
4　Section4_勾配降下法

F(x0,x1)=x02+x12 を勾配降下法で求める

```python
import numpy as np

def numerical_gradient(f, x):
    h = 1e-4
    grad = np.zeros_like(x)

    for idx in range(x.size):
        tmp_val = x[idx]
        x[idx] = tmp_val + h
        fxh1 = f(x)

        x[idx] = tmp_val - h
        fxh2 = f(x)

        grad[idx] = (fxh1 - fxh2) / (2*h)
        x[idx] = tmp_val

    return grad

def gradient_descent(f, init_x, lr=0.01, step_num=100):
    x = init_x

    for i in range(step_num):
        grad = numerical_gradient(f, x)
        x -= lr * grad

    return x

def function_2(x):
    return (x[0]**2 + x[1]**2)

init_x = np.array([-3.0, 4.0])
out = gradient_descent(function_2, init_x=init_x, lr=0.1, step_num=100)
print(out)

```

```
[-6.11110793e-10  8.14814391e-10]
```

5　Section5_誤差逆伝播法




```python
import numpy as np

class MulLayer:
    def __init__(self):
        self.x = None
        self.y = None

    def forward(self, x, y):
        self.x = x
        self.y = y
        out = x * y

        return out

    def backward(self, dout):
        dx = dout * self.y
        dy = dout * self.x

        return dx, dy

apple = 100
apple_num = 2
tax = 1.1
mul_apple_layer = MulLayer()
mul_tax_layer = MulLayer()

apple_price = mul_apple_layer.forward(apple, apple_num)
price = mul_tax_layer.forward(apple_price, tax)
print(price)

dprice = 1
dapple_price, dtax = mul_tax_layer.backward(dprice)
dapple, dapple_num = mul_apple_layer.backward(dapple_price)
print(dapple, dapple_num, dtax)

```

```
220.00000000000003
2.2 110.00000000000001 200
```