医療とAI・ビッグデータ応用

MLP②

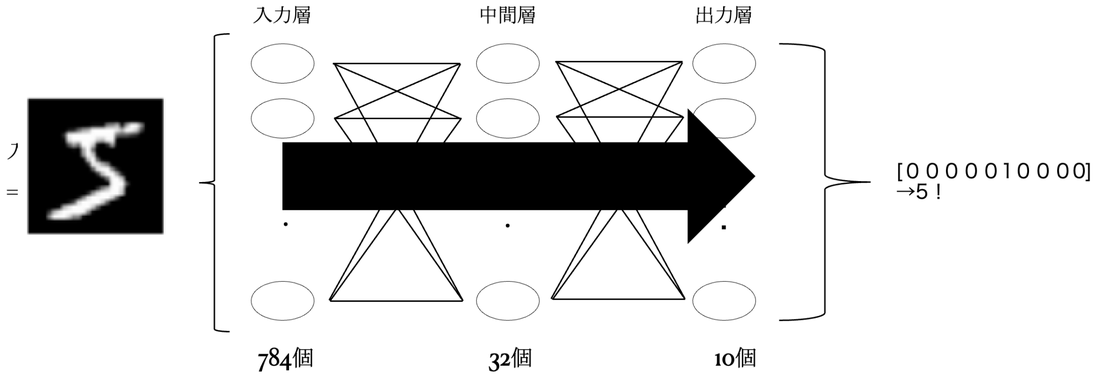
本スライドは、自由にお使いください。
使用した場合は、このQRコードからアンケートに回答をお願いします。

統合教育機構
須藤毅顕

前回まで

モデルの作成

```
from keras.models import Sequential
from keras.layers import Dense

model = Sequential()
model.add(Dense(32, input_shape=(784,), activation='relu'))
model.add(Dense(10, activation='softmax'))
model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
model.summary()
```



学習

```
result = model.fit(x_train, y_train, epochs=30, batch_size=64, validation_split=0.2)
```

```
Epoch 1/30
750/750 [==============================] - 4s 4ms/step - loss: 0.4633 - accuracy: 0.8709 - val_loss: 0.2517 - val_accuracy: 0.9298
Epoch 2/30
750/750 [==============================] - 3s 4ms/step - loss: 0.2401 - accuracy: 0.9309 - val_loss: 0.2020 - val_accuracy: 0.9448
Epoch 3/30
750/750 [==============================] - 3s 4ms/step - loss: 0.1906 - accuracy: 0.9456 - val_loss: 0.1802 - val_accuracy: 0.9498
                                                    :
Epoch 28/30
750/750 [==============================] - 3s 4ms/step - loss: 0.0288 - accuracy: 0.9922 - val_loss: 0.1434 - val_accuracy: 0.9629
Epoch 29/30
750/750 [==============================] - 4s 5ms/step - loss: 0.0270 - accuracy: 0.9930 - val_loss: 0.1353 - val_accuracy: 0.9660
Epoch 30/30
750/750 [==============================] - 3s 4ms/step - loss: 0.0264 - accuracy: 0.9930 - val_loss: 0.1381 - val_accuracy: 0.9654
```

60000枚 → 48000枚 / 12000枚

64枚ずつ取り出して学習
64×750 = 48000
→750回重みを更新

12000枚の画像で検証

この作業を
30回繰り返す

予測

最後に再度予測してみる

予測はmodel.predict()

一応名前を変更して学習後はtest2とする

```
test2 = model.predict(x_test)
```

```
313/313 [==============================] - 1s 2ms/step
```

2枚目を再度確認

```
print(test2[1])
```

```
[8.0701529e-11 3.9249046e-10 9.9999940e-01 8.3521821e-09 1.4485680e-28
 6.2819618e-07 2.5197353e-11 1.3647900e-22 2.3160052e-10 1.9060435e-24]
```

8.07e-11 は 8.07×10^{-11} = 0.0000000000807

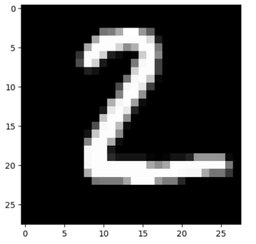
```
import numpy as np
print(np.around(test2[1],3))
print(y_test[1])
```

```
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
[0. 0. 1. 0. 0. 0. 0. 0. 0. 0.]
```

np.aroung(配列, num)で、
配列を少数第num位で四捨五入

99.9999...%で2と予想している

```
import matplotlib.pyplot as plt
plt.imshow(x_test[1],'gray')
plt.show()
```




```
print(y_test[1])
```

```
2
```

結果の作図

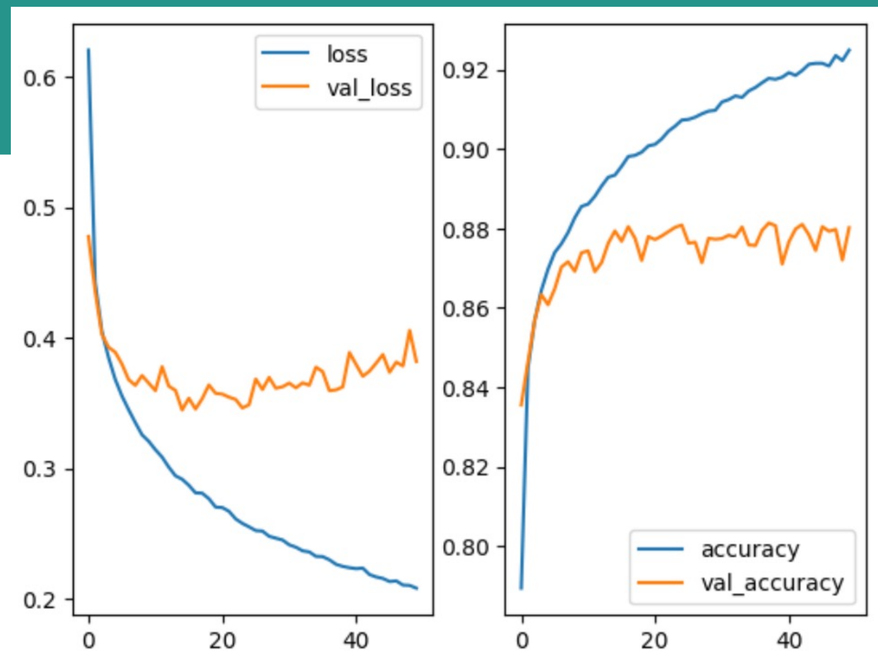
```
import matplotlib.pyplot as plt

plt.subplot(1,2,1)
plt.plot(result.history['loss'],label='loss')
plt.plot(result.history['val_loss'],label='val_loss')
plt.legend()
plt.subplot(1,2,2)
plt.plot(result.history['accuracy'],label='accuracy')
plt.plot(result.history['val_accuracy'],label='val_accuracy')
plt.legend()
plt.show()
```

縦1, 横2の1つ目

誤差(loss)の折れ線グラフ

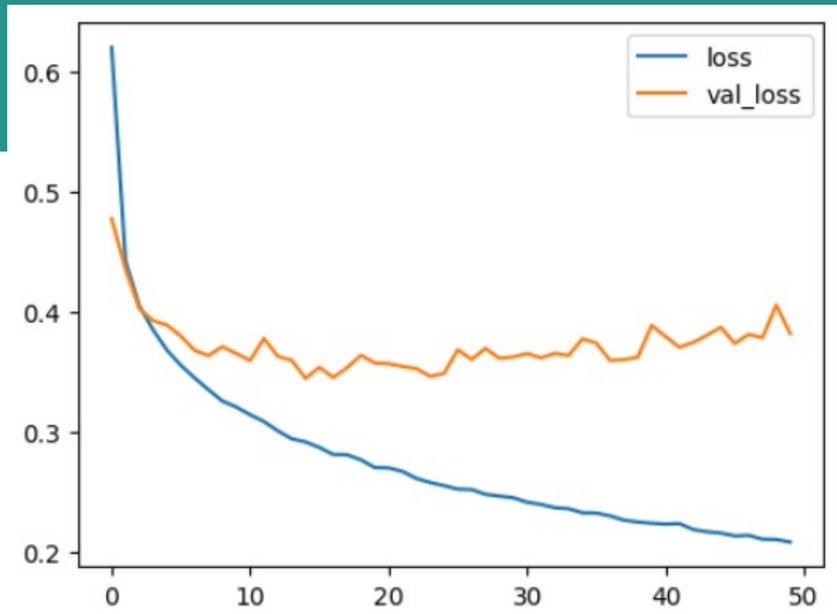
縦1, 横2の2つ目

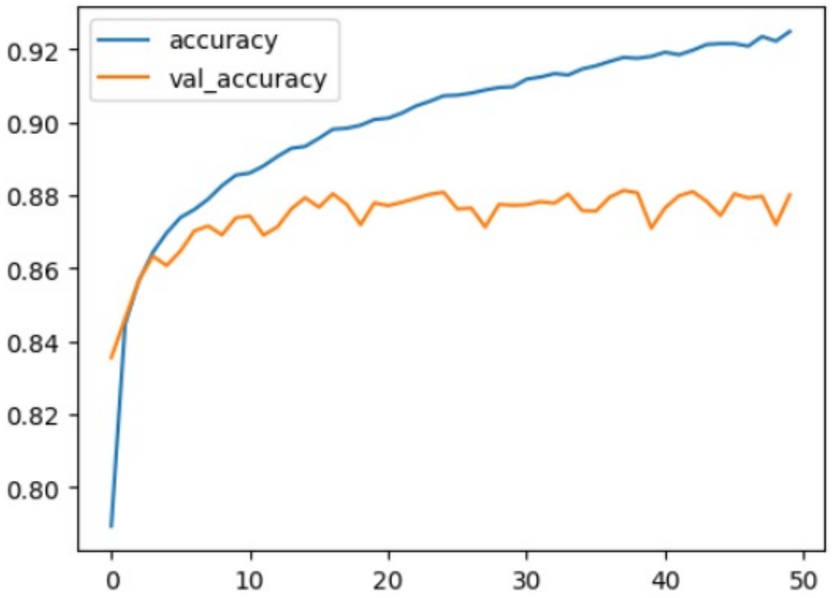
正解率(accuracy)の折れ線グラフ



結果の作図

```
import matplotlib.pyplot as plt
plt.figure(figsize=(12,4))
plt.subplot(1,2,1)
plt.plot(result.history['loss'],label='loss')
plt.plot(result.history['val_loss'],label='val_loss')
plt.legend()
plt.subplot(1,2,2)
plt.plot(result.history['accuracy'],label='accuracy')
plt.plot(result.history['val_accuracy'],label='val_accuracy')
plt.legend()
plt.show()
```





result.historyの中身について

print(result.history)

{'loss': [0.6204796433448792, 0.4424095153808594, 0.4049777686595917, 0.38482892513275146, 0.3680422008037567, 0.3553660809993744, 0.34484514594078064, 0.3349671959877014, 0.32561713457107544, 0.3206530511379242, 0.3141988515853882, 0.30852627754211426, 0.3008130192756653, 0.29420095682144165, 0.29154443740844727, 0.2869287729263057, 0.28109729290008545, 0.28085023164749146, 0.27662160992622375, 0.2701963186264038, 0.26984351873397827, 0.2669712901154175, 0.26113253831863403, 0.25769904255867004, 0.2550542652606964, 0.2521992623806, 0.251813590526580 8, 0.24781620502471924, 0.24636663496494293, 0.24498197436332703, 0.2412831038236618, 0.2394535541534423 8, 0.2366907894611358 6, 0.2358267456293106, 0.23242957890033722, 0.23221394419670105, 0.229829117655754 1, 0.22631986439228058, 0.2247573286294937, 0.22372491657733917, 0.22302721440792084, 0.22342391312122345, 0.218465417623519 9, 0.21663862466812134, 0.21550878882408142, 0.21314330399036407, 0.2136351317167282, 0.210426956415176 4, 0.2101719230413437, 0.2080526500940323],

'accuracy': [0.789354145526886, 0.8447291851043701, 0.8566874861717224, 0.8643541932106018, 0.8697083592414856, 0.8739166855812073, 0.8761041760444641, 0.8789583444595337, 0.8826666474342346, 0.8855208158493042, 0.886104166507721, 0.8880624771118164, 0.8906458616256714, 0.8928750157356262, 0.8933958411216736, 0.8956249952316284, 0.898104190826416, 0.8983749747276306, 0.8991875052452087, 0.9007708430290222, 0.9011458158493042, 0.9025416374206543, 0.9044791460037231, 0.9057499766349792, 0.9072708487510681, 0.9074375033378601, 0.9079999923706055, 0.9088541865348816, 0.9095208048820496, 0.9097291827201843, 0.9118333458900452, 0.9124166369438171, 0.9133541584014893, 0.9129791855812073, 0.9146041870117188, 0.9154791831970215, 0.9166874885559082, 0.9177916646003723, 0.9175416827201843, 0.9180625081062317, 0.9192083477973938, 0.9185208082199097, 0.9197708368301392, 0.9213333129882812, 0.9215624928474426, 0.9215624928474426, 0.9208750128746033, 0.9235208630561829, 0.922249972820282, 0.9248958230018616],

'val_loss': [0.4776163697242737, 0.4357101321220398, 0.40258854627609253, 0.39271479845046997, 0.3889164924621582, 0.3798101842403412, 0.3678809702396393, 0.3634991049766540 5, 0.3710480630397796 6, 0.3652504086494446, 0.3594720363616943 4, 0.3778232038021087 6, 0.3629121482372284, 0.3596421778202057, 0.3446278870105743 4, 0.3536724448204040 5, 0.3453534245491028, 0.3533513247966766 4, 0.3638331294059753 4, 0.3573807775974273 7, 0.3567837774753570 6, 0.3544683754444122 3, 0.3527243733406067, 0.3461835086345672 6, 0.3486511111259460 4, 0.3683689832687378, 0.3603420555591583, 0.3695347905158996 6, 0.3612982034683227 5, 0.3623996675014496, 0.3652012944221496 6, 0.3616231977939605 7, 0.3653631210327148 4, 0.3636190593242645, 0.3774882853031158 4, 0.3739925920963287 4, 0.3594782650470733 6, 0.3600547611713409 4, 0.3623170256614685, 0.3886697292327881, 0.3794552385807037 4, 0.3704958558082580 6, 0.3743937611579895, 0.3805387318134308, 0.3871587216854095 5, 0.373552829027175 9, 0.3813273906707763 7, 0.3784124851226806 6, 0.4056456685066223, 0.3818448781967163],

'val_accuracy': [0.8355000019073486, 0.8462499976158142, 0.8567500114440918, 0.8633333444595337, 0.8607500195503235, 0.8647500276565552, 0.8702499866485596, 0.8715833425521851, 0.8691666722297668, 0.8738333582878113, 0.8743333220481873, 0.8690833449363708, 0.8713333606719971, 0.8762500286102295, 0.8793333172798157, 0.8767499923706055, 0.8804166913032532, 0.8774999976158142, 0.871916651725769, 0.877916693687439, 0.8771666884422302, 0.878083348274231, 0.8791666626930237, 0.8802499771118164, 0.8808333277702332, 0.8762500286102295, 0.8765000104904175, 0.8713333606719971, 0.8774999976158142, 0.8772500157356262, 0.8774166703224182, 0.878250002861023, 0.8778333067893982, 0.8803333044052124, 0.8758333325386047, 0.875666677951812 7, 0.8794999718666077, 0.8813333511352539, 0.8806666731834412, 0.8709999918937683, 0.8765833377838135, 0.8798333406448364, 0.8809999823570251, 0.878333333015441 9, 0.8744166493415833, 0.8804166913032532, 0.8792499899864197, 0.8797500133514404, 0.871999979019165, 0.8801666498184204]}

result.historyの中身について

print(result.history)　　エポック30回分の誤差と正解率

{'loss': [0.6204796433448792, 0.4424095153808594, 0.4049777686595917, 0.3848289251327514 6, 0.3680422008037567, 0.3553660809993744, 0.34484514594078064, 0.3349671959877014, 0.32561713457107544, 0.3206530511379242, 0.3141988515853882, 0.30852627754211426, 0.3008130192756653, 0.2942009568214416 5, 0.29154443740844727, 0.2869287729263305 7, 0.28109729290008545, 0.2808502316474914 6, 0.27662160992622375, 0.2701963186264038, 0.2698435187339782 7, 0.2669712901115417 5, 0.26113253831863403, 0.2576990425586700 4, 0.2550542652606964, 0.2521992623806, 0.2518135905265808, 0.2478162050247192 4, 0.24636663496494293, 0.2449819743633270 3, 0.2412831038236618, 0.2394535541534423 8, 0.2366907894611358 6, 0.2358267456293106, 0.2324295789003372 2, 0.2322139441967010 5, 0.229829117655754 1, 0.2263198643922805 8, 0.2247573286294937, 0.2237249165773391 7, 0.2230272144079208 4, 0.2234239131212234 5, 0.2184654176235199, 0.2166386246681213 4, 0.2155087888240814 2, 0.2131433039903640 7, 0.2136351317167282, 0.2104269564151764, 0.2101719230413437, 0.2080526500940323],

'accuracy': [0.789354145526886, 0.8447291851043701, 0.8566874861717224, 0.8643541932106018, 0.8697083592414856, 0.8739166855812073, 0.8761041760444641, 0.8789583444595337, 0.8826666474342346, 0.8855208158493042, 0.886104166507721, 0.8880624771118164, 0.8906458616256714, 0.8928750157356262, 0.8933958411216736, 0.8956249952316284, 0.898104190826416, 0.8983749747276306, 0.8991875052452087, 0.9007708430290222, 0.9011458158493042, 0.9025416374206543, 0.9044791460037231, 0.9057499766349792, 0.9072708487510681, 0.9074375033378601, 0.9079999923706055, 0.9088541865348816, 0.9095208048820496, 0.9097291827201843, 0.9118333458900452, 0.9124166369438171, 0.9133541584014893, 0.9129791855812073, 0.9146041870117188, 0.9154791831970215, 0.9166874885559082, 0.9177916646003723, 0.9175416827201843, 0.9180625081062317, 0.9192083477973938, 0.9185208082199097, 0.9197708368301392, 0.9213333129882812, 0.9215624928474426, 0.9215624928474426, 0.9208750128746033, 0.9235208630561829, 0.922249972820282, 0.9248958230018616],

'val_loss': [0.4776163697242737, 0.4357101321220398, 0.40258854627609253, 0.39271479845046997, 0.3889164924621582, 0.3798101842403412, 0.3678809702396393, 0.3634991049766540 5, 0.37104806303977966, 0.3652504086494446, 0.3594720363616943 4, 0.3778232038021087 6, 0.3629121482372284, 0.3596421778202057, 0.3446278870105743 4, 0.3536724448204040 5, 0.3453534245491028, 0.3533513247966766 4, 0.3638331294059753 4, 0.3573807775974273 7, 0.3567837774753570 6, 0.3544683754444122 3, 0.3527243733406067, 0.3461835086345672 6, 0.3486511111259460 4, 0.3683689832687378, 0.3603420555591583, 0.3695347905158996 6, 0.3612982034683227 5, 0.3623996675014496, 0.3652012944221496 6, 0.3616231977939605 7, 0.3653631210327148 4, 0.3636190593242645, 0.3774882853031158 4, 0.3739925920963287 4, 0.3594782650470733 6, 0.3600547611713409 4, 0.3623170256614685, 0.3886697292327881, 0.3794552385807037 4, 0.3704958558082580 6, 0.3743937611579895, 0.3805387318134308, 0.3871587216854095 5, 0.3735528290271759, 0.3813273906707763 7, 0.3784124851226806 6, 0.4056456685066223, 0.3818448781967163],

'val_accuracy': [0.8355000019073486, 0.8462499976158142, 0.8567500114440918, 0.8633333444595337, 0.8607500195503235, 0.8647500276565552, 0.8702499866485596, 0.8715833425521851, 0.8691666722297668, 0.873833358287811 3, 0.8743333220481873, 0.8690833449363708, 0.8713333606719971, 0.8762500286102295, 0.8793333172798157, 0.8767499923706055, 0.8804166913032532, 0.8774999976158142, 0.871916651725769, 0.877916693687439, 0.8771666884422302, 0.878083348274231, 0.8791666626930237, 0.8802499771118164, 0.8808333277702332, 0.8762500286102295, 0.8765000104904175, 0.8713333606719971, 0.8774999976158142, 0.8772500157356262, 0.8774166703224182, 0.878250002861023, 0.8778333067893982, 0.8803333044052124, 0.8758333325386047, 0.8756666779518127, 0.8794999718666077, 0.8813333511352539, 0.8806666731834412, 0.8709999918937683, 0.8765833377838135, 0.8798333406448364, 0.8809999823570251, 0.878333330154419, 0.8744166493415833, 0.8804166913032532, 0.8792499899864197, 0.879750013351440 4, 0.871999979019165, 0.8801666498184204]}

{‘loss’:[1回目の学習用データの損失,2回目の学習用データの損失,...,30回目の学習用データの損失],
‘accuracy’:[1回目の学習用データの正解率,2回目の学習用データの正解率,...,30回目の学習用データの正解率],
‘val_loss’:[1回目の検証用データの損失,2回目の検証用データの損失,...,30回目の検証用データの損失],
‘val_accuracy’:[1回目の検証用データの正解率,2回目の検証用データの正解率,...,30回目の検証用データの正解率]}

辞書型のデータの取得方法

print(result.history['loss'])

[0.6204796433448792, 0.4424095153808594, 0.4049777686595917, 0.3848289251327514 6, 0.3680422008037567, 0.3553660809993744, 0.344845145940780 64, 0.3349671959877014, 0.3256171345710754 4, 0.3206530511379242, 0.3141988515853882, 0.3085262775421142 6, 0.3008130192756653, 0.2942009568214416 5, 0.2915444374084472 7, 0.2869287729263305 7, 0.2810972929000854 5, 0.2808502316474914 6, 0.2766216099262237 5, 0.2701963186264038, 0.2698435187339782 7, 0.2669712901115417 5, 0.2611325383186340 3, 0.2576990425586700 4, 0.2550542652606964, 0.2521992623806, 0.2518135905265808, 0.2478162050247192 4, 0.2463666349649429 3, 0.2449819743633270 3, 0.2412831038236618, 0.2394535541534423 8, 0.2366907894611358 6, 0.2358267456293106, 0.2324295789003372 2, 0.2322139441967010 5, 0.2298291176557541, 0.2263198643922805 8, 0.2247573286294937, 0.2237249165773391 7, 0.2230272144079208 4, 0.2234239131212234 5, 0.2184654176235199, 0.2166386246681213 4, 0.2155087888240814 2, 0.2131433039903640 7, 0.2136351317167282, 0.2104269564151764, 0.2101719230413437, 0.2080526500940323]

出力結果は各エポックの誤差がリストになっている

x = [要素,要素,...,要素]

a = [1,1,3,3,3]
これはリスト型

x = {key:value,key:value,...,key:value}

b = {'name':'sudo','age':36}
これは辞書型

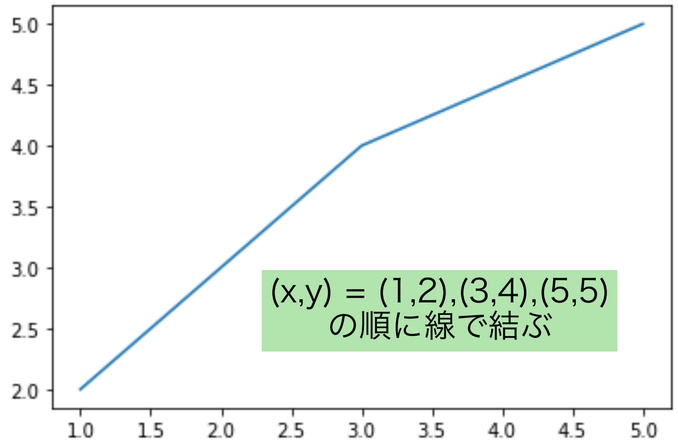
```
b = {'name':'sudo','age':36}
print(type(b))
print(b['name'])
print(b['age'])
```

```
<class 'dict'>
sudo
36
```

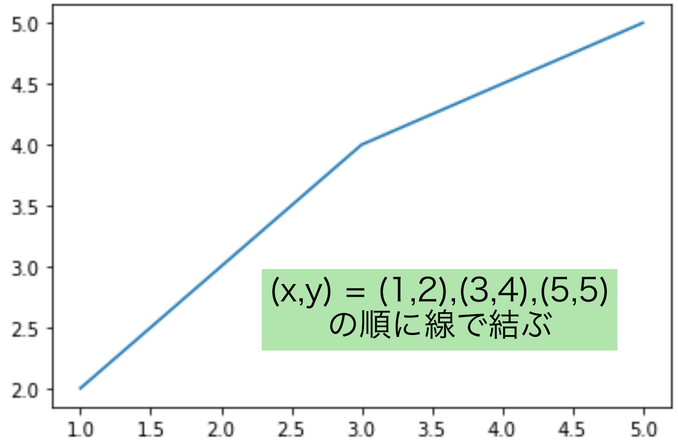
辞書型は変数名[key]で
valueを取り出せる!

result.history['loss']で{'loss':[〜〜], ...}の[〜〜]を取り出している

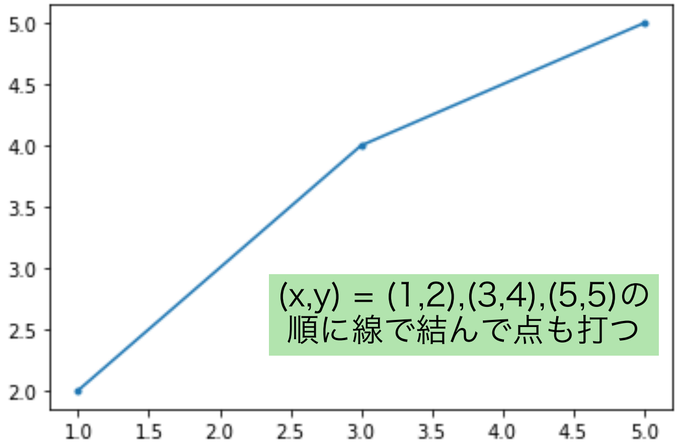
```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y)
plt.show()
```



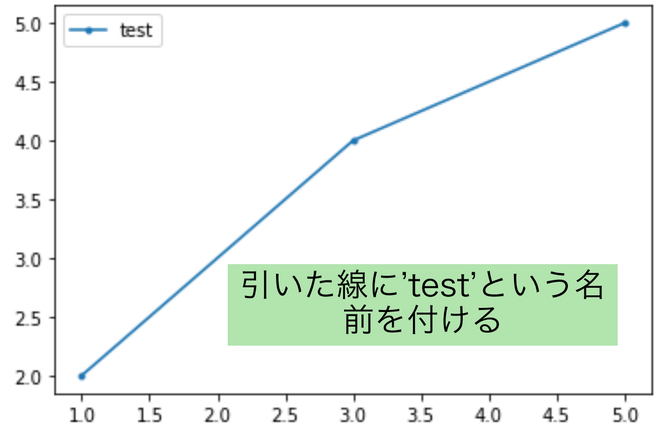
```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y)
plt.show()
```



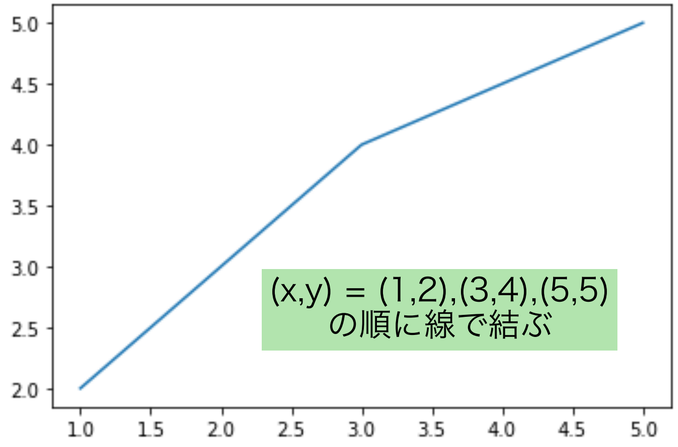

```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y,marker='.')
plt.show()
```



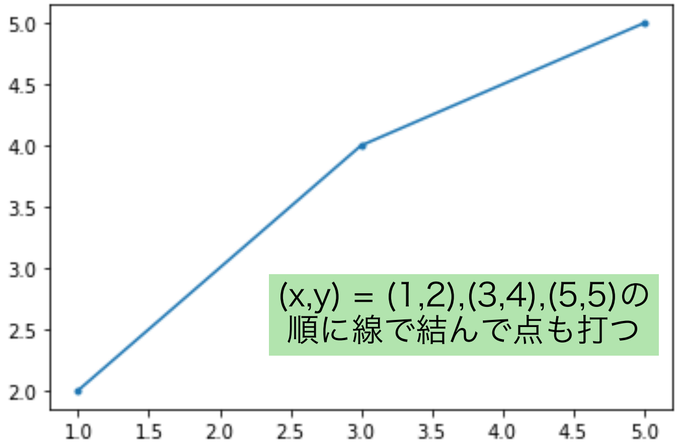

```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y,marker='.',label='test')
plt.legend()
plt.show()
```



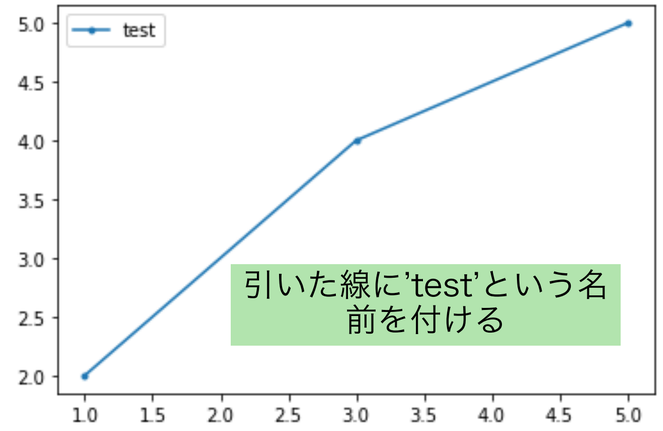
```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y)
plt.show()
```



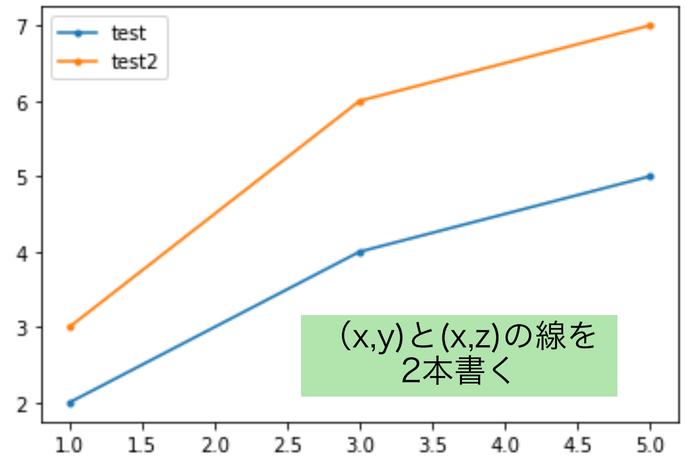

```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y,marker='.')
plt.show()
```



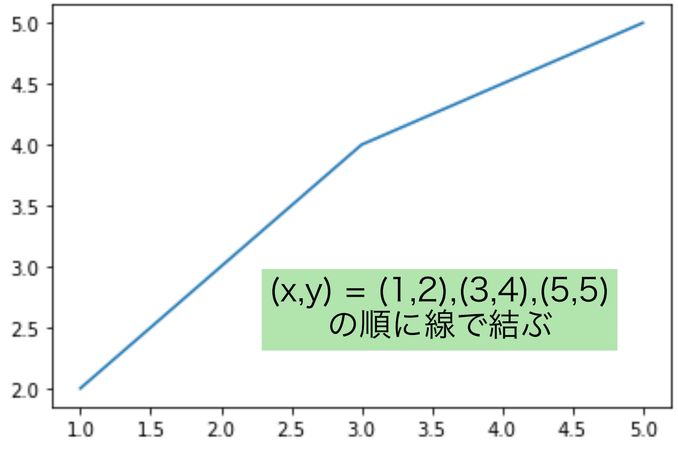

```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y,marker='.',label='test')
plt.legend()
plt.show()
```



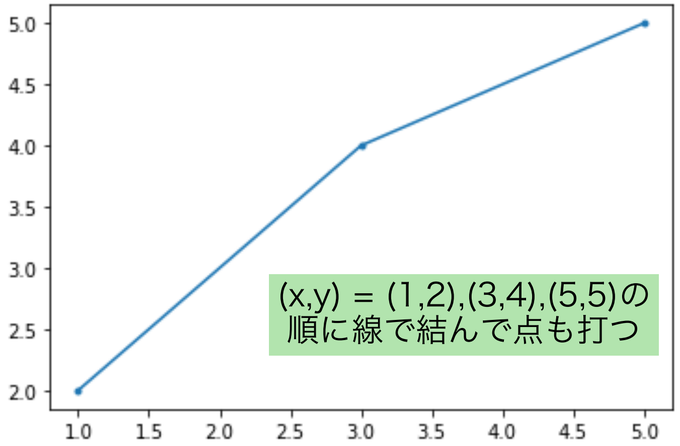

```
x = [1,3,5]
y = [2,4,5]
z = [3,6,7]
plt.plot(x,y,marker='.',label='test')
plt.plot(x,z,marker='.',label='test2')
plt.legend()
plt.show()
```



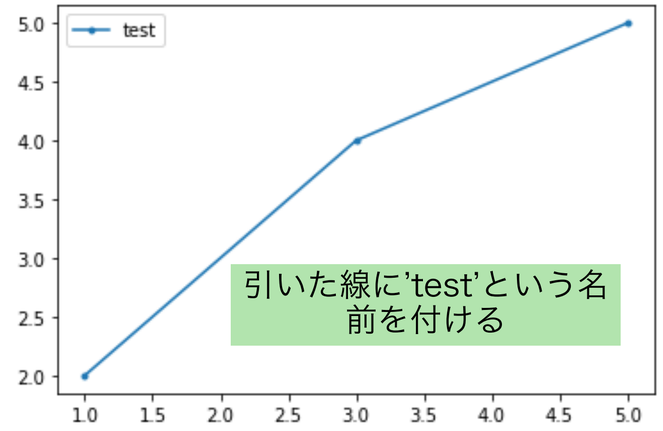
```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y)
plt.show()
```



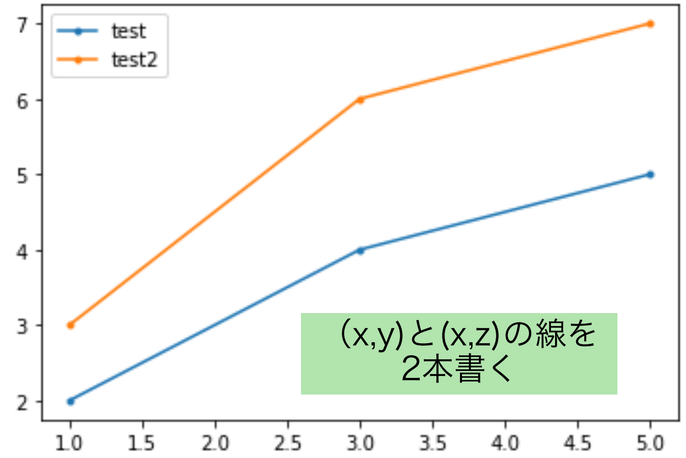

```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y,marker='.')
plt.show()
```



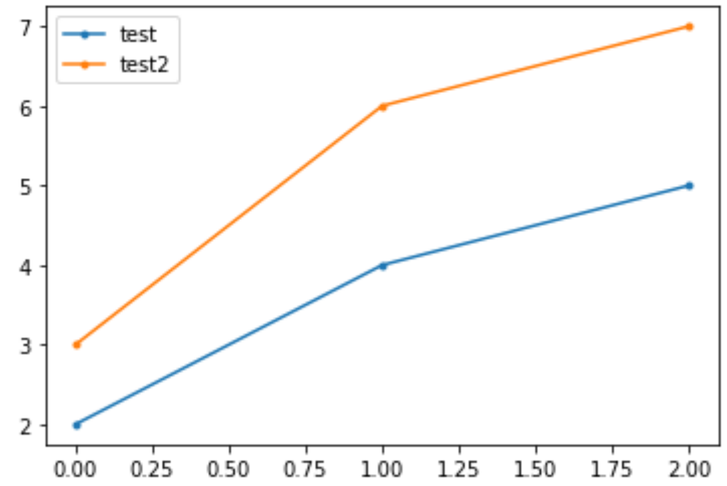

```
x = [1,3,5]
y = [2,4,5]
plt.plot(x,y,marker='.',label='test')
plt.legend()
plt.show()
```




```
x = [1,3,5]
y = [2,4,5]
z = [3,6,7]
plt.plot(x,y,marker='.',label='test')
plt.plot(x,z,marker='.',label='test2')
plt.legend()
plt.show()
```




```
y = [2,4,5]
z = [3,6,7]
plt.plot(y,marker='.',label='test')
plt.plot(z,marker='.',label='test2')
plt.legend()
plt.show()
```



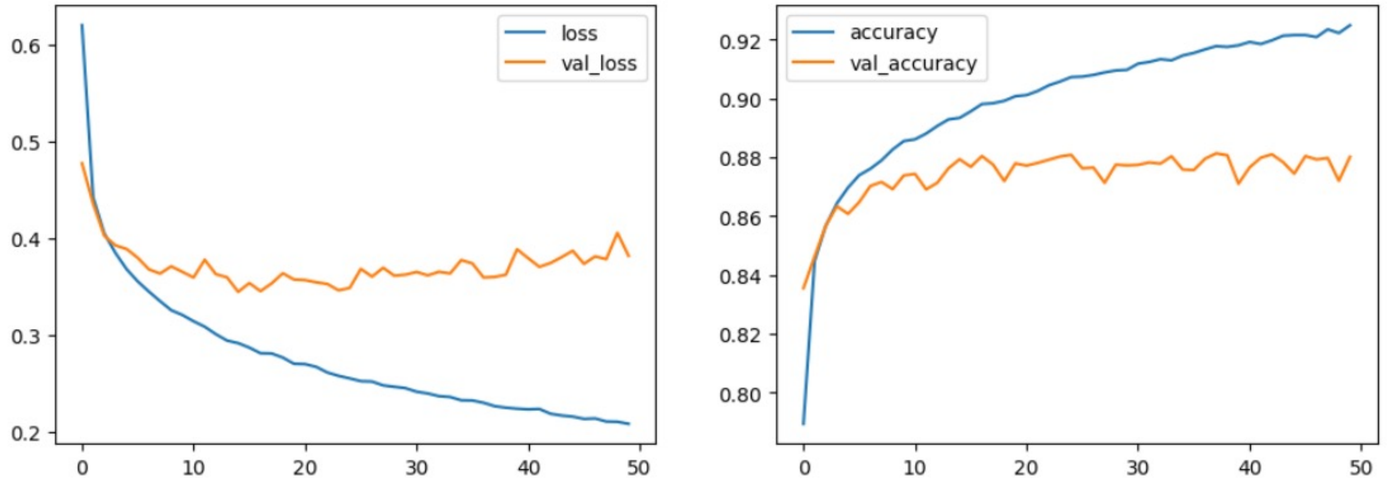
x軸の変数が与えられない時はy軸の個数だけ順に0,1,2,3,..と与えられる。

```
plt.plot(result.history['loss'],label='loss')
plt.plot(result.history['val_loss'],label='val_loss')
```


'loss': [0.6204796433448792, 0.4424095153808594, 0.4049777686595917, 0.3848289251327514 6, 0.3680422008037567, 0.3553660809993744, 0.34484514594078064, 0.3349671959877014, 0.3256171345710754 4, 0.3206530511379242, 0.3141988515853882, 0.30852627754211426, 0.3008130192756653, 0.2942009568214416 5, 0.29154443740844727, 0.28692877292633057, 0.28109729290008545, 0.280850231647491 46, 0.27662160992622375, 0.2701963186264038, 0.26984351873397827, 0.2669712901115417 5, 0.26113253831863403, 0.2576990425586700 4, 0.2550542652606964, 0.2521992623806, 0.2518135905265808, 0.24781620502471924, 0.2463666349649429 3, 0.2449819743633270 3, 0.2412831038236618, 0.23945355415344238, 0.2366907894611358 6, 0.2358267456293106, 0.2324295789003372 2, 0.2322139441967010 5, 0.2298291176557541, 0.2263198643922805 8, 0.2247573286294937, 0.2237249165773391 7, 0.2230272144079208 4, 0.2234239131212234 5, 0.218465417623519 9, 0.2166386246681213 4, 0.2155087888240814 2, 0.2131433039903640 7, 0.2136351317167282, 0.2104269564151764, 0.2101719230413437, 0.2080526500940323],

'val_loss': [0.4776163697242737, 0.4357101321220398, 0.4025885462760925 3, 0.3927147984504699 7, 0.388916492462158 2, 0.3798101842403412, 0.3678809702396393, 0.3634991049766540 5, 0.3710480630397796 6, 0.3652504086494446, 0.3594720363616943 4, 0.3778232038021087 6, 0.3629121482372284, 0.3596421778202057, 0.3446278870105743 4, 0.3536724448204040 5, 0.3453534245491028, 0.3533513247966766 4, 0.3638331294059753 4, 0.3573807775974273 7, 0.3567837774753570 6, 0.3544683754444122 3, 0.3527243733406067, 0.3461835086345672 6, 0.3486511111259460 4, 0.3683689832687378, 0.3603420555591583, 0.3695347905158996 6, 0.3612982034683227 5, 0.3623996675014496, 0.3652012944221496 6, 0.3616231977939605 7, 0.3653631210327148 4, 0.3636190593242645, 0.3774882853031158 4, 0.3739925920963287 4, 0.3594782650470733 6, 0.3600547611713409 4, 0.362317025661468 5, 0.3886697292327881, 0.3794552385807037 4, 0.3704958558082580 6, 0.3743937611579895, 0.3805387318134308, 0.3871587216854095 5, 0.3735528290271759, 0.3813273906707763 7, 0.3784124851226806 6, 0.4056456685066223, 0.3818448781967163],

どちらも要素の数が30個のリスト
xは[0,1,2,...,49]が省略されている



```
score = model.evaluate(x_test, y_test)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

model.evaluate()で評価

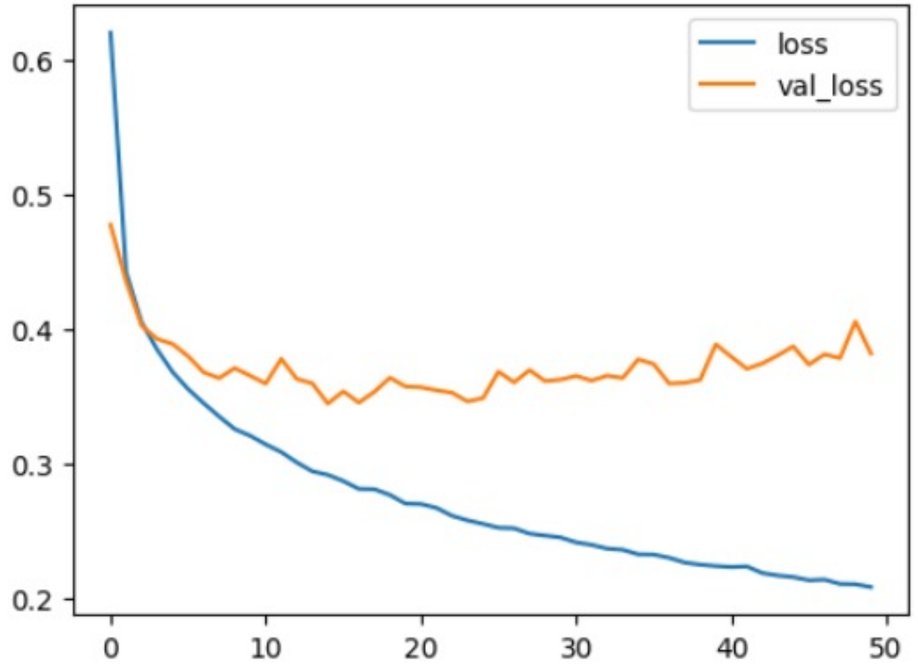
出来上がったモデルを別で用意している10000枚の画像で評価する

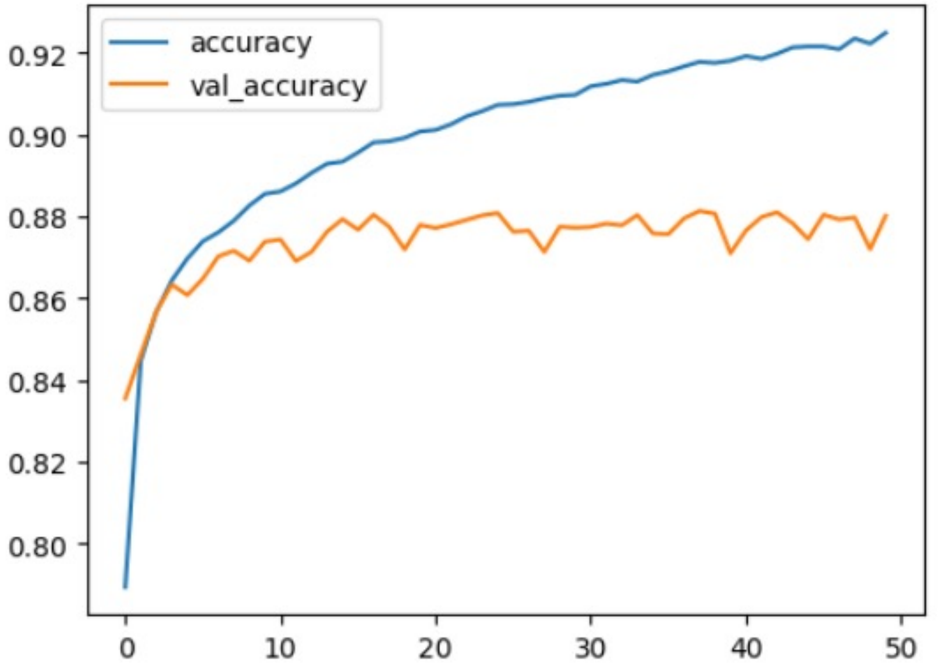
Test loss: 0.40565115213394165
Test accuracy: 0.8694000244140625

score = model.evaluate(特徴量,正解)
で、scoreにはmodelを用いた予測結果の損失と正解率が代入される
score[0]で損失、score[1]で正解率が得られる。

```
a = 5
print(a)          出力 5
print(‘aは’)      出力 aは
print(‘aは’,a)    出力 aは5
```

今回のモデルで学習した結果





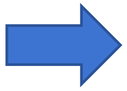
Test loss: 0.40565115213394165
Test accuracy: 0.8694000244140625

もっと精度をあげたい

ニューロンの数を増やす

```
model = Sequential()
model.add(Dense(32,input_shape=(784,),activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy’,
                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_12 (Dense)             (None, 32)                25120
_________________________________________________________________
dense_13 (Dense)             (None, 10)                330
=================================================================
Total params: 25,450
Trainable params: 25,450
Non-trainable params: 0
_________________________________________________________________
```

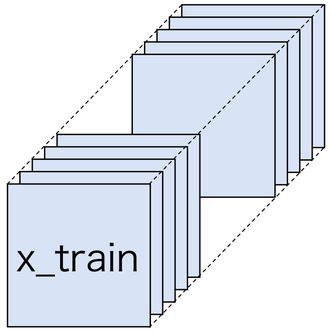


```
model = Sequential()
model.add(Dense(128,input_shape=(784,),activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy’,
                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

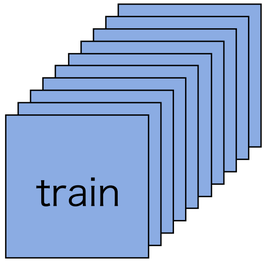
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 128)               100480
_________________________________________________________________
dense_9 (Dense)              (None, 10)                1290
=================================================================
Total params: 101,770
Trainable params: 101,770
Non-trainable params: 0
_________________________________________________________________
```

結果の分析

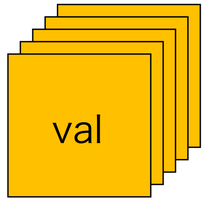
60000枚



48000枚

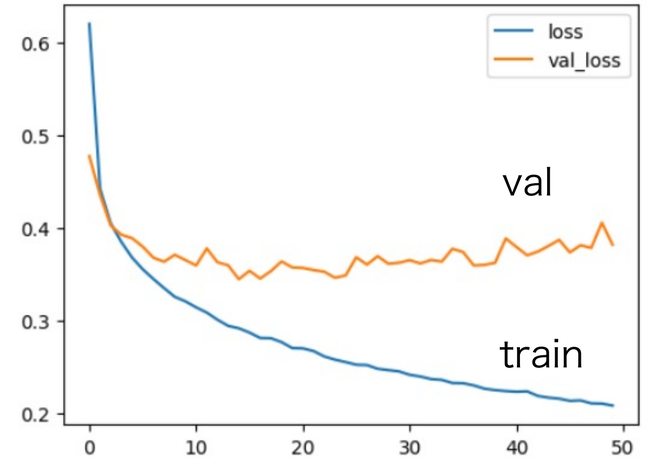


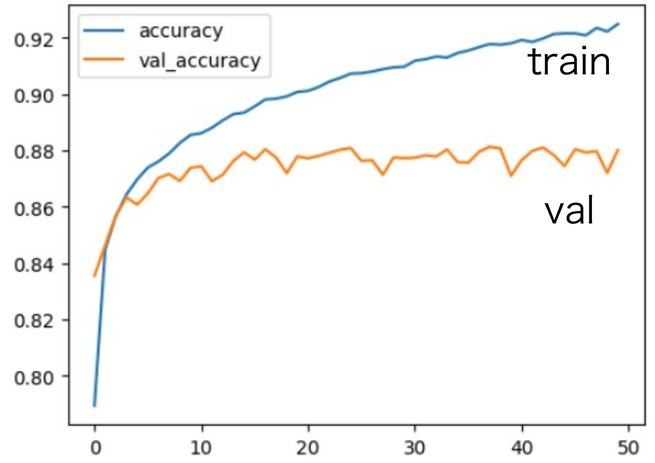
12000枚



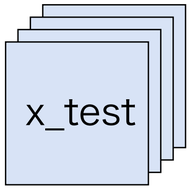
①trainを64枚ずつランダムに取り出して、学習、更新(750回/epoch)

②1epoch終了後、trainとval両方でlossとaccuracyを算出(50epoch)





10000枚



③最後にtestで最終評価
(lossとaccuracy)

Test loss: 0.40565115213394165
Test accuracy: 0.8694000244140625

result.historyの中身について

print(result.history)

{'loss': [0.6204796433448792, 0.4424095153808594, 0.4049777686595917, 0.38482892513275146, 0.3680422008037567, 0.3553660809993744, 0.34484514594078064, 0.3349671959877014, 0.32561713457107544, 0.3206530511379242, 0.3141988515853882, 0.30852627754211426, 0.3008130192756653, 0.29420095682144165, 0.29154443740844727, 0.2869287729263057, 0.28109729290008545, 0.28085023164749146, 0.27662160992622375, 0.2701963186264038, 0.26984351873397827, 0.2669712901154175, 0.26113253831863403, 0.25769904255867004, 0.2550542652606964, 0.2521992623806, 0.251813590526580 8, 0.24781620502471924, 0.24636663496494293, 0.24498197436332703, 0.2412831038236618, 0.2394535541534423 8, 0.2366907894611358 6, 0.2358267456293106, 0.23242957890033722, 0.2322139441967010 5, 0.229829117655754 1, 0.22631986439228058, 0.2247573286294937, 0.2237249165773391 7, 0.2230272144079208 4, 0.2234239131212234 5, 0.218465417623519 9, 0.2166386246681213 4, 0.2155087888240814 2, 0.2131433039903640 7, 0.213635131716728 2, 0.210426956415176 4, 0.210171923041343 7, 0.2080526500940323],

'accuracy': [0.789354145526886, 0.8447291851043701, 0.8566874861717224, 0.8643541932106018, 0.8697083592414856, 0.8739166855812073, 0.8761041760444641, 0.8789583444595337, 0.8826666474342346, 0.8855208158493042, 0.886104166507721, 0.8880624771118164, 0.8906458616256714, 0.8928750157356262, 0.8933958411216736, 0.8956249952316284, 0.898104190826416, 0.8983749747276306, 0.8991875052452087, 0.9007708430290222, 0.9011458158493042, 0.9025416374206543, 0.9044791460037231, 0.9057499766349792, 0.9072708487510681, 0.9074375033378601, 0.9079999923706055, 0.9088541865348816, 0.9095208048820496, 0.9097291827201843, 0.9118333458900452, 0.9124166369438171, 0.9133541584014893, 0.9129791855812073, 0.9146041870117188, 0.9154791831970215, 0.9166874885559082, 0.9177916646003723, 0.9175416827201843, 0.9180625081062317, 0.9192083477973938, 0.9185208082199097, 0.9197708368301392, 0.9213333129882812, 0.9215624928474426, 0.9215624928474426, 0.9208750128746033, 0.9235208630561829, 0.922249972820282, 0.9248958230018616],

'val_loss': [0.4776163697242737, 0.4357101321220398, 0.40258854627609253, 0.39271479845046997, 0.3889164924621582, 0.3798101842403412, 0.3678809702396393, 0.3634991049766540 5, 0.3710480630397796 6, 0.3652504086494446, 0.3594720363616943 4, 0.3778232038021087 6, 0.3629121482372284, 0.3596421778202057, 0.3446278870105743 4, 0.3536724448204040 5, 0.3453534245491028, 0.3533513247966766 4, 0.3638331294059753 4, 0.3573807775974273 7, 0.3567837774753570 6, 0.3544683754444122 3, 0.3527243733406067, 0.3461835086345672 6, 0.3486511111259460 4, 0.3683689832687378, 0.3603420555591583, 0.3695347905158996 6, 0.3612982034683227 5, 0.3623996675014496, 0.3652012944221496 6, 0.3616231977939605 7, 0.3653631210327148 4, 0.3636190593242645, 0.3774882853031158 4, 0.3739925920963287 4, 0.3594782650470733 6, 0.3600547611713409 4, 0.3623170256614685, 0.3886697292327881, 0.3794552385807037 4, 0.3704958558082580 6, 0.3743937611579895, 0.3805387318134308, 0.3871587216854095 5, 0.373552829027175 9, 0.3813273906707763 7, 0.3784124851226806 6, 0.4056456685066223, 0.3818448781967163],

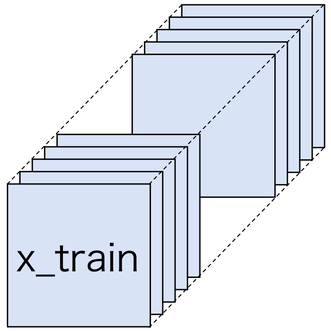
'val_accuracy': [0.8355000019073486, 0.8462499976158142, 0.8567500114440918, 0.8633333444595337, 0.8607500195503235, 0.8647500276565552, 0.8702499866485596, 0.8715833425521851, 0.8691666722297668, 0.8738333582878113, 0.8743333220481873, 0.8690833449363708, 0.8713333606719971, 0.8762500286102295, 0.8793333172798157, 0.8767499923706055, 0.8804166913032532, 0.8774999976158142, 0.871916651725769, 0.877916693687439, 0.8771666884422302, 0.878083348274231, 0.8791666626930237, 0.8802499771118164, 0.8808333277702332, 0.8762500286102295, 0.8765000104904175, 0.8713333606719971, 0.8774999976158142, 0.8772500157356262, 0.8774166703224182, 0.878250002861023, 0.8778333067893982, 0.8803333044052124, 0.8758333325386047, 0.875666677951812 7, 0.879499971866607 7, 0.8813333511352539, 0.8806666731834412, 0.8709999918937683, 0.8765833377838135, 0.8798333406448364, 0.8809999823570251, 0.878333333015441 9, 0.8744166493415833, 0.8804166913032532, 0.8792499899864197, 0.8797500133514404, 0.871999979019165, 0.8801666498184204]}

'loss': 0.2080526500940323,
'accuracy': 0.9248958230018616,

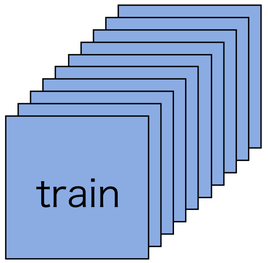
'val_loss': 0.3818448781967163,
'val_accuracy': 0.8801666498184204

結果の分析

60000枚



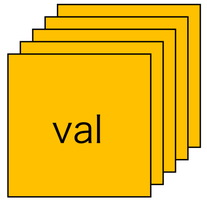
48000枚



①trainを64枚ずつランダムに取り出して、学習、更新(750回/epoch)

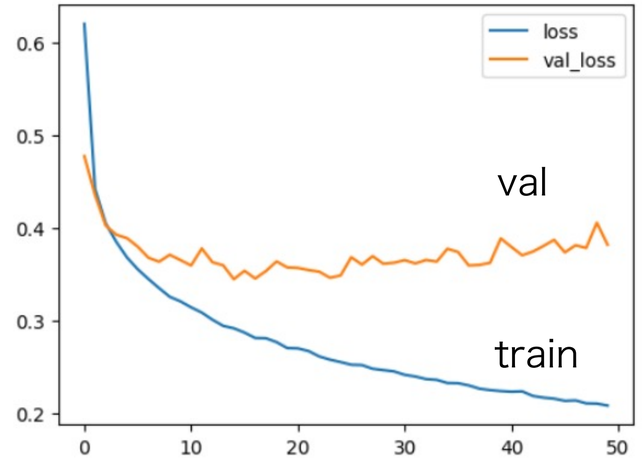
'loss': 0.21
'accuracy': 0.92

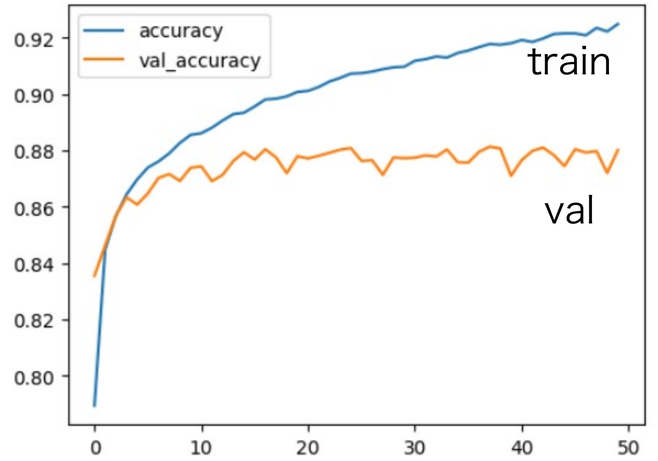
12000枚



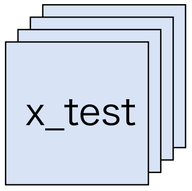
②1epoch終了後、trainとval両方でlossとaccuracyを算出(30epoch)

'val_loss': 0.38
'val_accuracy': 0.88





10000枚

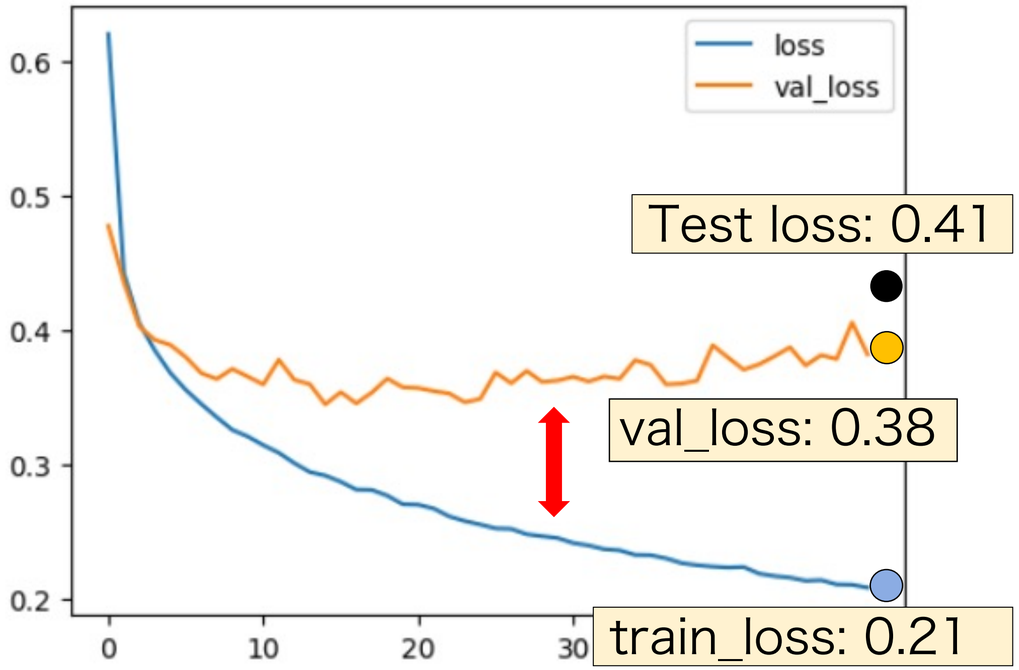


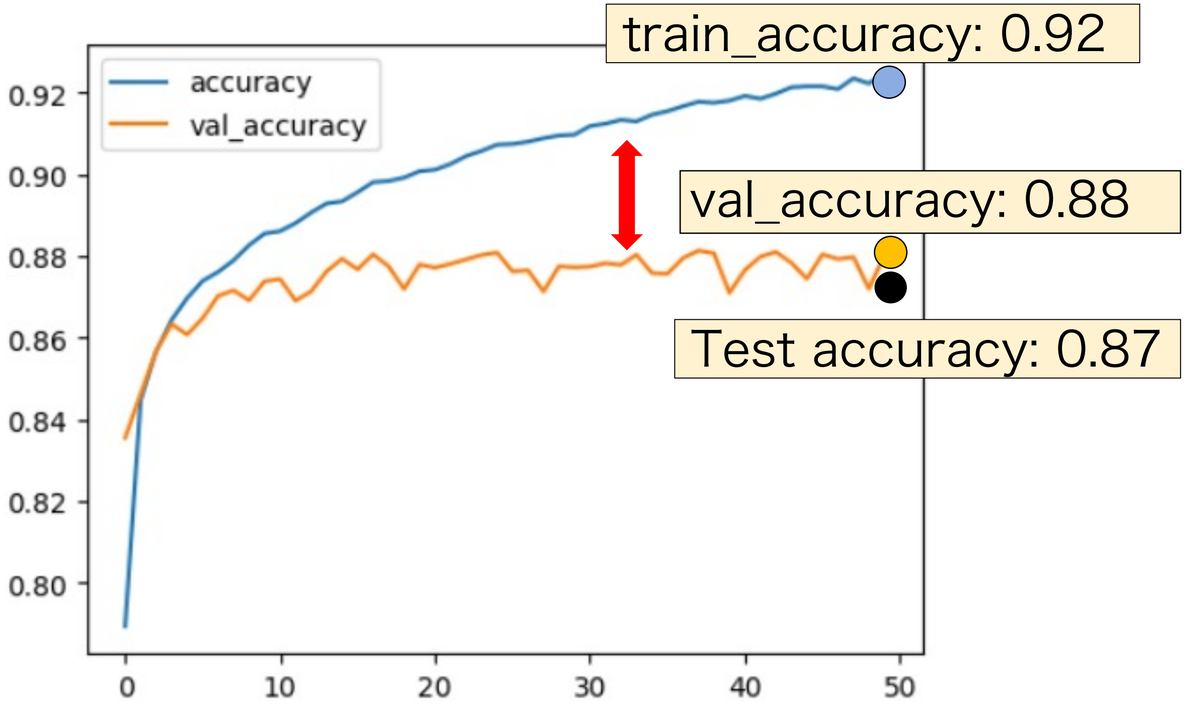
③最後にtestで最終評価
(lossとaccuracy)

Test loss: 0.41
Test accuracy: 0.87

Test loss: 0.40565115213394165
Test accuracy: 0.8694000244140625

trainはlossも小さくaccuracyも高いのに、valは精度が悪い (testも悪い)



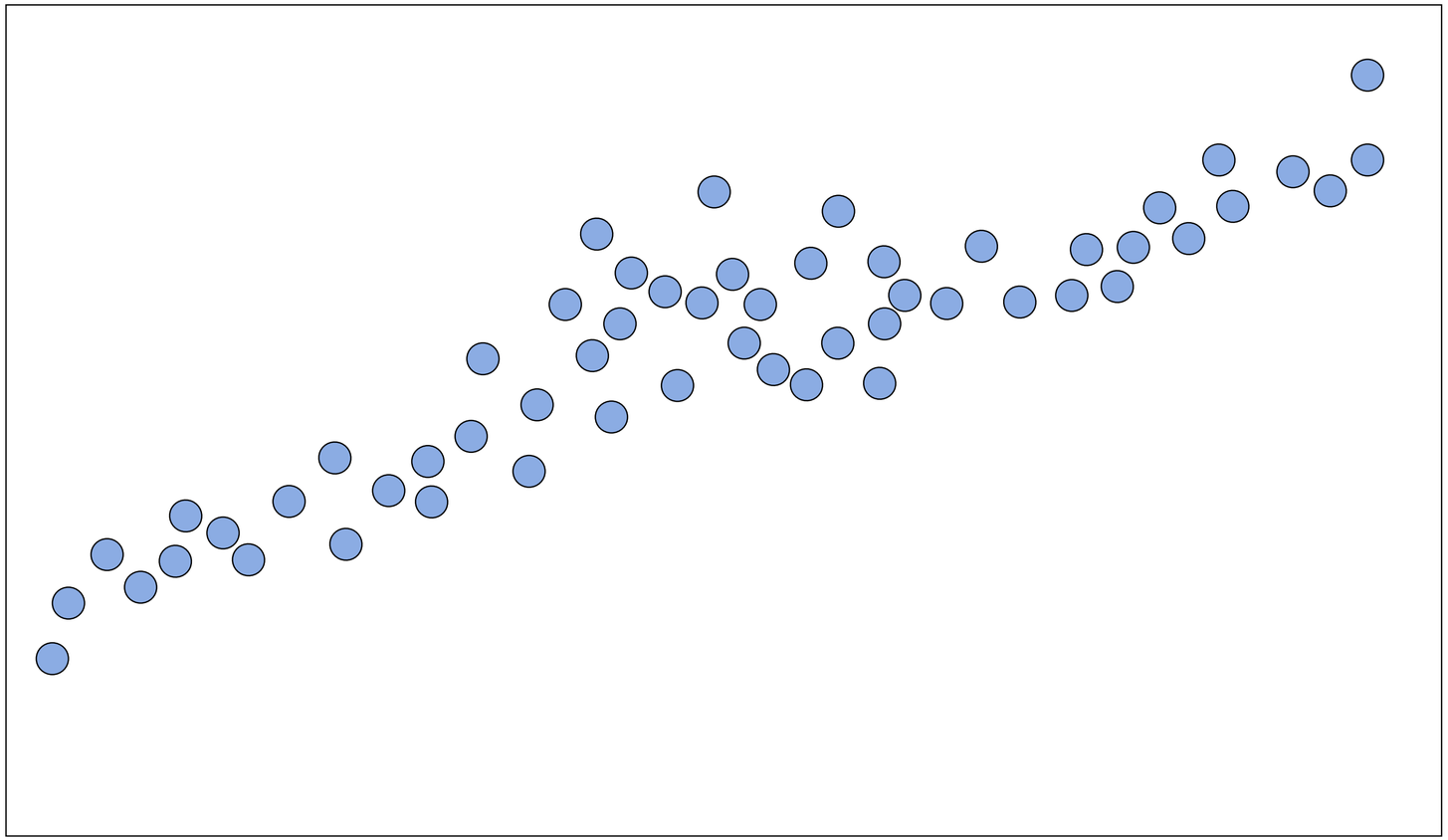


→ trainはうまく学習出来ているのに、valは出来ていない
→ trainのデータに合わせて学習し過ぎ

この状態を過学習と言う

学習のイメージ

学習はデータから当てはまりの良い関数(係数)を導く作業です



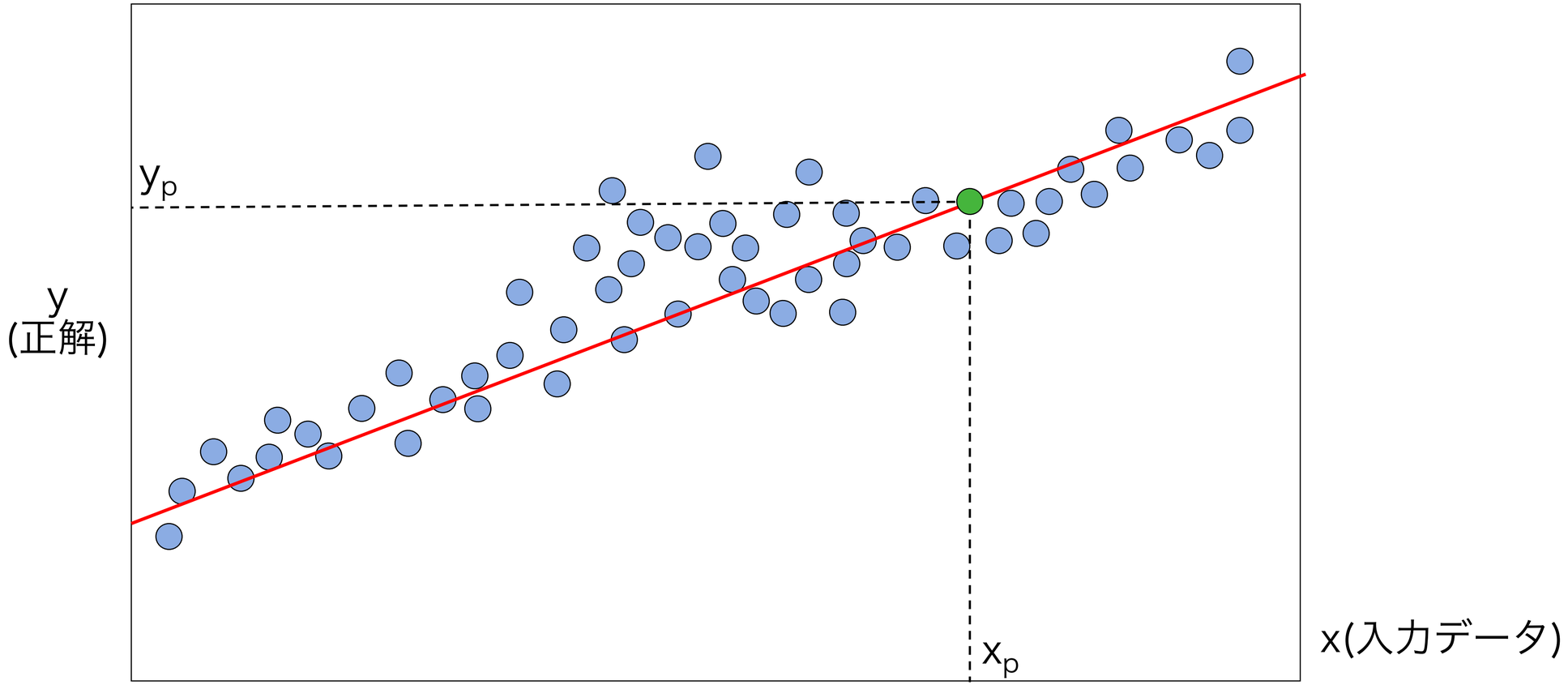
一番シンプルな線形回帰 $f_1(x)$ を想定します(xが増えるとyが一定の割合で増える)

$y = f_1(x) = a_1 x + a_2$　となり、このa_1とa_2を探します

深層学習のwがa_1、bがa_2に相当します

学習のイメージ

学習はデータから当てはまりの良い関数(係数)を導く作業です



a1とa2が求まると、図のような直線が求まるので、

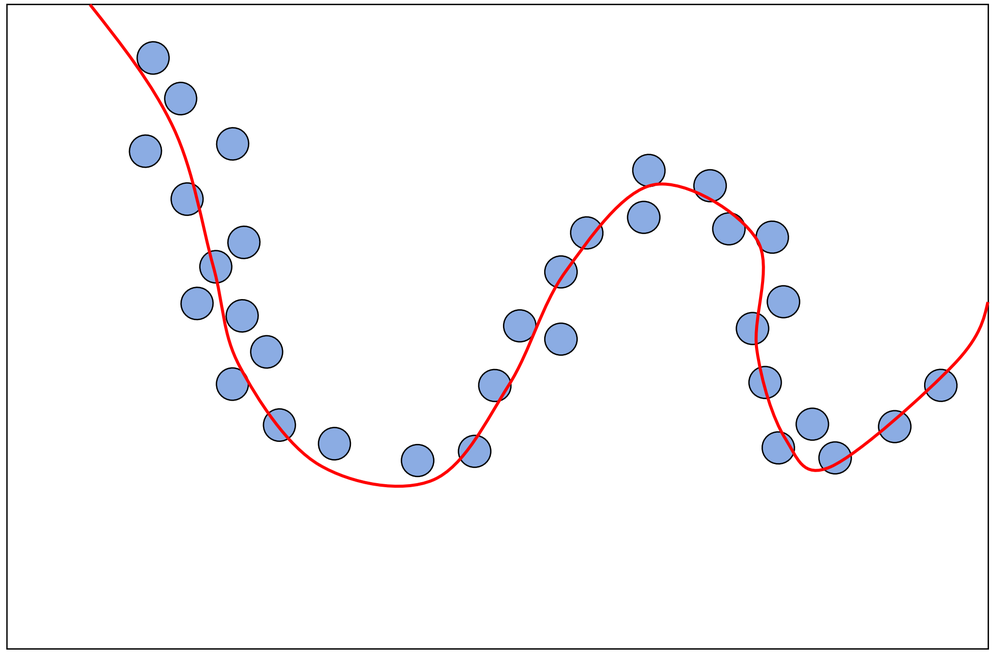
例えば x_pの時の予測結果y_pは、

$y_p = f(x_p) = a_1 x_p + a_2$　で予測することが出来ます

学習のイメージ

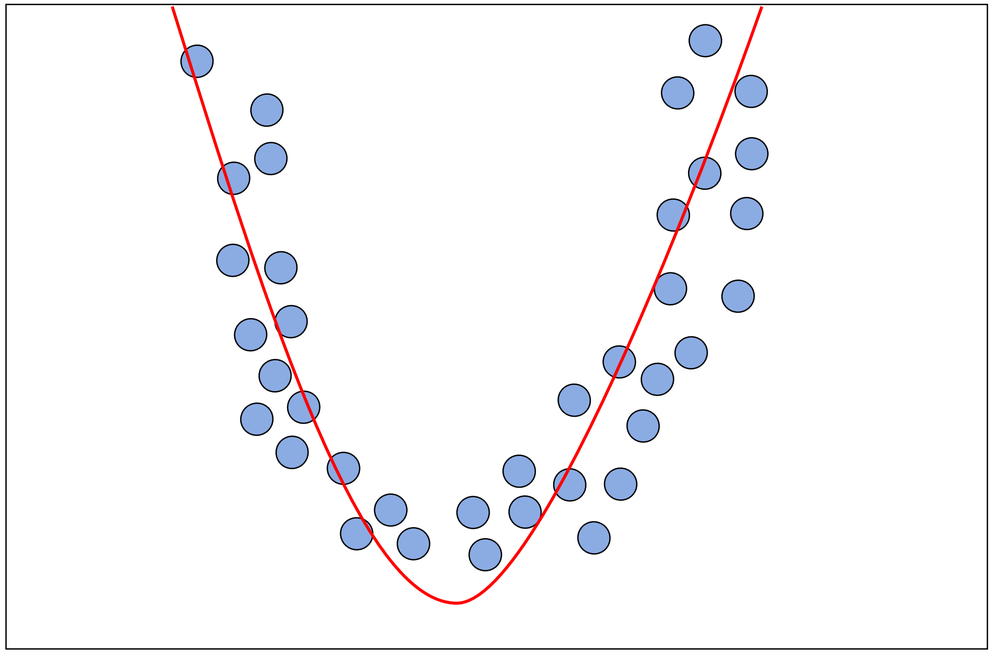
学習はデータから当てはまりの良い関数(係数)を導く作業です

y
(正解)



x(入力データ)

y
(正解)

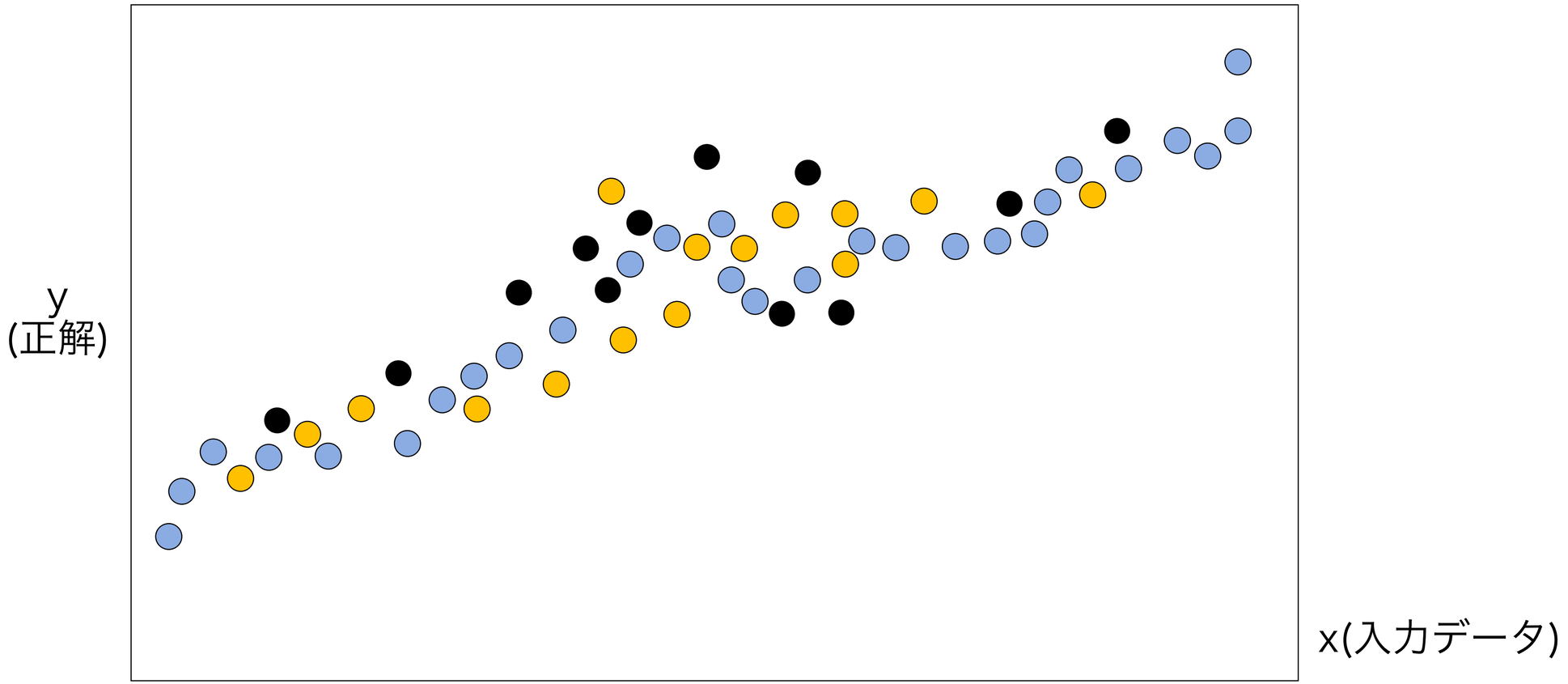


x(入力データ)

$y = a_1x + a_2$では(どんなa_1、a_2を与えても)直線にしかならない

曲線や3次元空間、4次元以上で表現出来るデータも適切な関数を設定すれば学習出来る

過学習のイメージ

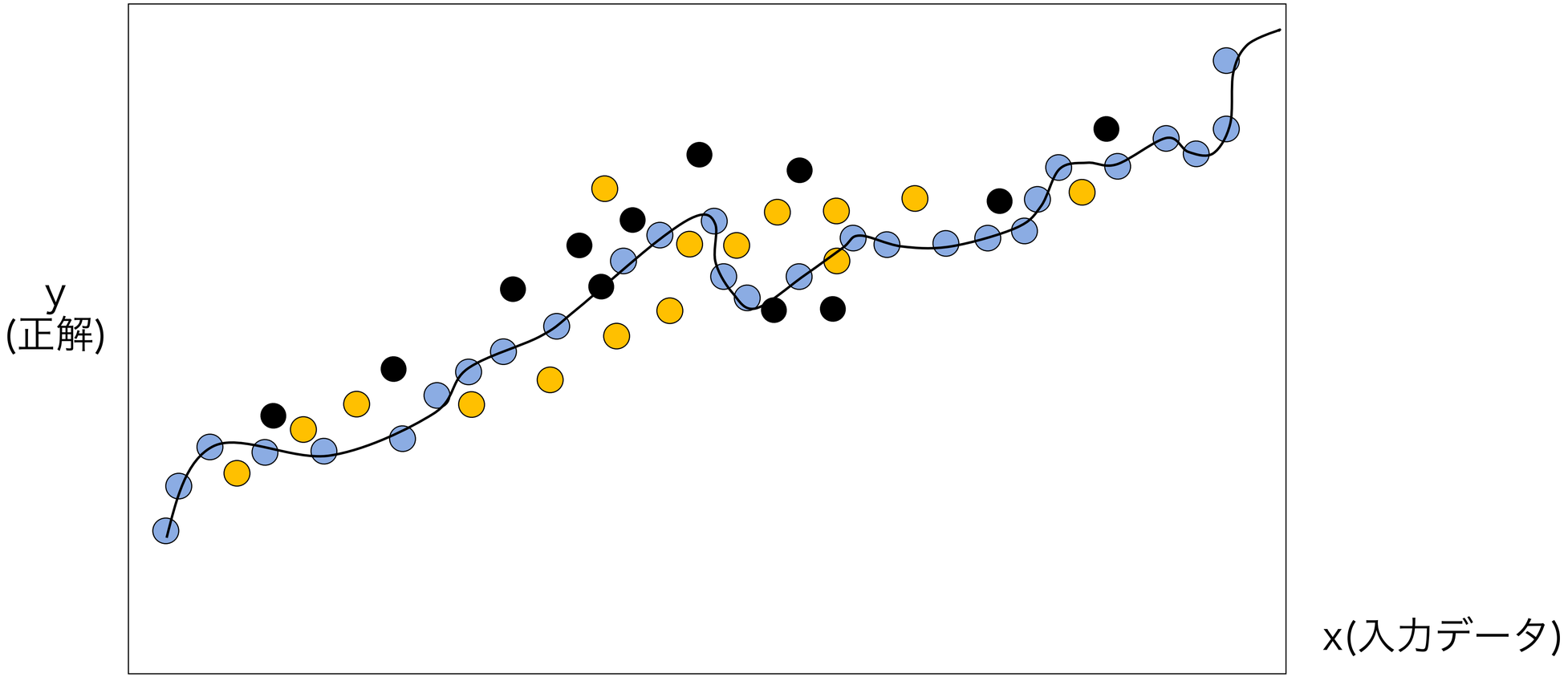


仮に深層学習のデータをまとめて2次元で表したとする
(本当は高次元で作図が難しい)

学習用データ　検証用データ　テスト用データ

過学習のイメージ

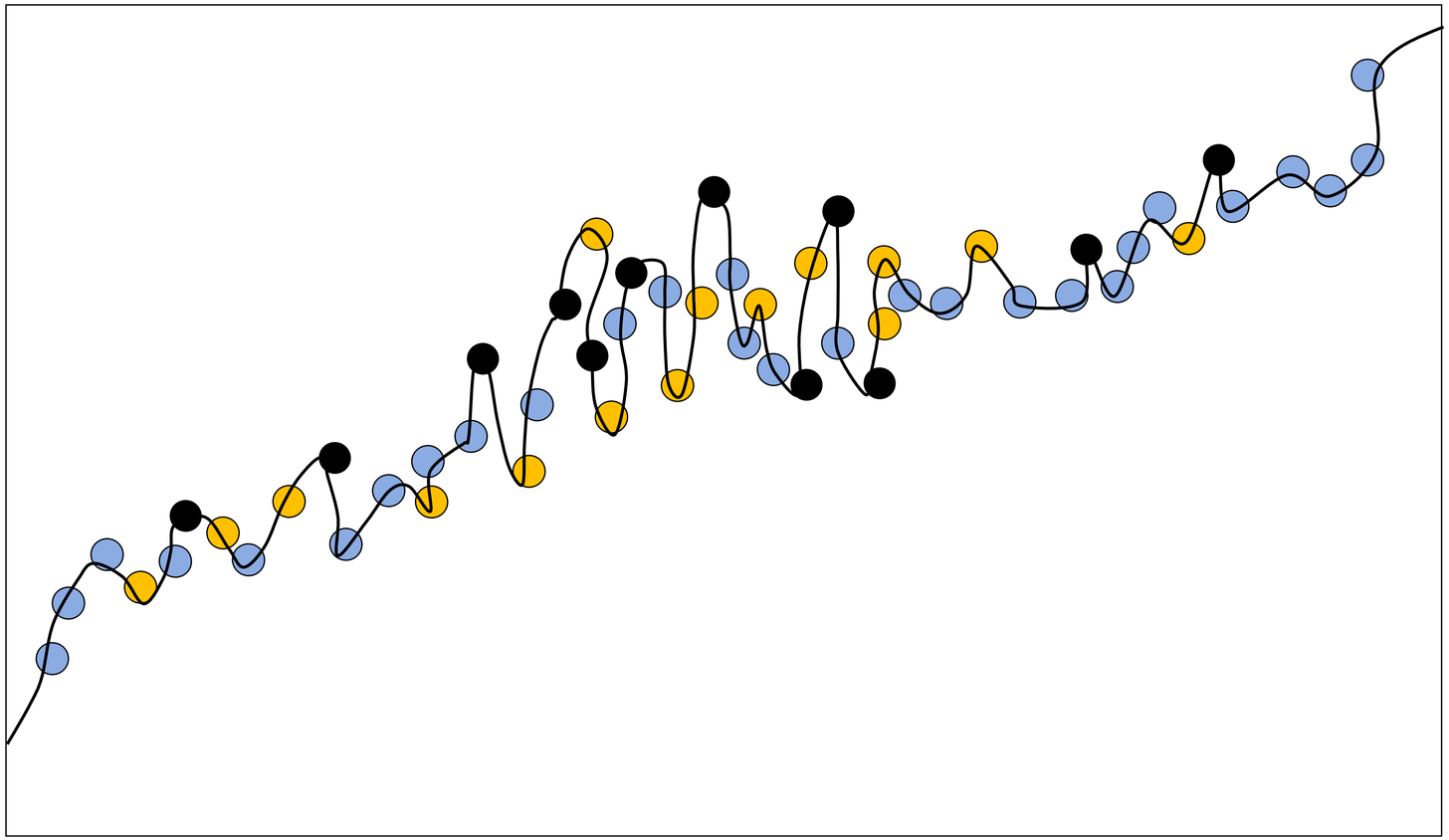
trainはlossも小さくaccuracyも高いのに、valは精度が悪い (testも悪い)



過学習はtrainのデータに合わせて学習し過ぎてしまった状態
この図だとtrainでは精度100%近いが、valやtestでは精度が落ちる

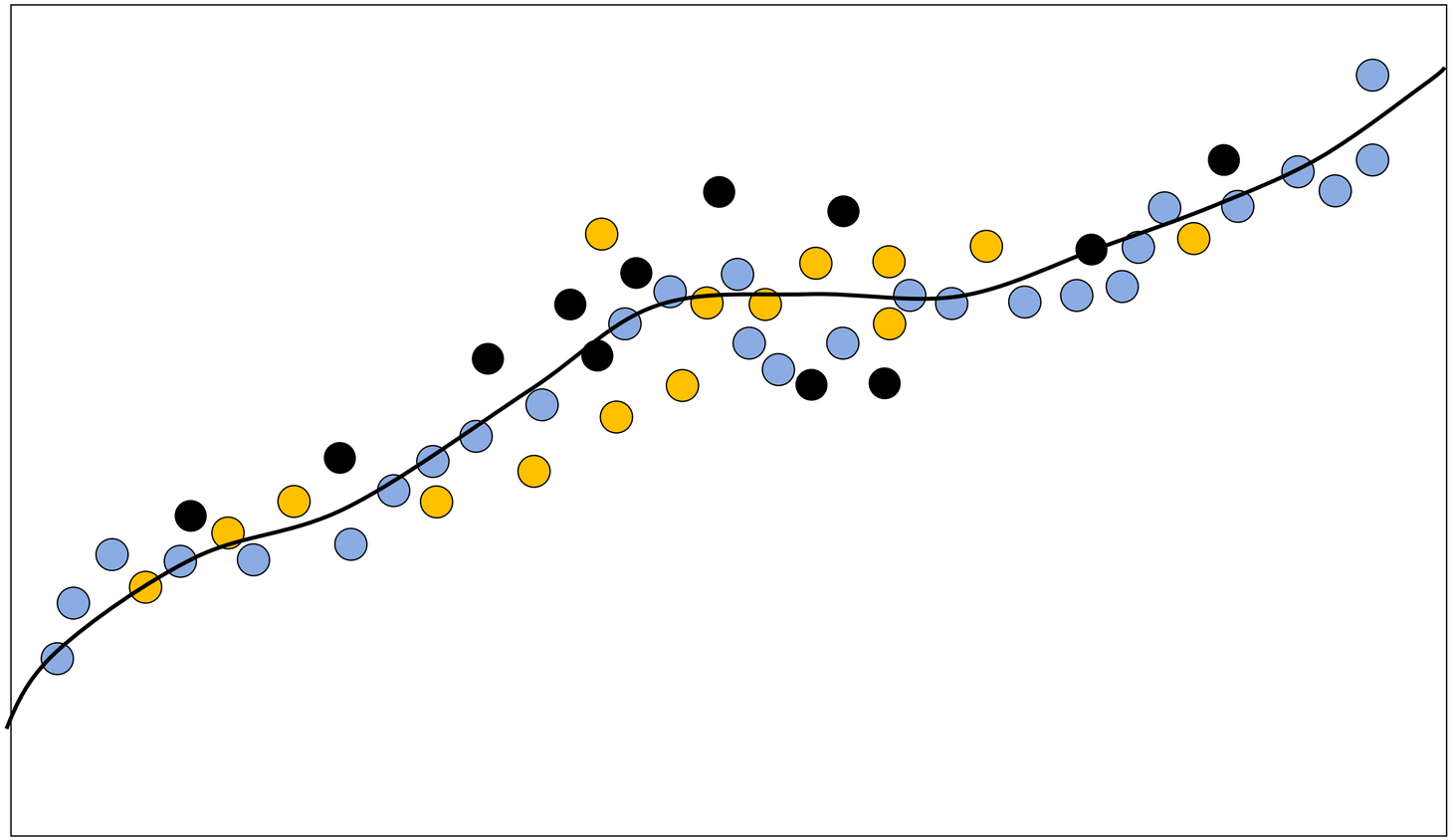
学習用データ　検証用データ　テスト用データ

完全に適合しているイメージ



実際はこのようにはなりません

過学習のイメージ



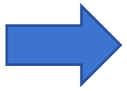
未知のデータでも精度が高くなるようなパラメータを探す作業

モデルの改変や学習用データに偏りがないかなど

ニューロンの数を増やす

```
model = Sequential()
model.add(Dense(32,input_shape=(784,),activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy’,
                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_12 (Dense)             (None, 32)                25120
_________________________________________________________________
dense_13 (Dense)             (None, 10)                330
=================================================================
Total params: 25,450
Trainable params: 25,450
Non-trainable params: 0
_________________________________________________________________
```



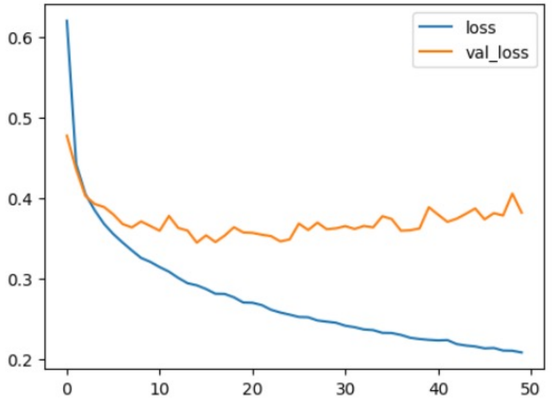
```
model = Sequential()
model.add(Dense(128,input_shape=(784,),activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy’,
                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

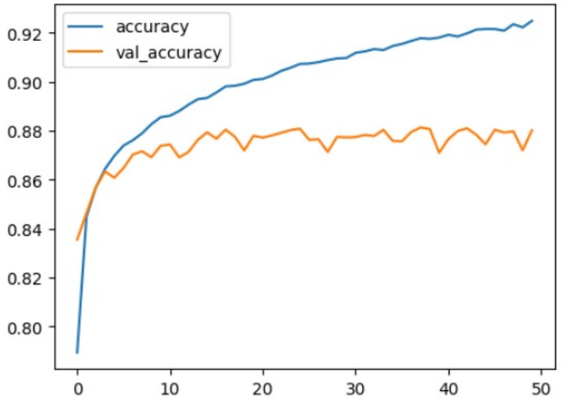
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 128)               100480
_________________________________________________________________
dense_9 (Dense)              (None, 10)                1290
=================================================================
Total params: 101,770
Trainable params: 101,770
Non-trainable params: 0
_________________________________________________________________
```

ニューロンの数を増やす

```
model = Sequential()
model.add(Dense(32,input_shape=(784,),activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy',
                    optimizer='Adam',metrics=['accuracy'])
model.summary()
```

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_12 (Dense)             (None, 32)                25120
_________________________________________________________________
dense_13 (Dense)             (None, 10)                330
=================================================================
Total params: 25,450
Trainable params: 25,450
Non-trainable params: 0
_________________________________________________________________
```

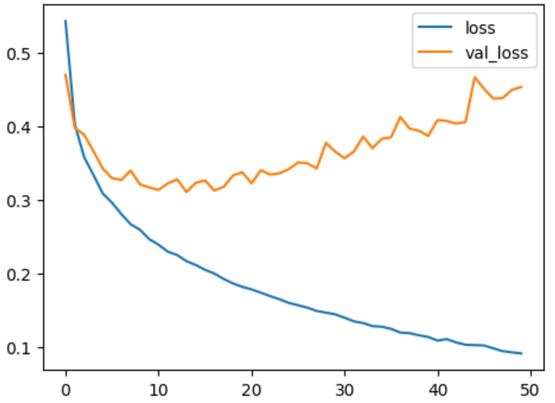


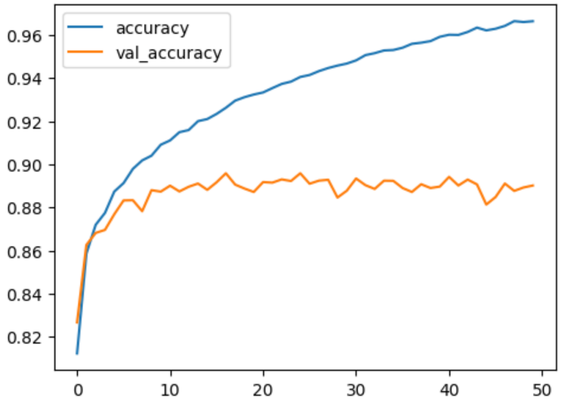


Test loss: 0.40565115213394165
Test accuracy: 0.8694000244140625

```
model = Sequential()
model.add(Dense(128,input_shape=(784,),activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy',
                    optimizer='Adam',metrics=['accuracy'])
model.summary()
```

```
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 128)               100480
_________________________________________________________________
dense_9 (Dense)              (None, 10)                1290
=================================================================
Total params: 101,770
Trainable params: 101,770
Non-trainable params: 0
_________________________________________________________________
```





Test loss: 0.4939178228378296
Test accuracy: 0.8852000236511123

層を追加してみよう

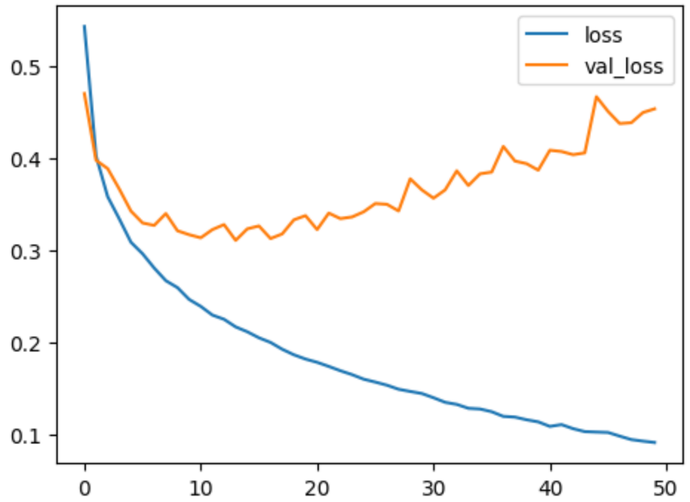
```
model = Sequential()
model.add(Dense(128,input_shape=(784,),activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy’,
                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

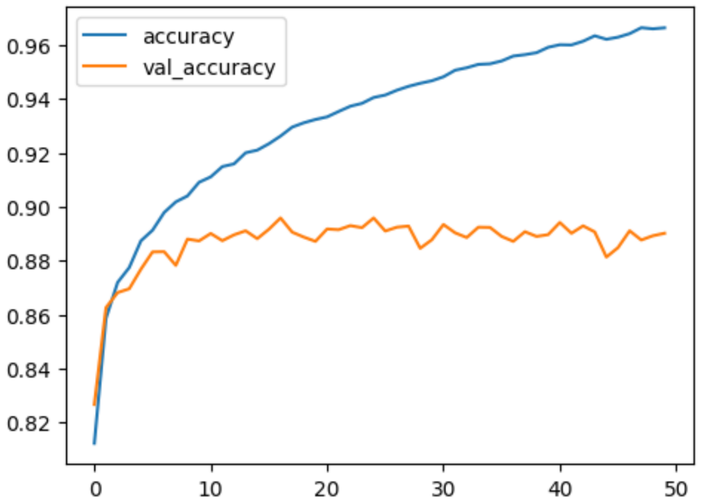
```
model = Sequential()
model.add(Dense(128,input_shape=(784,),activation='relu’))
model.add(Dense(64,activation='relu’))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy’,
                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 128)               100480
_________________________________________________________________
dense_9 (Dense)              (None, 10)                1290
=================================================================
Total params: 101,770
Trainable params: 101,770
Non-trainable params: 0
_________________________________________________________________
```

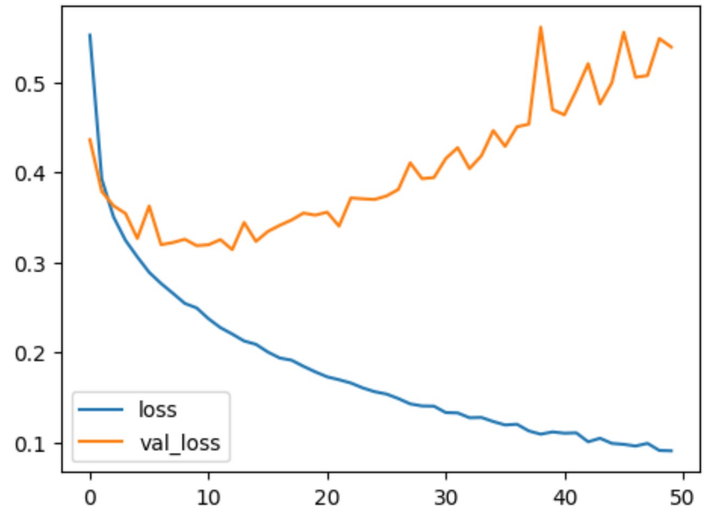
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 128)               100480
_________________________________________________________________
dense_5 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_6 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_7 (Dense)              (None, 10)                330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

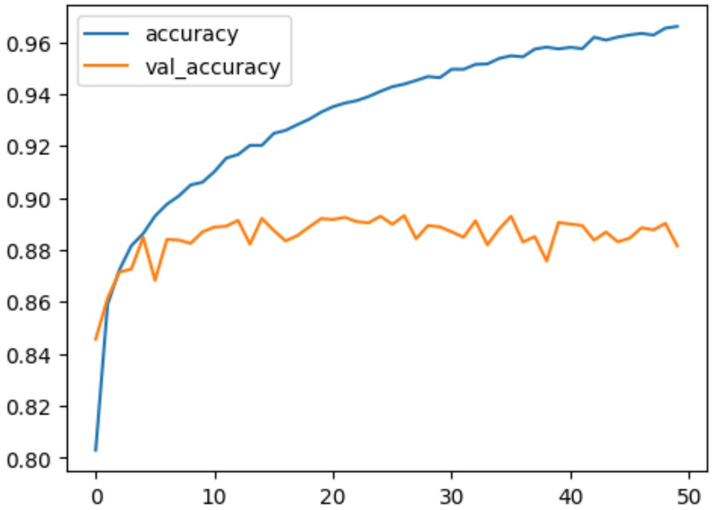
層を増やしても今回のデータでは精度あまり上がっていない





Test loss: 0.4939178228378296
Test accuracy: 0.885200023651123





Test loss: 0.5994181036949158
Test accuracy 0.877399810218811

なぜ過学習が起きるのか

モデルの複雑さ： モデルが非常に複雑である場合（例えば、パラメータが多すぎる）、そのモデルは訓練データのノイズまで学習してしまう。モデルがデータの真のパターンよりも、データに含まれるランダムな誤差や無関係な特徴を学習してしまう。

データの不足： 訓練データが不十分である場合、モデルは利用可能なデータに過剰に適合してしまう。十分なバリエーションのデータがなければ、モデルが一般化するための「良い」パターンを学ぶことができない。

トレーニングの長さ： トレーニングを長く続けすぎると、モデルが訓練データセットの特異性を学習し、新しいデータに対してうまく一般化できなくなる。

データの品質： データに偏りがあったり、誤った情報が含まれていたりすると、モデルが誤ったパターンを学習する原因となる。

Dropoutを加えてみよう

```
model = Sequential()
model.add(Dense(128,input_shape=(784,),activation='relu'))
model.add(Dense(64,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy',
                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

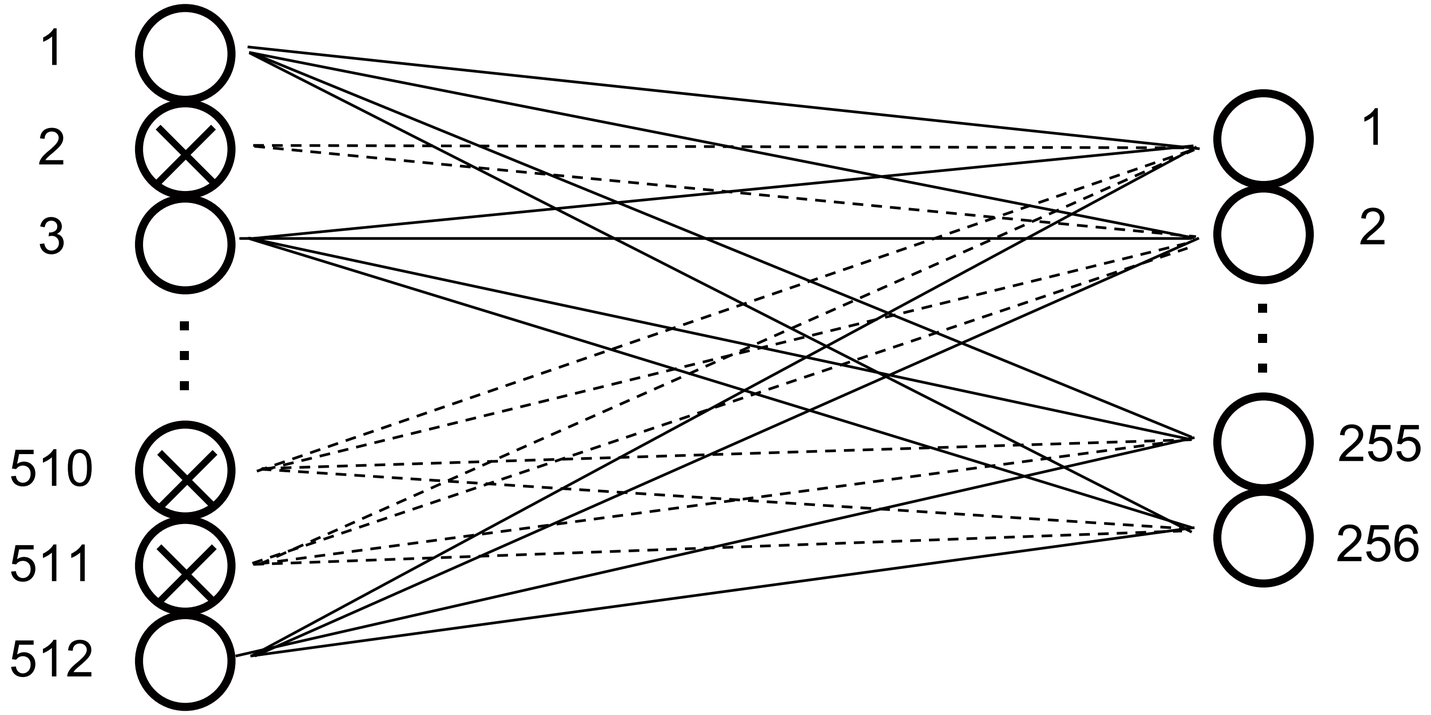
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 128)               100480
_________________________________________________________________
dense_5 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_6 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_7 (Dense)              (None, 10)                330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

```
from keras.layers import Dropout

model = Sequential()
model.add(Dense(128,input_shape=(784,),activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(64,activation='relu'))
model.add(Dense(32,activation='relu'))
model.add(Dense(10,activation='softmax'))
model.compile(loss='categorical_crossentropy',

                        optimizer='Adam',metrics=['accuracy'])
model.summary()
```

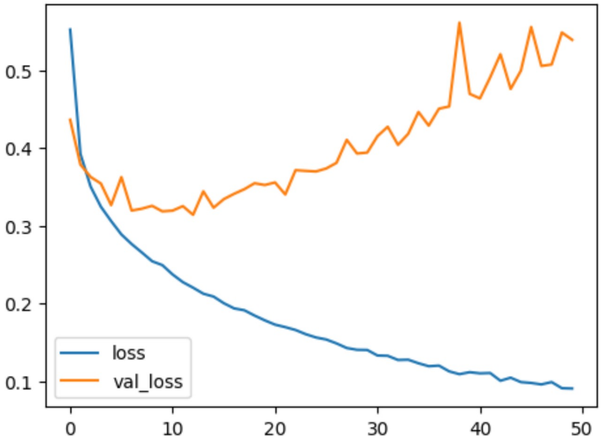
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 128)               100480
_________________________________________________________________
dropout (Dropout)            (None, 128)               0
_________________________________________________________________
dense_9 (Dense)              (None, 64)                8256
_________________________________________________________________
dense_10 (Dense)             (None, 32)                2080
_________________________________________________________________
dense_11 (Dense)             (None, 10)                330
=================================================================
Total params: 111,146
Trainable params: 111,146
Non-trainable params: 0
_________________________________________________________________
```

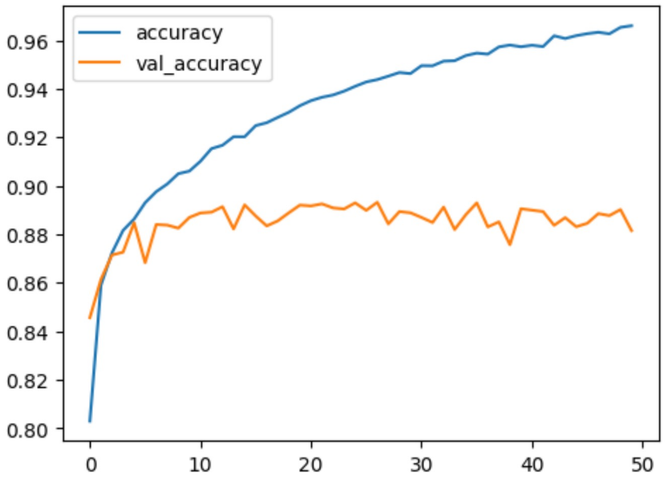
Dropout

過学習を防ぐための対策の1つで、学習時に設定した確率で出力を０にする手法。
推論時には何も行わず、学習時にのみ行われる。これにより、特定のニューロン
の評価だけに依存し過ぎることを避けて、より頑健な(=データの本質的な構造を捉えた)
特徴を学習することを促す。

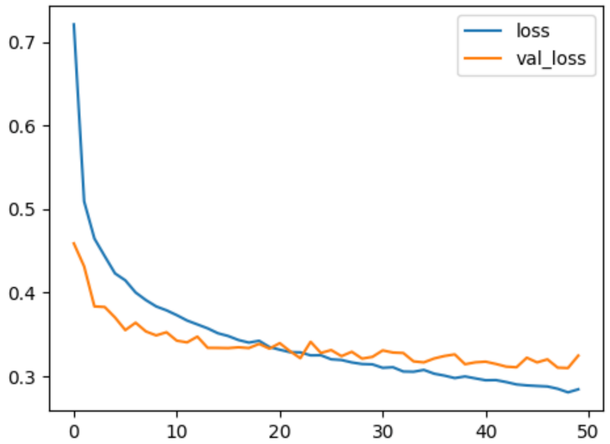


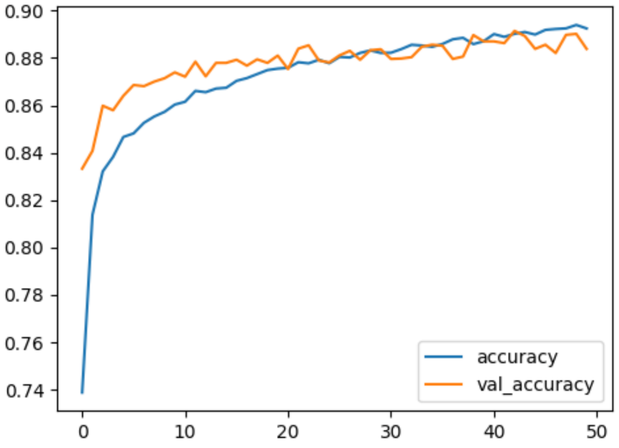
Dropoutを加えると過学習を抑制できる





Test loss: 0.5994181036949158
Test accuracy 0.8773999810218811





Test loss: 0.3330557644367218
Test accuracy: 0.8855000138282776

実際は過学習を抑えつつ精度をどれだけ上げられるかを検討する

層はいくらでも増やすことが出来ます。

色々試してみましょう。

Layer (type)	Output Shape	Param #
dense_12 (Dense)	(None, 256)	200960
dropout_1 (Dropout)	(None, 256)	0
dense_13 (Dense)	(None, 64)	16448
dense_14 (Dense)	(None, 128)	8320
dropout_2 (Dropout)	(None, 128)	0
dense_15 (Dense)	(None, 64)	8256
dense_16 (Dense)	(None, 32)	2080
dense_17 (Dense)	(None, 10)	330

Total params: 236,394
Trainable params: 236,394
Non-trainable params: 0

Test loss:
0.34160017967224121
Test accuracy:
0.88550001382827759

今回のデータの量、質だと
MLPではパラメータを増やし
ても90%以上の精度は
なかなか出にくいようです。

課題

・WebClassにある課題4をやりましょう

締め切りは1週間後の5/16の23:59です。
締め切りを過ぎた課題は受け取らないので注意して下さい。
(1週間後に正解をアップします)